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Cost-Price Relationships in a Concentrated Economy

Falk Bräuning, José L. Fillat, and Gustavo Joaquim

Abstract:
We use local projections with granular instrumental variables to estimate the aggregate pass-through of costs into prices and how it is affected by industry concentration. On average, we find, prices increase above trend growth for three quarters after an exogenous cost shock, and the price increase is accompanied by a decline in output. The estimated pass-through of the shock into prices one quarter ahead is 0.7. The price response to shocks becomes about 27 percent larger when there is an increase in concentration similar to the one observed over the last 20 years. This differential effect depending on concentration is primarily driven by a larger pass-through of positive shocks that increase costs. Consistent with a market power channel, margins decrease less in more concentrated industries after cost increases. Within industries, 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.

JEL Classifications: E30, E31, L11, L16

Keywords: cost-price pass-through, industry concentration, inflation, supply shock identification

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Falk Bräuning (Falk.Braeuning@bos.frb.org) and José L. Fillat (Jose.Fillat@bos.frb.org) are senior economists and policy advisors in the Federal Reserve Bank of Boston Research Department. Gustavo Joaquim (Gustavo.Joaquim@bos.frb.org) is an economist in the Federal Reserve Bank of Boston Research Department.

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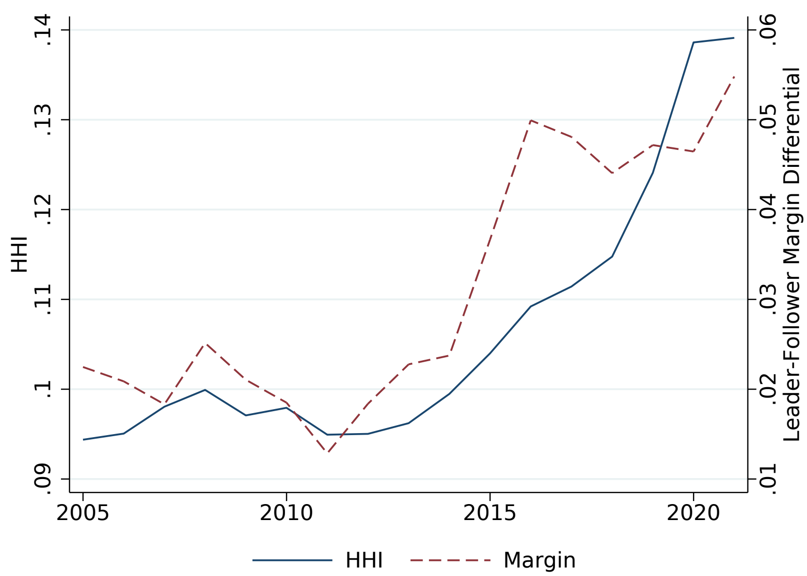
Introduction

One of the stark economic trends in the US economy is the rise in industry concentration during the last two decades (e.g., Gutiérrez and Philippon, 2017; Grullon, Larkin, and Michaely, 2019). Based on the Compustat data that we use in this study, Figure 1 shows that industry concentration increased about 50 percent from 2005 to 2020. During the same period, profit margins of industry leaders trended upward relative to the profits of other firms in their industry, consistent with the findings of Covarrubias, Gutiérrez, and Philippon (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-Hirschman 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. *Sources*: Compustat and authors' calculations.

[1]The results in Covarrubias, Gutiérrez, and Philippon (2020) 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 verify similar trends in concentration using the full US Census data; see Appendix Figure C.1.

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, Eeckhout, and Unger, 2020). In the context of recent supply shocks—for example, supply chain disruptions, commodity and energy price shocks, and a tight labor market—and related inflationary pressure, policymakers as well as academics have argued fiercely about the potential roles that concentration and market power play in the pass-through of costs.[2] While several recent papers explore the theoretical links between concentration and aggregate price dynamics, especially the pass-through of cost shocks into output prices, empirical evidence on this important question is limited.[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: (1) cost shocks cause prices to increase above trend growth for three quarters after impact before returning to trend; (2) the pass-through is 27 percent larger in more concentrated industries, and (3) the larger pass-through in concentrated economies is driven mostly by shocks that result in cost increases, while the pass-through of negative shocks is relatively muted regardless of concentration levels. We also find that firm-level profit margins decrease less in more concentrated industries and less for industry leaders in response to positive cost shocks.

Our empirical strategy exploits industry-level data on producer prices and real output from the US Bureau of Labor Statistics (BLS) in addition to firm-level data on sales and costs from the Compustat database.[4] Using data from 2005 through 2019, we estimate the

[2]See, for example, Romesh Vaitilingam, ”Inflation, Market Power, and Price Controls: Views of Leading Economists,” *VoxEU*, February 25, 2022, `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 industrial organization 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

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 developed by Gabaix and Koijen (2020). This approach builds on two key assumptions. First, granular firm-level data allow for the 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—that is, 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-time level as residuals from saturated regression models that include industry-by-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 US 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. The identified shocks to cost growth are also economically meaningful, with a standard deviation of about 6 percentage points.

Using these identified cost shocks, we first estimate the average pass-through into 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 the local (pre-shock) trend growth of costs. Our findings show that cost shocks cause an economically and statistically

on prices is also most relevant for wholesale prices (Gopinath and Itskhoki, 2011).

[5]For example, as we discuss below, the identified idiosyncratic cost changes may be related to a revaluation of inventory or an implementation of firm-specific cost savings plans described in a company's 10-Q filings or in the annual reports available to investors.

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 percent 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 directly observed cost measures (endogenous) lead to attenuated estimates close to 0, highlighting the importance of using exogenous variation in costs for identification. As a robustness exercise for our baseline GIV identification, we use industries' heterogeneous exposure to imported inputs (directly and through the input-output linkages) coupled with shocks to (1) exchange rates or (2) global supply chain disruptions as alternative measures of cross-industry variation in costs. We find qualitatively similar results.

Crucially, we find that the pass-through of cost shocks to prices becomes larger 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 do so by altering our local projection models to (1) allow for industry-specific slope coefficients on the cost shock and to (2) include an interaction term between the cost shock and the Herfindahl-Hirschman Index (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 using different measures of industry concentration. The economic significance of the effect is also large: The pass-

[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, Eeckhout, and Unger, 2020).

[7]The empirical pass-through literature, exploiting shocks to specific inputs and/or specific industries, finds estimates well below 1.0 (e.g., Nakamura and Zerom, 2010), close to 1.0 (e.g., Fabra and Reguant, 2014), and greater than 1.0 (e.g., Miller, Osborne, and Sheu, 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.

through is 27 percent larger in an economy with a higher concentration of a magnitude similar to the increase observed during our sample period of 2005 through 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 increase with concentration. Along with the larger pass-through into prices, we also find that output drops significantly more in concentrated industries, lending additional credibility to the supply interpretation. Importantly, we find that the increase in prices is relatively larger relative to the decrease in output, which implies that demand is more inelastic in more concentrated industries. Moreover, in robustness tests, we verify that our differentially larger pass-through depending on concentration holds for the cost shocks derived from industries' heterogeneous exposure to imported inputs as described above.

We further extend our model to allow for an asymmetric pass-through of cost shocks depending on the sign of the shock. Across industries, we do not find that there is, on average, significant asymmetric pass-through. However, our results show that the pass-through of positive cost shocks (increases in cost) into prices is larger in more concentrated industries, while the pass-through of negative cost shocks into prices does not differ significantly across different levels of industry concentration. The asymmetric effects that we find are consistent with standard models because the cost shocks that we measure are economically large: The standard deviation of our cost shock measure accounts for 6 percentage points of the average growth in firms' costs, as discussed below.[8]

To better understand the economic mechanism, we estimate how operating margins respond to cost shocks using firm-level data. We show that cost shocks significantly reduce margins, on average, across all firms and industries, in line with a pass-through smaller than 1.0. But a within-industry analysis reveals that, consistent with the effects of market power, the decline in the margins of industry leaders (the top five firms in an industry according to sales) is significantly muted in more concentrated industries. In fact, industry leaders are

[8] The fact that we find asymmetric effects only in more concentrated industries is consistent with the idea that the higher the concentration is, the more convex the pricing function is. See Ritz (forthcoming).

able to shield their profit margins entirely from cost shocks. In light of the large asymmetric pass-through into prices and output at the industry level, we also estimate asymmetric margin responses at the firm level. The results indicate that positive cost shocks drive the average responses of margins, which is in line with the price and output responses. Finally, we find evidence that industry 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 examine firm-level prices, we do find a nonlinear relationship between firm size and margins, as larger firms retain higher margins compared with small firms after a given cost shock. This is consistent with the nonlinear relationship between pass-through and firm size documented at the firm level in Feenstra, Gagnon, and Knetter (1996) and Garetto (2016).

Related Literature. Our paper contributes to various strands of the macro 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. Studies find that various secular trends can be partially attributed to the increase in industry concentration and in market power, such as the decrease in labor share (e.g., De Loecker, Eeckhout, and Unger, 2020; Barkai, 2020), the increase in savings supply (Farhi and Gourio, 2018), underinvestement (Gutiérrez and Philippon, 2017), and overall aggregate productivity growth (e.g., Liu, Mian, and Sufi, 2022; Farhi and Gourio, 2018). A closely related literature documents the rise of superstar firms and the implications for aggregate dynamics (e.g., Olmstead-Rumsey, 2019; Autor, Dorn, Katz, Patterson, and Van Reenen, 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 affect macroeconomic outcomes.

Second, this project also contributes to the large literature on estimating cost pass-through. The empirical literature focuses mostly on specific cost shocks (those involving, for example, exchange rates, taxes, fuel and energy prices, or minimum wage) and/or specific industries.[9] We contribute to this literature by estimating the cost pass-through for industry-wide shocks to all operating expenses in a broad set of industries. Our finding of an almost complete pass-through occurring one period ahead contrasts with the finding of incomplete pass-through that typifies most of the exchange-rate pass-through literature (e.g., Koujianou Goldberg and Hellerstein, 2013). Nakamura and Zerom (2010) estimate that non-traded costs and strategic considerations—both of which are captured in our aggregate analysis—account for most of the incomplete pass-through.

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 at both the firm and industry levels. At the firm level, the standard intuition (for example, from a textbook Cournot model) is that greater market power makes prices *less* cost-reflective and hence reduces the magnitude 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 also finds different signs 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, Itskhoki, and Konings, 2019, and Baqaee and Farhi, 2020). Therefore, the relationship between market structure and industry and aggregate pass-through is also ambiguous. Our empirical results discipline this theoretical

[9]See Goldberg and Knetter (1997) and 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, Osborne, and Sheu (2017), and Ganapati, Shapiro, and Walker (2020), among many others.

[10]For instance, Ritz (forthcoming) shows that the usual intuition can be overturned 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, whereas Miller, Osborne, and Sheu (2017), Ganapati, Shapiro, and Walker (2020), and Harasztosi and Lindner (2019) find that market power increases pass-through.

ambiguity. Our estimation leverages industry-level cost shocks and thus speaks directly to a combination of the underlying demand elasticity, 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. A longstanding literature, following the seminal paper by Peltzman (2000), studies asymmetric pass-through of costs into prices. The main finding 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 (for example, 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, especially when cost shocks are not infinitesimal. The author shows that such convexities may arise in both perfect and imperfect competition. Hence, one cannot identify whether a market is competitive from the asymmetry of the cost response alone. Although we cannot 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 is symmetric on average, and 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. Thus, our findings are consistent with the presence of a more concave demand with increasing elasticity in more concentrated economies where a large positive cost shock results in a larger increase in prices compared with the effect of a similarly sized negative cost shock. Conversely, more competitive environments feature a less concave demand function with a symmetric pass-through.

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, Levchenko, and Mejean, 2014; Carvalho and Grassi, 2019; Gaubert and Itskhoki, 2021;

Chodorow-Reich, Ghent, and Haddad, 2021). Through our instrumental variables approach based on Gabaix and Koijen (2020), we leverage the granularity of the data to construct a measure of industry cost shocks that is independent of broad economic conditions and sector-specific demand.[12] This paper 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 heterogeneous pass-through that depends on industry concentration, and in Section 4, we explore asymmetric responses that depend on 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 United States. Total operating expenses (XOPRQ) is our main cost measure. Operating expenses are the sum of the costs of goods sold (COGSQ), which include all spending directly allocated to production and selling as well as general and administrative expenses (XSGAQ). Administrative expenses include other costs of operating a business that are not directly tied to production, such as non-production employee salaries and sales and marketing expenses. We also use the Compustat data to measure industry sales concentration by the Herfindahl–Hirschman Index (HHI) at the three-digit North American Industry Classification System (NAICS) level.[13] To guarantee our data are representative of the underlying market structure in a given industry, we exclude from our regression analysis

[12]For applications of the GIV, see, for instance, Galaasen, Jamilov, Juelsrud, and Rey (2020), Adrian, Berrospide, and Lafarguette (2020), and Gabaix and Koijen (2021).

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

industries that have fewer than two firms in the Compustat data at any moment in our sample and retail industries (NAICS 44/45).[14] We acknowledge that the Compustat data set may not be representative of the entire population of US firms. However, it contains the largest firms, all of which are publicly traded and, due to their size, 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 that is not available, or not available at the same frequency, in other data sets.[15]

For a second data source, we use producer price data from the US Bureau of Labor Statistics (BLS) at the three-digit NAICS level. We exploit the availability of producer prices at the industry level to link within-industry across-time variation in concentration and estimate the effect of cost shocks on prices. Moreover, the effect of concentration is likely more relevant for wholesale prices (Gopinath and Itskhoki, 2011) than for 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 United States. To measure the effect of concentration on real outcomes, we also collect data on industry employment and output from the BLS at the three-digit NAICS level. Our sample for the regression analysis comprises 35 industries. The sample period used in our main analysis runs from 2005Q2 through 2019Q4 and is overall constrained by the availability of Producer Price Index (PPI) data, in particular before 2004.[16] We exclude the COVID-19 crisis period from our baseline analysis, but our results are robust to extending our sample through 2022Q1.

[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 for retail (see, for instance, Rossi-Hansberg, Sarte, and Trachter (2018)). Our results are robust to changing these filters to exclude industries with fewer than 20 firms at any moment in our sample. As is 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 on all US businesses with paid employees in all industries at an annual frequency.

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

Appendix Figure C.2 shows the year-over-year inflation rate in our data set (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 similar across inflation measures, producer-price inflation is eight times more volatile than consumer-price inflation. The magnitude of our estimated effects must thus be interpreted accordingly, as they refer to the more volatile producer prices.

As with previous studies in this area, our analysis is subject to several empirical challenges when measuring 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 given NAICS industries. Second, as with other studies that leverage Compustat data to measure market concentration, sales values reported in Compustat refer to the sales values of the publicly listed entities in the United States. However, sales are not broken down by geographic region. Instead, they refer to a company's consolidated sales, including sales in foreign countries, and therefore do not single out sales within the United States. However, De Loecker and Eeckhout (2018) use global data from Worldscope to compute firm revenue shares, and their results for US firms are consistent with findings from earlier studies using only Compustat data for US sales.

Moreover, the set of goods and services included in the PPI provided by the BLS comprises the entire marketed output of US producers—public and private firms—while our sample includes only firms in the Compustat data. This is not problematic for our approach for two reasons. First, because we leverage the granularity of the data, most of the industry shocks would come from the largest firms within each industry. In fact, Gabaix and Koijen (2020) suggest taking this approach even if data from all firms are observed. Second, although the level of industry concentration measured by the HHI computed from Compustat data can be different from the level obtained from US Census data (Ali, Klasa, and Yeung, 2008), our identification rests on within-industry *changes* in HHI during a period when increases in concentration have been associated with an increase in market power (Covarrubias, Gutiérrez, and Philippon, 2020). Our results are robust to using alternative measures of concentration, such as the share of sales by the top five firms in a given industry. Finally, from a broader perspective, all of these measurement challenges in the market definition and sample of firms 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. We show by industry the HHI, average margin, and average margin of the largest five firms in each industry at the beginning of our sample period (in 2005Q2) and the change from the beginning to the end (2019Q4). For the vast majority of industries—defined at the three-digit NAICS level—we observe an increase in concentration as measured by the HHI. In addition to a broad increase in industry concentration, we see that, on average, margins increased during our sample period, not only for the largest five firms in any given industry, but also for the rest of the 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 related to, for example, excluded industries, see the data section). Start values represent (mean) values at the beginning of the sample. Delta measures the change from the beginning of the sample to the end of the sample. HHI is the Herfindahl-Hirschman 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. *Sources*: Compustat and authors' calculations.

2 Cost-Shock Pass-Through into 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 costs and prices are endogenous—higher product demand can lead to increases 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 (GIV) method 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, because a few large firms account for a large share of the economic activity in a given industry, 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. In the first step, we recover firm-level idiosyncratic cost shocks as the residuals from a regression of firm-level log cost on various fixed effects and controls. This estimation approach enables us to control for industry trends and firm trends in costs and isolate idiosyncratic changes in firm costs. Specifically, identification of these idiosyncratic cost innovations is based on the following regression model:

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

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 that depend on the exact model and include 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, $\eta_{j,t}$,

Table 2: Models Used to Residualize Firm-Level Costs

	(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 × Log Sales (Lag)	No	No	No	No	No	Yes
Time × Log Sales (Lead)	No	No	No	No	No	Yes
R^2	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 for computing the firm-level cost innovations underlying the GIV construction. *Sources*: Compustat, BLS, and authors' calculations.

capture firm-level deviations from industry-time averages and from firm trends. Given that we include four lags of the dependent variable, the deviations can be interpreted as percentage point innovations to the firm-level growth in year-over-year costs that is not explained by aggregate demand factors, which are captured by the different fixed effects and firm-level controls.

Table 2 reports the regression summary statistics (number of observations, R^2, and root-mean-square error) for the different specifications used to obtain the firm-level cost innovations used in this paper. Column (1) presents the least stringent specification, which includes only industry-by-time fixed effects. Column (2) instead includes firm fixed effects and time fixed effects. Column (3) presents our baseline model, which includes industry-by-time fixed effects, firm fixed effects, and a firm-specific time trend. Unless otherwise noted, all results in this paper refer to this specification. Columns (4) and (5) include sales, assets, and leverage, with time-varying coefficients. Finally, column (6) adds lag and lead time-varying sales. The R^2 values in Table 2 show that our set of controls and fixed effects accounts for a large share of the variation in costs both across and within industries and also within firms.

In the second step, to construct our GIV cost shock at the industry level, we compute the weighted average of the estimated firm-level residuals, $\hat{\eta}_{j,t}$, by industry, i:

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

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, cost shocks involving larger firms have larger weights. In the robustness-test version, we also consider aggregation schemes in which we compute the weighted sum for the residuals of only the largest five firms within a given industry. As we show below, our results are robust to these variations.

The GIV cost shocks can be interpreted as the sales-share-weighted mean of percentage point innovations to cost growth within a given industry. Appendix Table B.1 shows summary statistics of the identified cost shocks. First, note that all shocks have a small, but positive mean driven by a right skew of the distributions. The interquartile range is, in general, close to zero with weighted mean percentage cost innovations varying from about –2 percentage points to about 3 percentage points. The standard deviation is 6 percentage points. 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. As discussed above, the size of the shocks is significant relative to the growth rate of costs.

In Appendix Table B.2, we present the pairwise correlations between our different cost measures. All shock measures are positively correlated, and not surprisingly, the correlation is stronger for specifications that are more similar. In particular, models that include industry-time fixed effects, firm fixed effects, and a firm-specific time trend exhibit a high correlation of about 0.8. These models also explain the largest share of variation in firm-level costs. As we will discuss, though they are slightly different from each other, the cost shocks yield similar impulse response estimates. Therefore, we focus 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 contained in the quarterly reports filed with the US Securities and Exchange Commission (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 approach to capture aggregate supply shocks. This approach is highly appealing because it enables us to directly compute aggregate cost shocks from shocks identified in micro (firm-level) accounting data, exploiting the granularity of the firm-size distribution. One concern with the GIV approach is that idiosyncratic cost shocks to large firms may pass through differently into aggregate prices relative to common (industry-wide) cost shocks that affect all firms. Therefore, for robustness, we redo our analysis with a different supply shock variable, which is computed based on (1) the dollar exchange rate and (2) the Global Supply Chain Pressure Index (GSCPI) made available by the Federal Reserve Bank of New York.[17] We use either of these variables 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 disruptions in the international supply of production factors or their costs in dollars. 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

[17]The GSCPI is based on several metrics that are commonly used 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 US 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 Federal Reserve Bank of New York, Global Supply Chain Pressure Index (GSCPI), https://www.newyorkfed.org/research/policy/gscpi#/overview. The GSCPI is a normalized variable such that it can be readily interpreted in units of standard deviation from the mean.

process of industry i sourced *domestically* (for example, from within the United States) 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 the United States) relative to the total value of all inputs and labor costs (adjusting for taxes and subsidies) of industry i. Given that the I/O matrix is available at only an annual frequency and highly stable over time, we use the beginning-of-sample matrix in our analysis. 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 (captured by the Leontief inverse). Multiplying this vector of industry exposures with the exchange rate (log) or the GSCPI gives us our alternative industry-level supply shock measure. Both the exchange rate and the supply chain pressure index are affecting firms' cost and therefore their supply, but contrary to our GIV approach, both of them are potentially demand confounded.

2.2 Cost-Shock Pass-Through

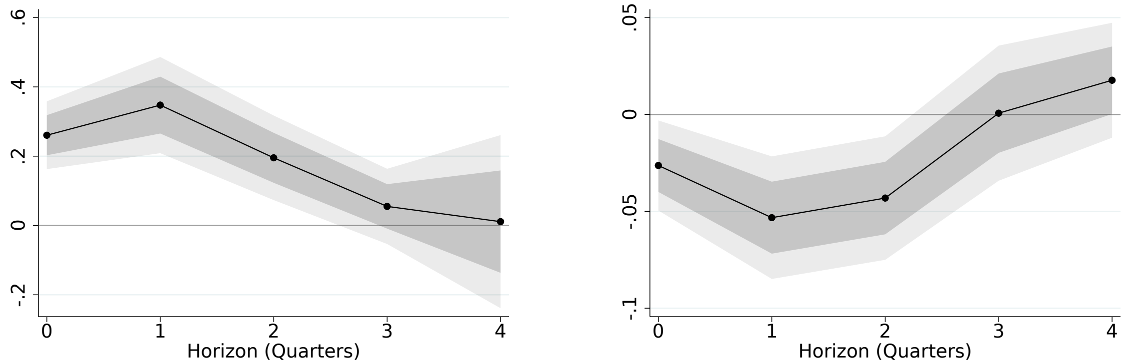
We use local projections to estimate the dynamic pass-through of the identified cost shocks into prices and other key outcome variables. Specifically, the response of prices h periods after impact is estimated using the following empirical specification at the industry i, quarter t level:

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

where $\log PPI_{i,t}$ is the logarithm of the Producer Price Index, and $GIV_{i,t}$ 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, including output, endogenous costs, and the GIV itself, as discussed below. Time t is measured in quarters. The vector of controls includes four lags of the dependent variable, four lags of the GIV shock, and an industry-specific linear time trend.[18] The model also includes industry and time fixed

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

Figure 2: Price and Output Responses to Cost Shock



(a) Prices on GIV

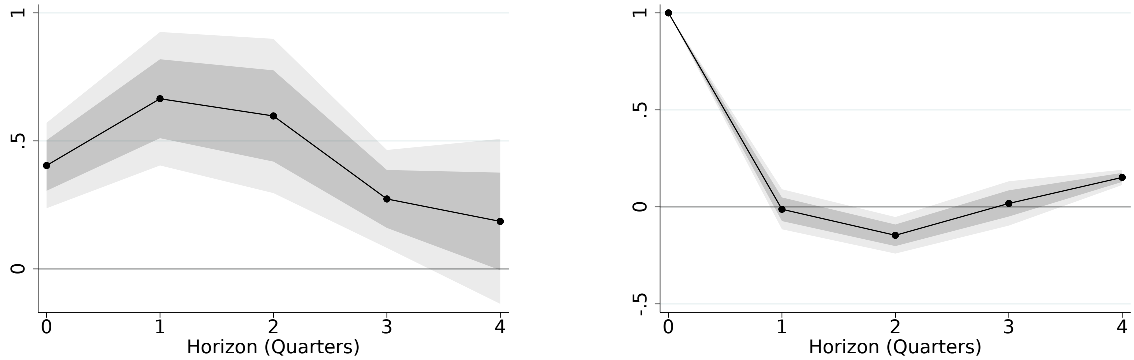
(b) Output on GIV

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. *Sources*: Compustat, BLS, and authors' calculations.

effects. As a result of this model specification, β^h presents the effect of a cost increase on prices h periods ahead measured as a percentage deviation (log difference) from the local level of the response variable, that is, the industry-specific deviation from the cyclical and trend component of prices. Moreover, to improve estimation efficiency, we include lags of the shocks that 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 a 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 (lagged) share of 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 impact, with an estimated response of 0.26, and lasts for two 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.

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. *Sources*: Compustat and authors' calculations.

They are also robust to estimating the equations in growth rates instead of levels.[19] Panel (b) reports the response of real industry-level output, which we estimate using an analogous version of equation (3). While a cost shock is accompanied by an increase in prices, economic activity significantly contracts. Similar to the price response, the effect on output lasts for as long as two quarters after impact, with a peak response at horizon $h = 1$. These findings on prices and quantities together lend additional credibility to the interpretation of our GIV measure as 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

[19] Appendix Figure C.3 shows similar results when we use alternative GIV shocks based on a different set of controls and when we aggregate the residualized cost innovations of industry leaders only. Appendix Figure C.4 estimates the responses of price *growth* instead of levels (relative to trend). We find that, consistent with the level response, price growth increases for two quarters relative to trend but then is below trend for two quarters such that the levels return 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

response to the shock contributes to the total supply effects we see in prices and output. On the other hand, Panel (b), in which the left-hand-side variable is the GIV itself, shows that the cost shocks are basically serially uncorrelated.

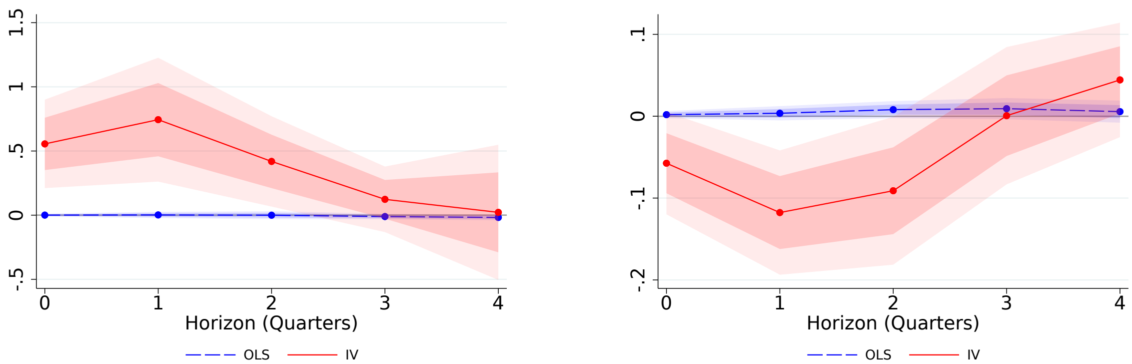
Our core results in Figure 2 present the responses of a reduced-form model. We can also uncover the structural form explicitly using local projections with instrumental variables (Stock and Watson, 2018). The structural parameter estimates obtained using this approach yield the price and output elasticities with respect to costs—objects of particular interest in economic theory and policy questions. Therefore, Figure 4 shows the results from swapping out the GIV cost shock with the (logarithm of) the operating expenses in equation (3). 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) 1 percent increase in costs generates a 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 precisely estimated to be 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 nor 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 with 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 fixed costs determine firm entry and exit. Therefore, we next provide estimates of price responses to different types of cost shocks. Unfortunately, accounting cost measures

verify that the impulse responses of other variables are not affected by the exclusion of this data point.

[21] First-stage diagnostics support the relevance of the instrument with robust F statistics that are substantially greater than 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

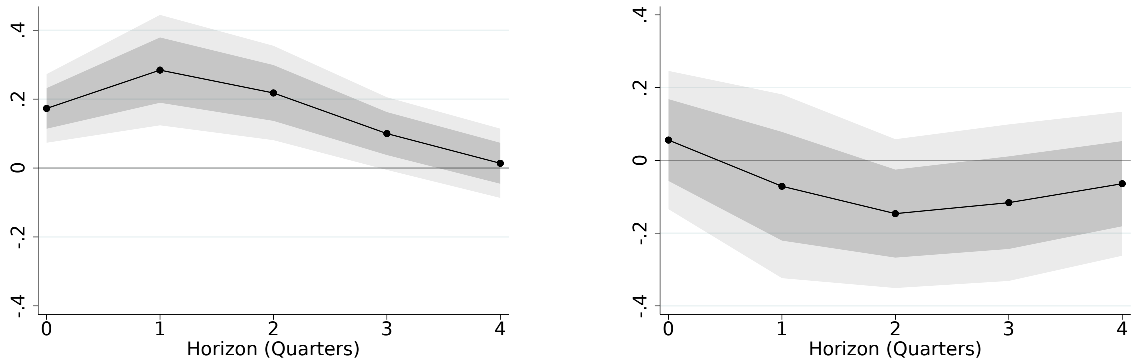
Note: The figure shows estimates from local projections of log PPI (Panel (a)) and log output (Panel (b)) on operating expenses. Red impulse responses present IV estimates using the GIV as an instrument for operating expenses, while blue responses use OLS. The specifications include a set of controls 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. *Sources*: Compustat, BLS, and authors' calculations.

do not sharply distinguish between the economic concepts of variable and fixed costs, as previously discussed. Yet, we can test the responses to different accounting measures that are more closely linked to one or the other. To do so, we disaggregate our total cost measure (operating expenses) into cost of goods sold—arguably a large share of which is variable cost—and selling, and general and administrative expenses, which include many lines of fixed costs. Across all firms, the mean of cost of goods sold/operating expenses is 0.60, and 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)). We find that, consistent with theory, 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.

We report GIV-based results as our baseline analysis because this allows us to exploit (1) reasonably exogenous variation in cost at the firm level and thus both across and within industries, and (2) to conduct additional tests, such as the responses to shocks in different cost components. However, we show in Appendix Figure C.5 the baseline responses of prices,

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 on only cost of goods sold in Panel (a) (a proxy for variable costs) and on the GIV based on only costs other 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, and 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. *Sources*: Compustat, BLS, and authors' calculations.

output, and costs to alternative supply shock measures stemming from changes in costs of imported inputs based on the dollar exchange rate or the GSCPI along with the exposure (direct and indirect) to international supply of production factors. Since these alternative approaches leverage time-invariant heterogeneous exposure to aggregate shocks, we do not include time fixed effects in the estimation. Therefore, our results can be interpreted as the within-industry relative log growth in prices associated with a relative increase in the aggregate factor. The results are broadly similar to those we obtain using the GIV-based supply shock measure, with both a devaluation of the dollar and an increase in supply chain pressures leading to cost and price increases above trend for about four quarters. On the other hand, while the point estimates are negative, we do find (in contrast to the GIV analysis) relatively large standard errors for the output response, in particular when using industries' heterogeneous exposure to imported inputs and exchange rate variations as cost shocks. This response is consistent with exchange rates being endogenously determined through supply and demand factors. Overall, these responses not only lend additional credibility to our analysis, but also highlight the strength of our approach in isolating supply shocks.

3 The Role of Concentration

The central question of this paper concerns how industry concentration affects the pass-through of cost shocks into prices. Therefore, we next estimate heterogeneous pass-through coefficients depending on an industry's 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 into prices and output is linear in the 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 we focus on within-industry variation in the HHI that abstracts from cross-industry differences in the HHI that may be correlated with differences in production processes, scale economies, etc., we also allow the effect of the cost shock to have heterogeneous effects across industries. Our estimation equation then becomes:

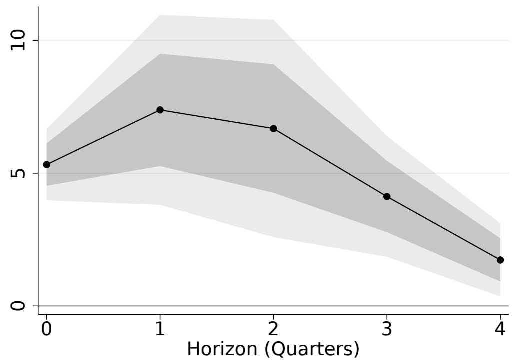
$$\log PPI_{i,t+h} = \beta_i^h GIV_{i,t} + \beta_{HHI}^h GIV_{i,t} \times HHI_{i,t} + X'_{i,t}\gamma^h + \alpha_i^h + \alpha_t^h + \varepsilon_{i,t+h}, \tag{5}$$

where the control vector $X_{i,t}$ now includes, in addition to the variables from equation (3), $HHI_{i,t}$ 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 the HHI.

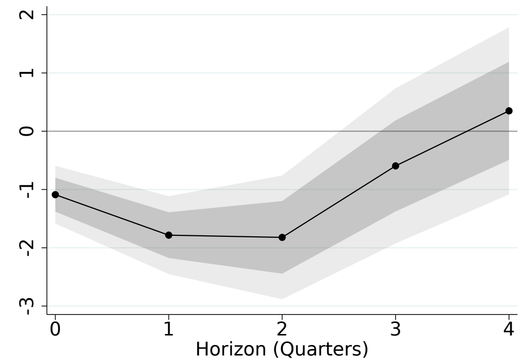
Given our set of controls, specifically industry-specific base effects, β_i^h, and the lagged HHI, we identify the effect of concentration on the pass-through from within-industry changes in the HHI. This empirical strategy enables us to rule out the possibility that we are attribut-

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

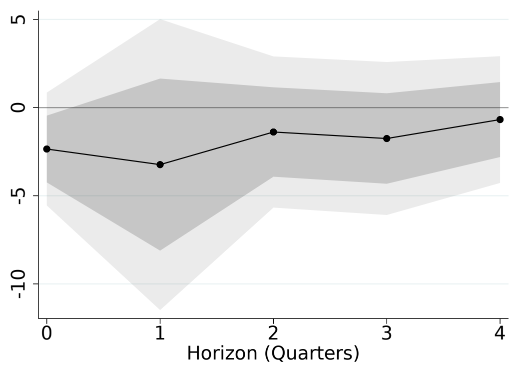
Figure 6: Differential Pass-Through Depending on Concentration



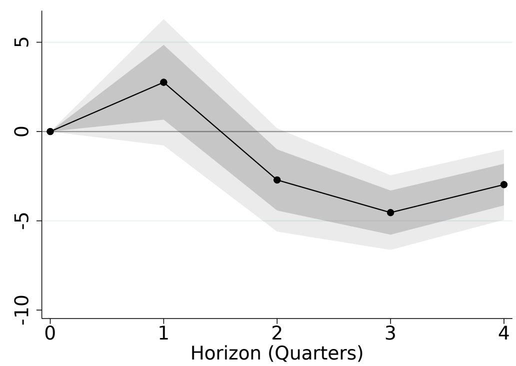
(a) Prices on GIV*HHI



(b) Output on GIV*HHI



(c) Cost on GIV*HHI



(d) GIV 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. *Sources*: Compustat, BLS, and authors' calculations.

ing the pass-through effect of concentration to cross-industry differences in concentration that may be correlated with other industry-specific variables, such as the degree of economies of scale or capital intensity.

Figure 6 shows the core result of this paper: Higher concentration significantly amplifies the pass-through of the cost shock into prices and outputs. Panel (a) shows that the pass-through into prices is significantly larger for as long as four quarters after impact, while Panel (b)) shows that output declines mores strongly for as long as 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 the 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) over the average response across all industries.

Given that baseline and given that the subsequent change in the 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 had 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 the HHI (as opposed to a commonly assumed 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 has experienced a 27 percent increase in the response to cost shocks due to the increase in concentration. This number is somewhat smaller than the ones obtained from a simple back-of-the-envelope calculation done in our baseline evaluation of the quantitative effects, but it is 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 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 we can 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

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_P^h)	.261	.348	.195	.055	.011
(b) Interaction effect ($\beta_{HHI,P}^h$)	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_Q^h)	-.026	-.053	-.043	.001	.018
(b) Interaction effect ($\beta_{HHI,Q}^h$)	-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

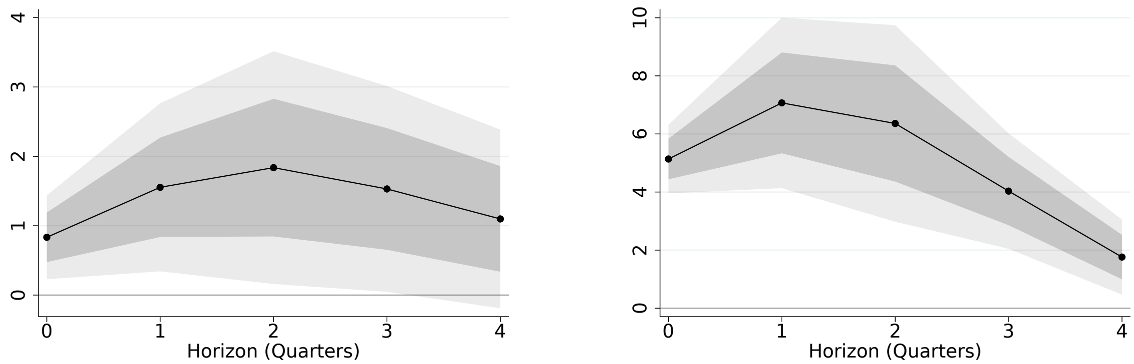
Note: Rows 1a and 2a report the estimates of β^h from Equation (3) for either the price (Panel 1) model or the output model (Panel 2). Rows 1b and 2b report the estimates of β_{HHI}^h from (6). Rows 1c and 2c report the median of the percentage change in industry-level responses attributed to the increase in concentration during our sample. That is, we compute the median of $\frac{\beta_i^h + HHI_{i,2018}\beta_{HHI}^h}{|\beta_i^h + HHI_{i,2005}\beta_{HHI}^h|} - 1$, 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 the HHI as $\left(\frac{\beta_{i,Q}^h + \beta_{HHI,Q}^h * HHI_{i,2018}}{\beta_{i,P}^h + \beta_{HHI,P}^h * HHI_{i,2018}}\right) / \left(\frac{\beta_{i,Q}^h + \beta_{HHI,Q}^h * HHI_{i,2005}}{\beta_{i,P}^h + \beta_{HHI,P}^h * HHI_{i,2005}}\right) - 1$. *Sources*: Compustat, BLS, and authors' calculations.

change in demand elasticity. The results show that at $h = 0$, demand becomes about 6 percent more inelastic.

Importantly, Appendix Figure C.6 shows that the differential price and output responses depending on concentration *cannot* be explained by a larger cost increase in concentrated sectors in response to a cost shock. In fact, we estimate no differential response of costs to a cost shock depending on concentration. The point estimates are small and lack statistical significance, especially when compared with those of Figure 6, Panel (a), suggesting that the insignificant differential cost response is also economically small. Moreover, Figure C.6 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 robust to a variety of different measurement and modeling choices. Figure 7 shows that our core result does not depend on measuring concentration with the HHI. Instead, in Panel (a), we find similar responses if we use the

Figure 7: Differential Price Response with Alternative Concentration Measures



(a) Price on GIV*Top 5 Share

(b) Price on GIV*HHI (Excess)

Note: The figure shows estimates from local projections of log PPI on the interaction term between cost shock (GIV) and alternative measures of industry concentration; that is, it is a robustness analysis of our main results in Figure 6, Panel (a). The alternative measures of industry concentration are the sales share of top 5 firms (Panel (a)), and the excess HHI (Panel (b)), both computed within industry. *Sources*: Compustat, BLS, and authors' calculations.

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 an alternative set of industries (Appendix Figure C.7) and alternative industry shocks (Appendix Figures C.8). We also find consistent results when we estimate the response of price growth as compared with price levels (Appendix Figures C.9). Finally, consistent with variable costs playing a more important role in price setting and our prior result for the level effect, we also find that the differential effect on prices depending on industry concentration is driven more by CoGS expenses than by non-CoGS expenses (Appendix Figure C.10).

For comparison with the GIV-based results, we also show, in Appendix Figure C.11, the differential responses of prices, output, and cost depending on concentration for our alternative measures of cost shocks (industry heterogenous exposure to imported goods coupled with shocks to exchange rates or global supply chains). Consistent with our findings from GIV shocks, the results show that changes in both variables are passed through into prices significantly more in more concentrated industries, while the costs do not differentially increase with concentration. We also see a differential decline in output, although the estimates are noisy, especially for the supply chain index. Again, this could be because neither changes in the dollar value nor changes in the supply chain pressure are a well-identified shock to supply (as opposed to our GIV) and are both potentially contaminated by demand factors.

4 Asymmetric Responses to a Positive vs. Negative Shock

Several papers argue that prices are subject to downward rigidity such that cost increases are passed through into prices more than cost decreases are (e.g., Peltzman, 2000; McShane, Chen, Anderson, and Simester, 2016). Others argue that such rigidities are not needed to find an asymmetric response of prices to cost shocks. For example, Ritz (2015) argues that the convexity of the demand function (a demand in which the price elasticity decreases as quantities increase), coupled with discrete supply shifts, can result in a differential response of prices to cost shocks. Therefore, to understand whether positive cost shocks affect prices differently 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 on 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 a variable that indicates the sign of the cost shock.

Formally, we estimate asymmetric effects using the following model:

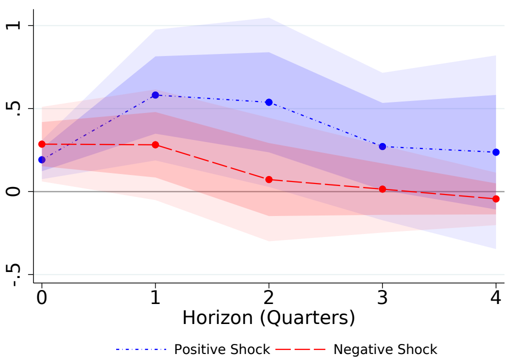
$$\begin{aligned}\log PPI_{i,t+h} =& \beta_i^{h,+} GIV_{i,t}^{+} + \beta_i^{h,-} GIV_{i,t}^{-} + \\ & + \beta_{HHI}^{h,+} GIV_{i,t}^{+} \times HHI_{i,t} + \beta_{HHI}^{h,-} GIV_{i,t}^{-} \times HHI_{i,t} + \\ & + X_{i,t}' \gamma^h + \alpha_i^h + \alpha_t^h + \varepsilon_{i,t+h},\end{aligned} \tag{6}$$

where the $GIV_{i,t}^{+}$ equals the GIV shock if the GIV shock is positive and zero otherwise, and $GIV_{i,t}^{-}$ equals the GIV shock if the GIV shock is less than or equal to zero and zero otherwise. Our key coefficients of interest in this model are $\beta_{HHI}^{h,+}$ and $\beta_{HHI}^{h,-}$, which measure the differential pass-through effect depending on the HHI, separately for positive shocks versus negative shocks. (Table B.3 reports conditional summary statistics of the shock, showing that the distributions are roughly similar.) The control vector $X_{i,t}$ now includes, in addition to the variables from equation (3), $HHI_{i,t}$ as well as four lags of $GIV_{i,t} \times HHI_{i,t}$ and $HHI_{i,t}$.[23] To isolate the asymmetric responses from general shifts in costs, we also include heterogeneous intercepts, by industry, depending on whether the current GIV is negative or positive. In our setting, if the effects of positive and negative cost shocks are symmetric, the impulse responses will overlap.

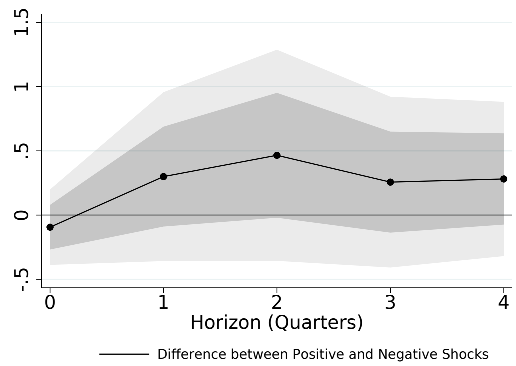
Figure 8 presents asymmetric price responses to cost shocks. Panel (a), which presents the average effects not differentiating on industry concentration, shows that prices do not respond significantly differently to positive versus negative cost shocks. (Panel (b) shows the differences along with standard confidence intervals.) On the other hand, Panel (c) reveals an important asymmetric effect depending on concentration: In more concentrated industries, positive cost shocks (increases) are passed through into prices substantially more than negative cost shocks are. The different pass-through is highly significant at relevant horizons (Panel d). This finding is consistent with either downward price rigidity rooted in market power or with differential convexity in the demand and pricing function, along with

[23] We do not separate the GIV into negative and positive values in any of the lag components and thus reduce the number of parameters to be estimated.

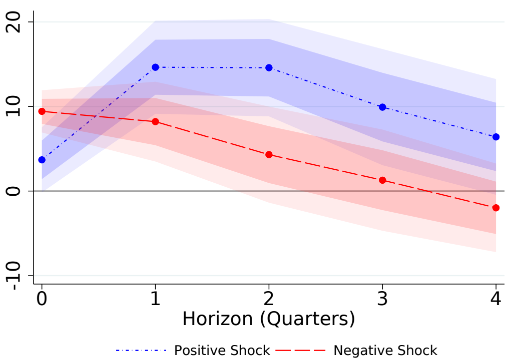
Figure 8: Asymmetric Price Responses



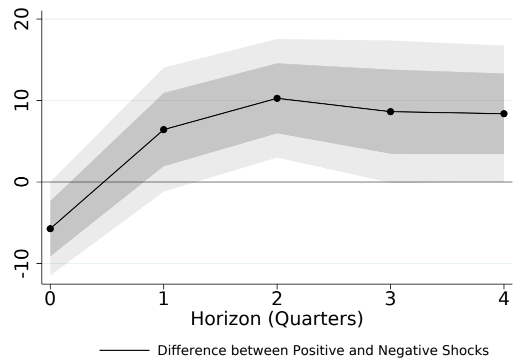
(a) Prices on GIV Level



(b) Prices on GIV Level (diff)



(c) Prices on GIV*HHI



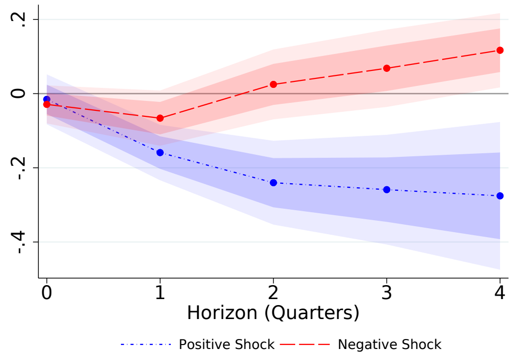
(d) Prices on GIV*HHI (diff)

Note: The figure shows estimates from local projections of log PPI on the cost shock (Panel (a)) and the interaction between the cost shock and the 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. *Sources*: Compustat, BLS, and authors' calculations.

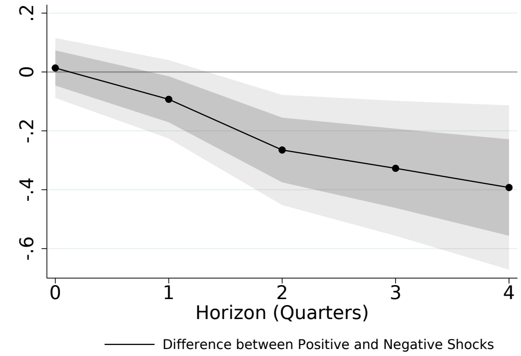
a discrete measure of cost shocks—their variation accounts for 6 percentage points of the average growth rate of operating costs in the data. Appendix Figure C.12 confirms that the asymmetric response depending on concentration is not driven by a differential cost response.

Figure 9 shows asymmetric output responses. Panel (a), which shows the level effect, reveals that output increases in response to a negative cost shock and that output does not significantly respond to positive cost shocks, consistent with a convex demand function that has a sufficiently increasing price elasticity. We also show the asymmetric response of output

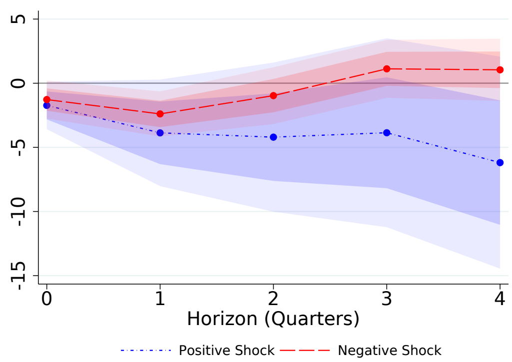
Figure 9: Asymmetric Output Responses



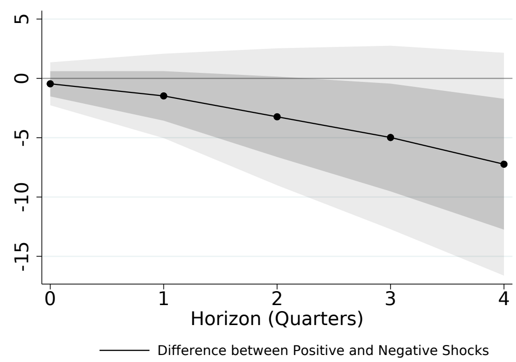
(a) Output on GIV Level



(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 the cost shock and the 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. *Sources*: Compustat, BLS, and authors' calculations.

as a function of market concentration in Panels (c) and (d). However, the difference is not statistically significant, which is contrary to the effects on prices that we find above.

5 Firms' Profit Margins

Next, we move our analysis of the effect of concentration and market power on pass-through from the industry level to the firm level. Using firm-level data from Compustat, we study how firms' profit margins respond to firms' innovation and industry cost shocks; that is, we consider the joint 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 objective 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 industry-level analysis, we also investigate whether firms' margin response varies depending on industry concentration, and whether industry leaders' responses relative to followers' responses vary additionally depending on the concentration of the industry. Formally, we estimate, in our most saturated regression, the following equation by least squares:

$$\begin{aligned} Margin_{j,t+h} =& \beta_i^h \cdot \hat{\eta}_{j,t} + \beta_L^h \cdot \hat{\eta}_{j,t} \times Leader_{j,t} + \beta_{HHI}^h \cdot \hat{\eta}_{j,t} \times HHI_{i(j),t} \\ &+ \beta_{HHI \times L}^h \cdot \hat{\eta}_{j,t} \times HHI_{i(j),t} \times Leader_{j,t} + \alpha_{i(j),t}^h + \alpha_j^h + \beta_j^h \cdot t + \varepsilon_{i,t+h}, \end{aligned} \tag{7}$$

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 five firms based on sales within a given industry and quarter. As before, the HHI is the Herfindhal-Hirschman Index of sales concentration for the industry in which the firm operates. Our key focus is on the differential response of leaders in a given industry. We also study the effect of industry concentration. Our main results first show effects without including Cost-Innovation*Leader and Cost-Innovation*HHI, or the triple interaction. We then show results for two models in which we include only one of the interaction terms. Then we present the full model with the triple interaction, as shown in equation (7).

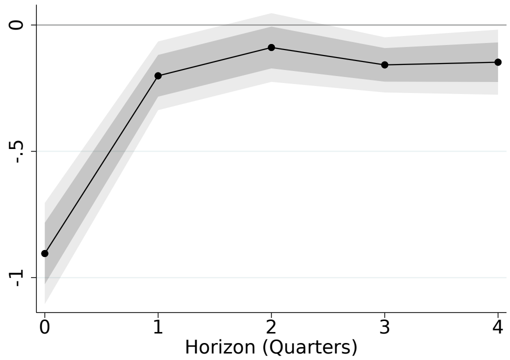
The full model specification includes industry-by-time fixed effects, which allow us to focus on a *within*-industry comparison of leader effects. We also include firm fixed effects and a firm-specific (linear) trend to account for additional heterogeneity across firms. Our firm-level cost innovation, $\hat{\eta}_{j,t}$, is the one in the construction of the GIV (residual from equation (1)). 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 are characterized by large negative operating margins that have a large influence on our estimates, specifically the 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 having 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.

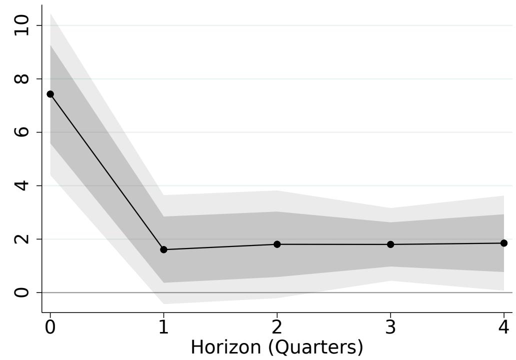
Figure 10, Panel (a) shows the response of margins to the cost innovation without allowing for differential effects depending on the industry leader and industry concentration. Margins decrease significantly upon impact and remain negative for another quarter. Because our cost innovations are in log terms, the estimated effect at $h = 0$ suggests that margins decrease by about 0.01 in response to a 1 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 industries. The estimate of close to 8.0 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' margins decrease significantly less relative to those of smaller firms in their industry. Given the

[24] In general, firms with negative margins tend to be smaller. Overall, more than one-quarter of the firm-quarters in the sample have negative margins, and about 5 percent of the firm-quarters in our full sample have negative margins smaller than –5.6; for comparison, the median margin is 0.09 (mean of –1.0). These large (in absolute value) negative margins have a strong effect on our regression estimates, which is why we exclude them from our baseline analysis.

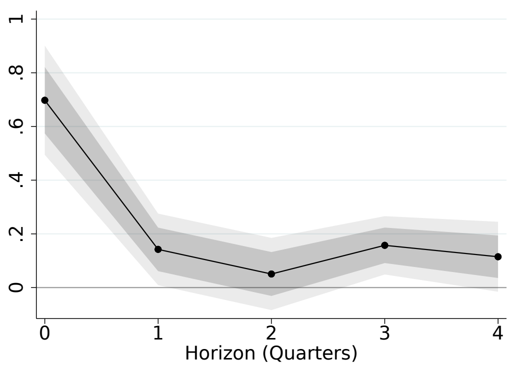
Figure 10: Margin Response to Cost Innovations at the Firm-Level



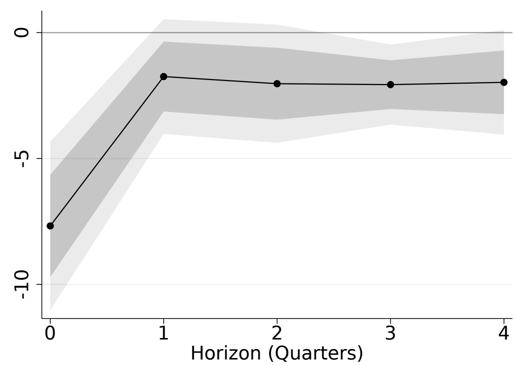
(a) Margin on Cost-Innovation



(b) Margin on Cost-Innovation*HHI



(c) Margin on Cost-Innovation*Leader

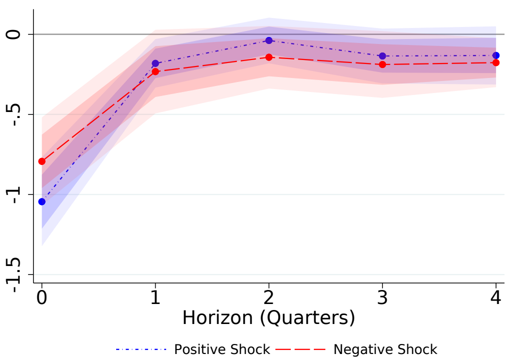


(d) Margin on Cost-Innovation*HHI*Leader

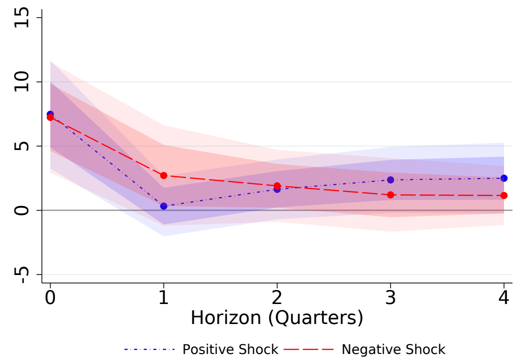
Note: The figure shows estimates from local projections of profit margin, defined as (sales-operating expenses)/sales on the cost shock (Panel (a)), the interaction between the cost shock and the HHI (Panel (b)), the interaction between the cost shock and the industry-leader indicator (Panel (c)), and the triple interaction between the cost shock, the HHI, and the 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. *Sources*: Compustat, BLS, and authors' calculations.

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 larger pass-through in more concentrated industries. Finally, Panel (d) shows a negative coefficient

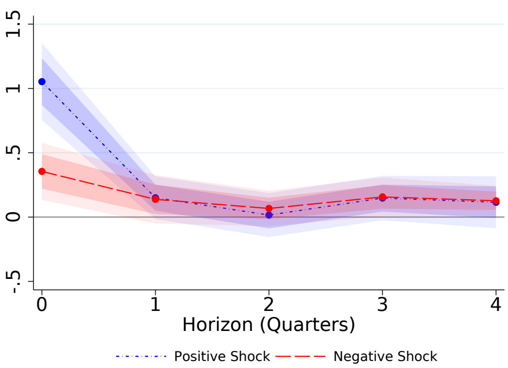
Figure 11: Asymmetric Margin Response to Cost Innovations at the Firm Level



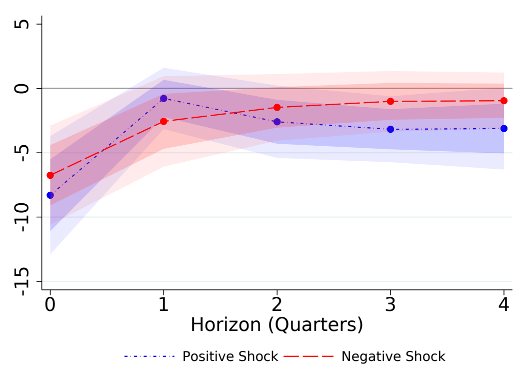
(a) Margin on Cost-Innovation



(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 the cost shock and the HHI (Panel (b)), the interaction between the cost shock and the industry-leader indicator (Panel (c)), and the triple interaction between the cost shock, the HHI and the 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. *Sources*: Compustat, BLS, and authors' calculations.

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 with negative cost innovations.[25] Thus, leaders, unlike followers, are able to maintain their level of profit margin in response to positive cost innovations, but they increase their profit margins as much as followers do 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 limitations), this key result resembles our earlier finding that positive cost shocks are passed through more into 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 industry concentration.

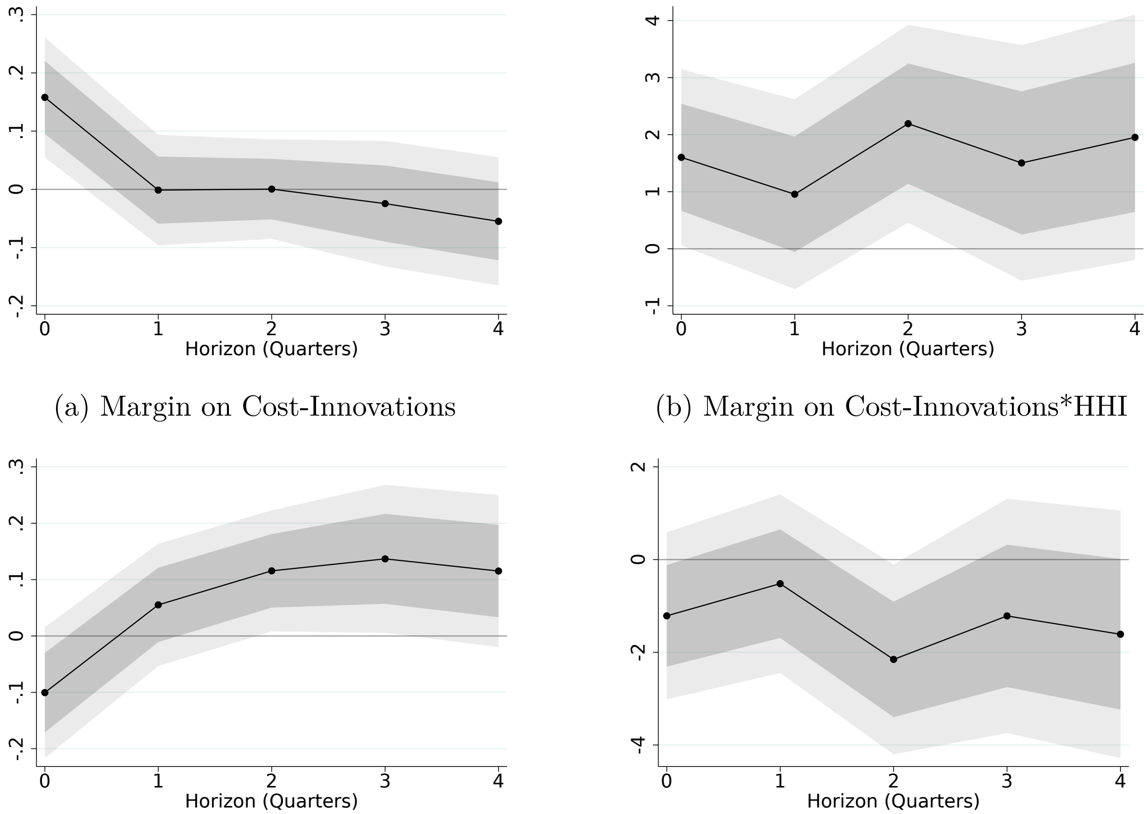
We have shown how a firm's margins react to an innovation to its costs. How does a firm's margin respond to increases in competitors' costs? Evidence on differential responses depending on leader versus followers and depending on concentration can shed additional light on the differential role of leaders 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 percent). This average effect goes back to about zero one quarter after impact. However, following that quarter, the margins of leaders remain 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 standard 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]

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

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

[27] We also checked for asymmetric effects of competitors' cost innovations on margins, but the standard

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 the HHI (Panel (b)), the interaction between competitors' cost innovations and the industry-leader indicator (Panel (c)), and the triple interaction between competitors' cost innovations, the HHI, and the 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. *Sources*: Compustat, BLS, and authors' calculations.

Our findings about 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 pass-through at the firm level and documents a highly nonlinear relationship between a firm's market share and pass-through. Feenstra, Gagnon, and Knetter (1996) and Garetto (2016) find that pass-through is largest when market shares are very large, as

errors were too large to make a reliable inference.

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 become greater. Since we do not observe firm-level prices, we run a similar analysis with margins in Figure C.13, in the Appendix. After a cost shock, margins are smaller (but not significantly) for the quartile comprising the second-smallest firms compared with the quartile comprising the smallest firms. However, the quartile with the largest firms shows significantly larger margins after a cost shock. This U-shaped function of size is maintained over four quarters after the shock albeit with much smaller differences. Under the assumption that our cost measures capture mostly variable costs, if margins are increasing in firm size, this implies a larger pass-through of costs for larger firms.

6 Conclusion

Industry concentration increased significantly in the United States from 2005 to 2020, and this trend is projected to have accelerated since the onset of the COVID-19 pandemic. We construct a measure of industry cost shocks from firm-level innovations to cost growth 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 into prices depending on industry concentration is particularly stronger for positive cost shocks.

While 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 a period for which the literature finds that concentration is associated with an increase in market power (e.g., Covarrubias, Gutiérrez, and Philippon, 2020). Second, our identifying variation in concentration is within industry and relative to trend and various fixed effects, and recent findings in the industrial organization 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 episodes of mergers and acquisitions (e.g., Nocke and Schutz, 2018; Nocke and Whinston, 2020; Miller and Sheu, 2021). Finally, a market power interpretation is also supported by our firm-level findings that in concentrated industries, leaders are able to maintain higher profit margins relative to followers by passing through cost shocks into prices.[28]

Our results also suggest that the rise in concentration is an important factor in the surge in inflation in 2021 and 2022. While recent inflationary pressures likely originate from a combination of strong demand and supply shocks, our findings show that concentration is an amplifying factor in the pass-through of supply shocks (but not the cause). Specifically, we find a larger pass-through in a concentrated economy, driven primarily by positive cost shocks, which is exactly what most sectors experienced during the COVID-19 pandemic. Therefore, our findings can also reconcile that high industry concentration has been an important factor driving higher inflationary pressures since the onset of COVID but did not necessarily have the same effect during the two decades leading up to the pandemic, when no large positive cost shocks occurred and inflation remained muted despite significant increases in concentration.

More broadly, our results 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 on the transmission of monetary policy (e.g., Wang and Werning, 2020; Mongey, 2021; Baqaee, Farhi, and Sangani, 2021). Although an empirical estimate of how monetary-shock transmission depends on and affects the underlying market structure is outside the scope of our paper, our estimates can be used to discipline the industry-level response in these models.

[28] Identification of the underlying forces that affect firm-level residual demand (super) elasticities, such as product differentiation, strategic interactions, or others, is beyond the scope of this paper.

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A Examples of Firm-Level Cost Innovations

Freeport-McMoRan Oil & Gas Inc. Freeport-McMoRan is a leading international mining company operating 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 of more than 230 percent relative to industry and firm trends. From public reports, we verify that in 2008:Q4, Freeport-McMoRan's operating expenses increased from about $3.4 billion in 2008:Q3 to approximately $20 billion in 2008:Q4 driven by large asset impairments related to the decline in commodity prices amid weakening global demand, which were recognized in Q4. 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 a revision of the carrying value of its inventories; including mill and leach stockpiles; long-lived assets; and goodwill. In response to weak economic conditions and collapsing commodity (copper) prices, the firm implemented a plan to dramatically reduce costs and capital expenditures. Operating expenses fell to $1.9 billion in 2009:Q1.[29]

Infineon Technologies AG Infineon is a global semiconductor manufacturer headquartered in Germany and also listed in the United States. Our cost-innovation measure in 2009:Q2 for this firm is –1.85. From public reports, we verify that in 2009:Q2, Infineon experienced a 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-saving plan led to an "annualized savings of about euro 240 million in operating expenses alone." Thus the large decrease in expenses was, in part, a result of a more efficient production process.

[29] As demand declined industry wide in late 2008, Freeport-McMoRan saw a decline in sales of about $2.5 billion from Q3 to Q4.

Centrus Enery Corp. Centrus is a global energy company and leading player in the chemical-manufacturing field as a major supplier of low-enriched uranium for commercial nuclear power plants. We estimate a cost-innovation measure of 1.37 for Centrus in 2012:Q4, translating to a 137 percent increase in costs relative to industry and firm trends. During the quarter, Centrus saw a small decline in net revenue of $160 million coupled with a steep increase in operating expenses of $930 million. Part of the cost increase was driven by the transition away from commercial uranium enrichment and the corresponding downsizing of its Paducah Gaseous Diffusion Plant. Though this event was initiated before the quarter in question, a significant portion of the project was expensed in 2012:Q4. In 2012 alone, Centrus "expensed $1.1 billion of previously capitalized costs related to the American Centrifuge project." Additionally, the ongoing downsizing at the Paducah Gaseous Diffusion Plant resulted in accelerated expenses, severance pay, and depreciation within the quarter.

B Additional Tables

Table B.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. *Sources*: Compustat and authors' calculations.

Table B.2: Correlation of Different Cost Shocks

	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. *Sources*: Compustat, BLS, and authors' calculations.

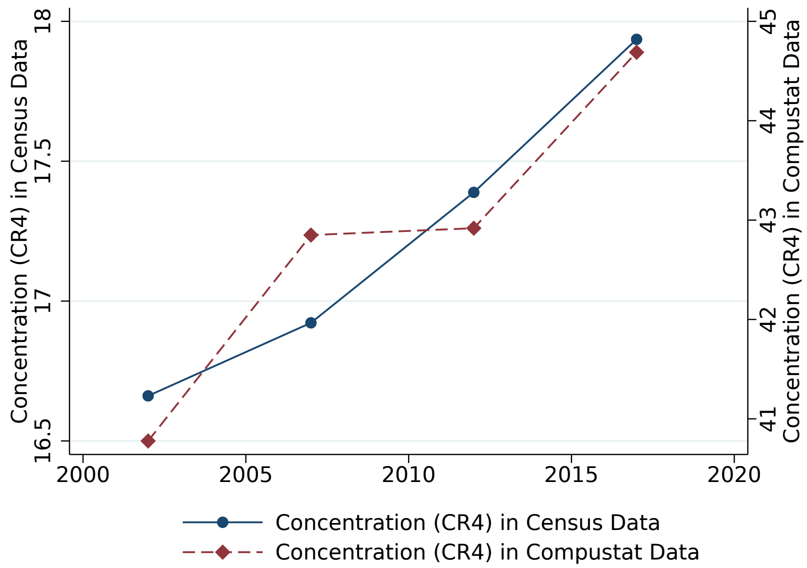
Table B.3: Conditional Summary Statistics of Cost Shocks

	mean	sd	min	p5	p25	p50	p75	p95	max
GIV 3 (Positive)	0.042	0.043	0.000	0.002	0.013	0.029	0.054	0.128	0.399
GIV 3 (Negative)	-0.042	0.050	-0.581	-0.125	-0.053	-0.028	-0.013	-0.002	-0.000
GIV 3 (Above Median HHI)	0.006	0.079	-0.668	-0.109	-0.022	0.003	0.038	0.121	0.425
GIV 3 (Below Median HHI)	-0.000	0.045	-0.351	-0.075	-0.023	0.000	0.025	0.068	0.226

Note: Summary statistics of industry-level cost shocks (GIV Model 3) conditional on the shock being positive or negative. *Sources*: Compustat, BLS, and authors' calculations.

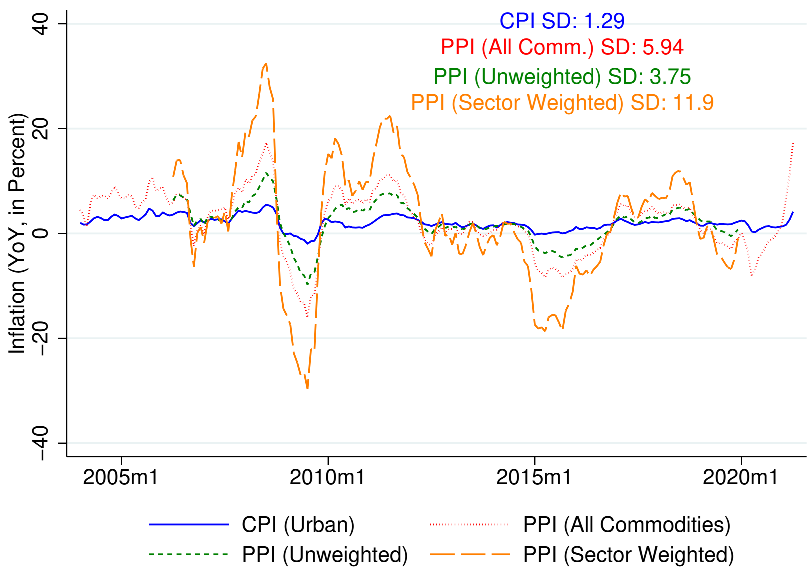
C Additional Figures

Figure C.1: Comparison of Concentration Ratios: Census vs. Compustat



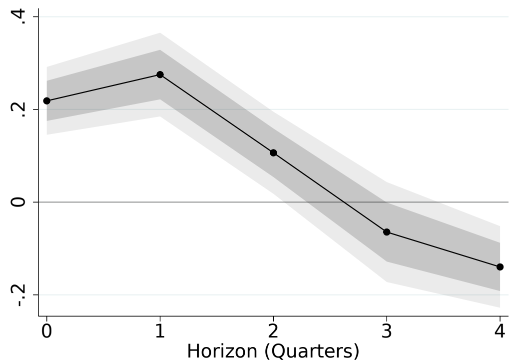
Note: The figure shows the aggregate share (percentages) of sales by industry leaders (top four firms in each industry). The raw data are at the NAICS-3 level and are aggregated using industry-sales shares as weights. Data are presented for the different US Census waves during our sample period. *Sources*: Compustat, US Census, and authors' calculations.

Figure C.2: Comparison of CPI and PPI Inflation

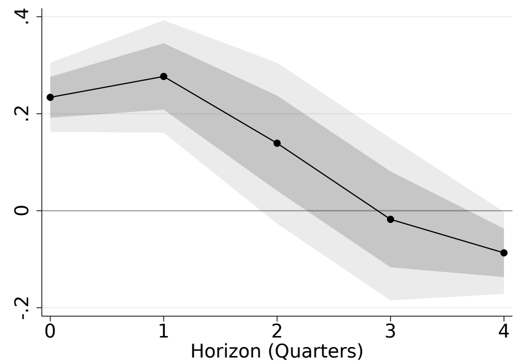


Note: The figure shows different inflation measures (YoY, in percentages) during our main sample period. Standard deviations of the different inflation measures are reported in the figure. PPI (Sector Weighted) is the sales-weighted average NAICS-3-level PPI inflation. Sales weights are computed based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

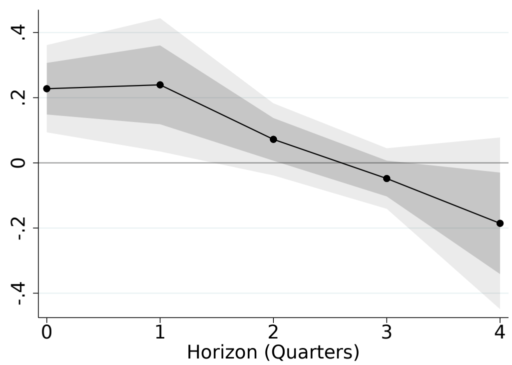
Figure C.3: Level Effect of Price Response with Different Cost Shock Measures



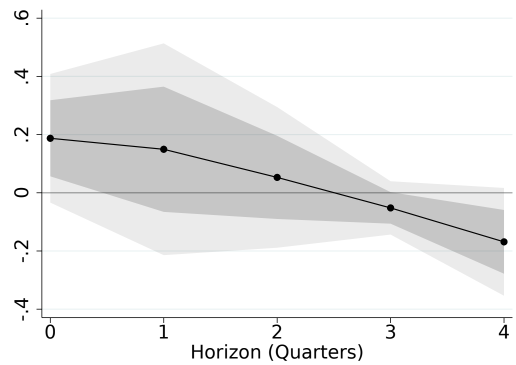
(a) Price on GIV (GIV 1 All)



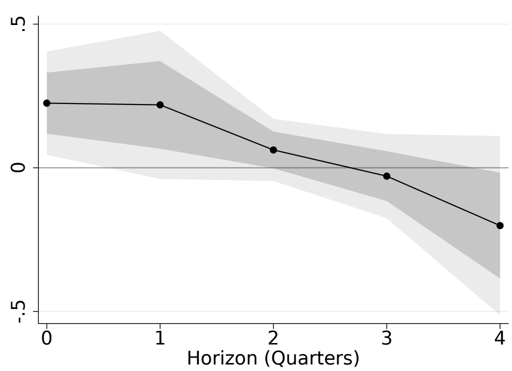
(b) Price on GIV (GIV 1 Top 5)



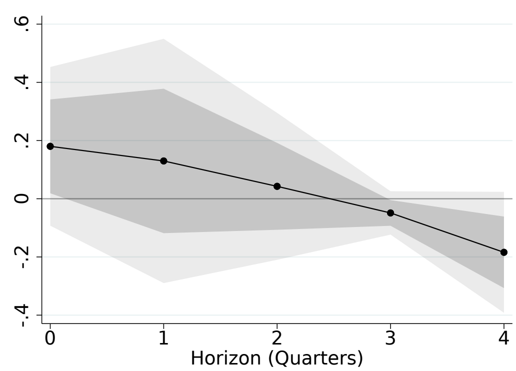
(c) Price on GIV (GIV 5 All)



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



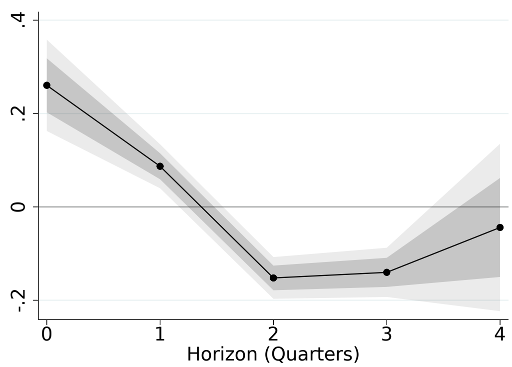
(e) Price on GIV (GIV 6 All)



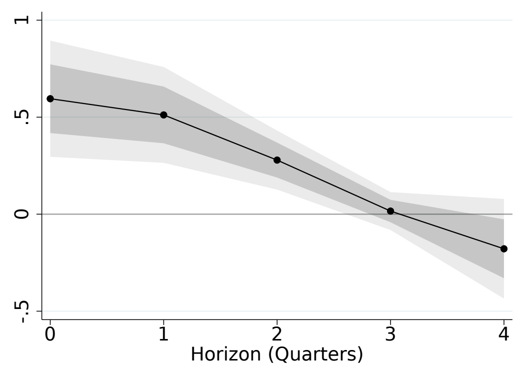
(f) Price on GIV (GIV 6 Top 5)

Note: Robustness analysis for 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 five firms within each industry are aggregated; see Gabaix and Koijen (2021). *Sources*: Compustat, BLS, and authors' calculations.

Figure C.4: Main Results in Log Differences



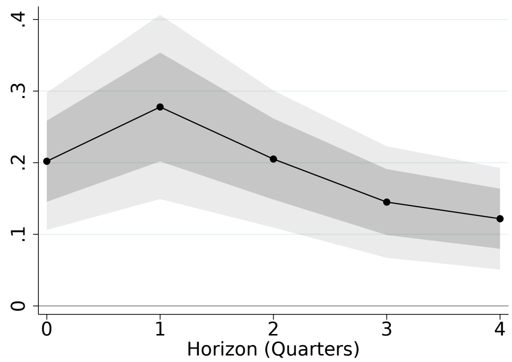
(a) Price Growth on GIV



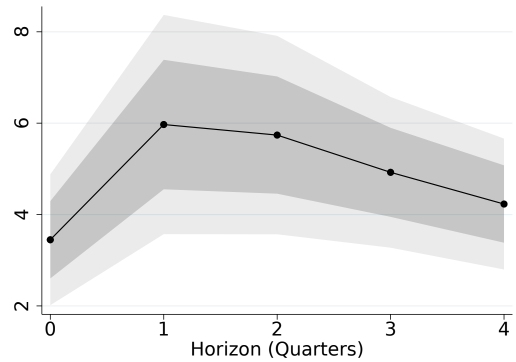
(b) Price Growth (YoY) on GIV

Note: Robustness analysis for 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 text. *Sources*: Compustat, BLS, and authors' calculations.

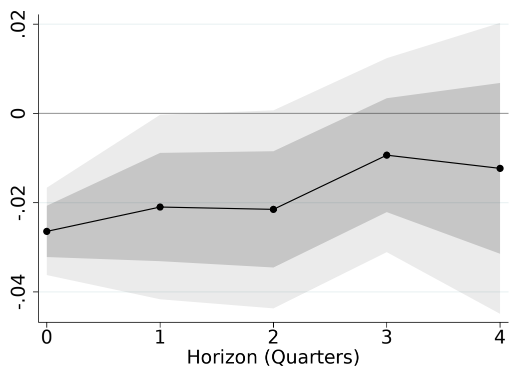
Figure C.5: Price, Output, and Cost Responses to Import Cost Shocks



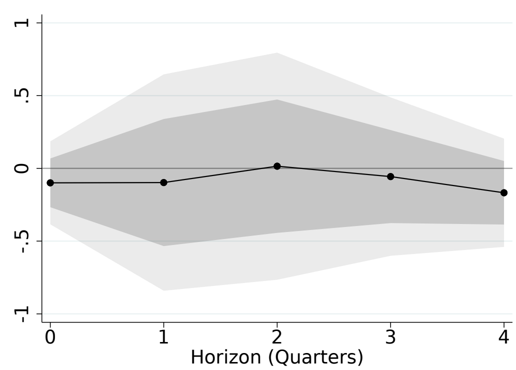
(a) Prices on GSCPI



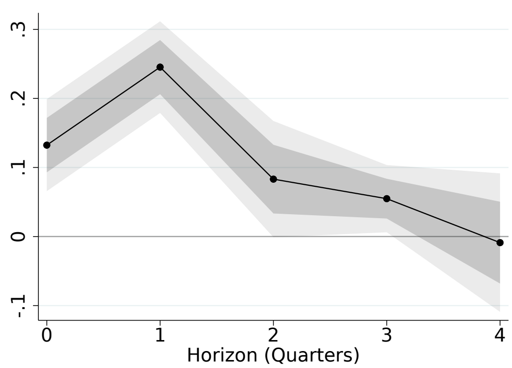
(b) Prices on Exchange Rate



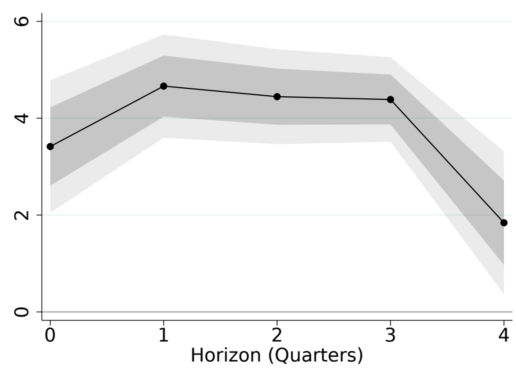
(c) Output on GSCPI



(d) Output on Exchange Rate



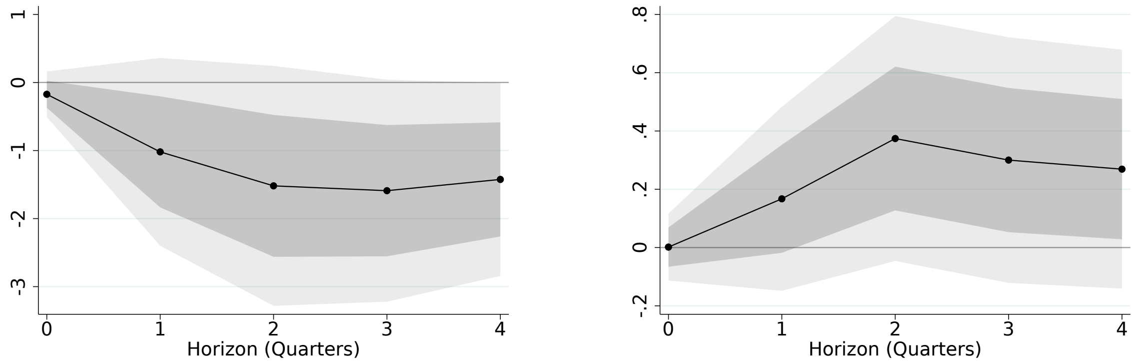
(e) Cost on GSCPI



(f) Cost on Exchange Rate

Note: Robustness analysis for our main results using import costs shocks instead of the GIV. Import cost shocks are either the Global Supply Chain Pressure Index (GSCPI) or the US dollar exchange rate, each multiplied by the product between the Loeontief inverse and the import shares of each sector. (When the panel shows the exchange rate rising, it means the dollar is depreciating.)
Sources: Compustat, BLS, Federal Reserve Bank of New York's Global Supply Chain Pressure Index, (https://www.newyorkfed.org/research/gscpi.html), and authors' calculations.

Figure C.6: Additional Results on the Role of Concentration: Effect of Endogenous Costs and Response of Costs

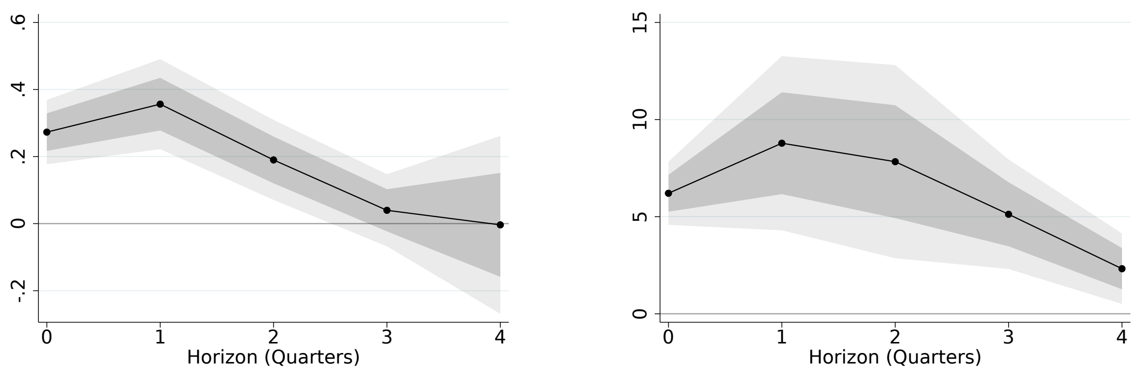


(a) Prices on Cost*HHI

(b) Output on Cost*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. *Sources*: Compustat, BLS, and authors' calculations.

Figure C.7: Only Industries with 20 or More Firms: $N > 20$

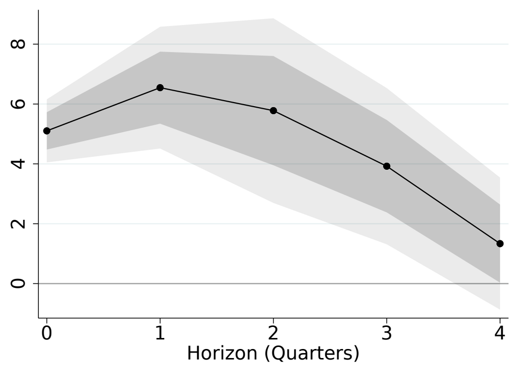


(a) Price on GIV

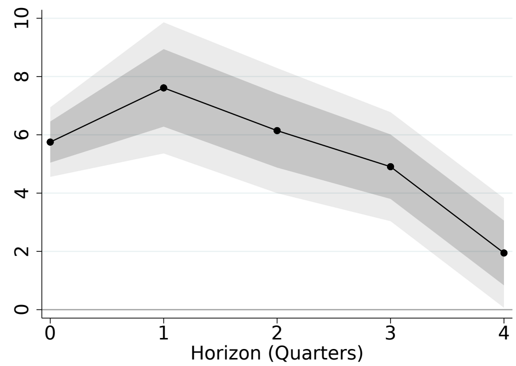
(b) Price on GIV*HHI

Note: Robustness analysis for our main results in Figure 2, Panel (a) and Figure 6, Panel (a). *Sources*: Compustat, BLS, and authors' calculations.

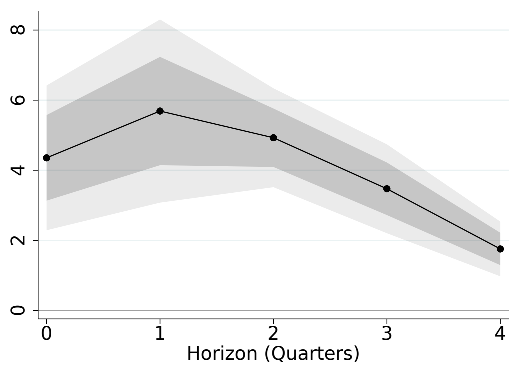
Figure C.8: Concentration Effect of Price Response with Different Cost Shock Measures



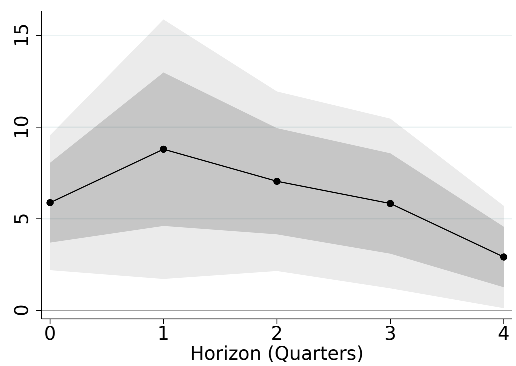
(a) Price on GIV (GIV 1 All)



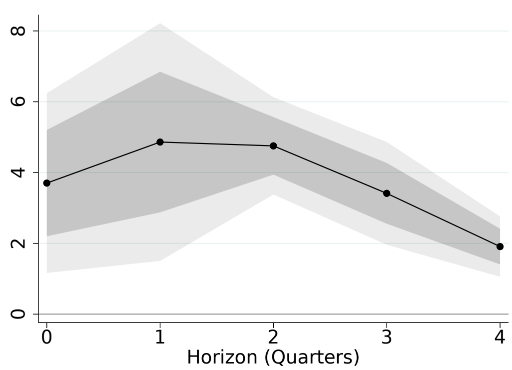
(b) Price on GIV (GIV 1 Top 5)



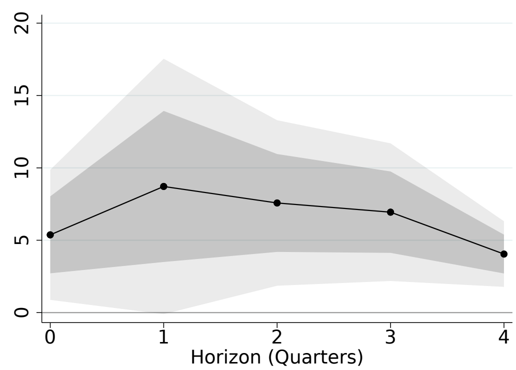
(c) Price on GIV (GIV 5 All)



(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 for 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 five firms within each industry are aggregated; see Gabaix and Koijen (2021). *Sources*: Compustat, BLS, and authors' calculations.

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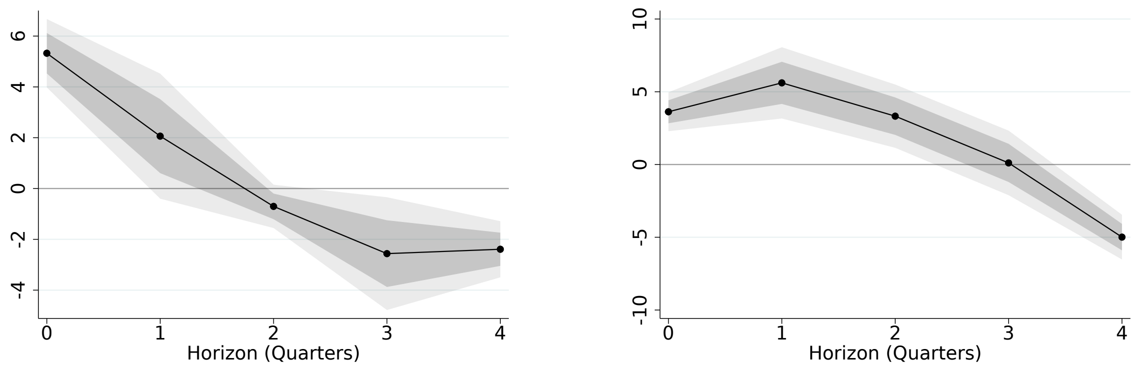
Figure C.9: Concentration Results in Log Year-over-Year Differences

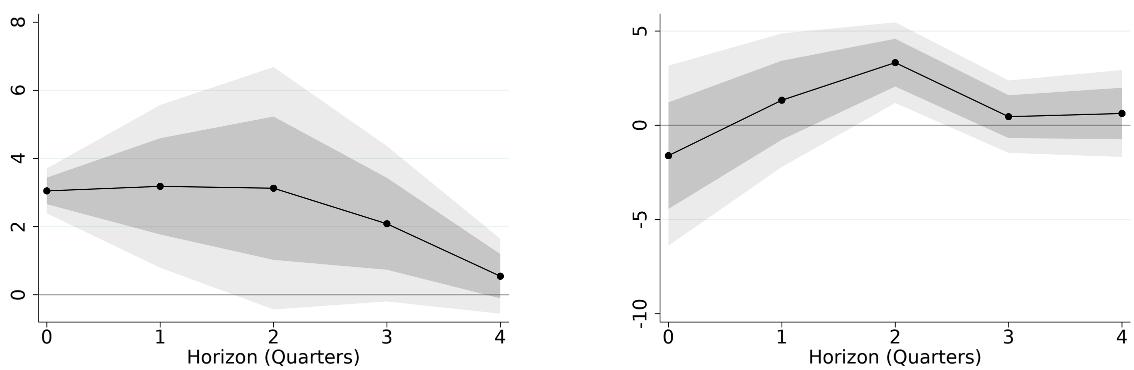


(a) Price Growth on GIV*HHI

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

Note: Robustness analysis for 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 text. *Sources*: Compustat, BLS, and authors' calculations.

Figure C.10: Results on Concentration with Different Cost Measure: CoGS vs. Non-CoGS

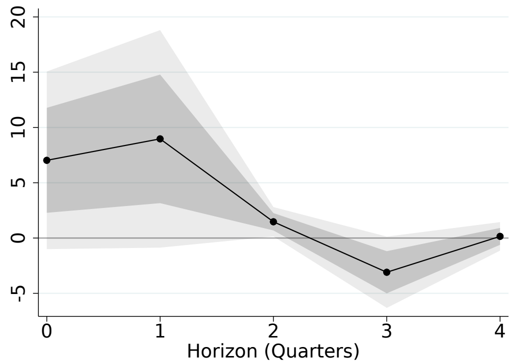


(a) Price on GIV*HHI

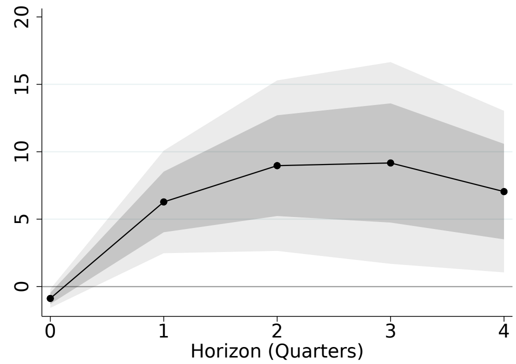
(b) Price on GIV*HHI

Note: Robustness analysis for our main results in Figure 6, Panel (a) using a proxy for variable costs (CoGS) and fixed costs (non-CoGS). *Sources*: Compustat, BLS, and authors' calculations.

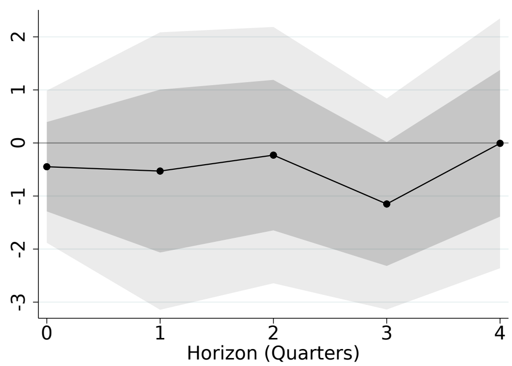
Figure C.11: Import Cost Shocks: Differential Pass-Through Depending on Concentration



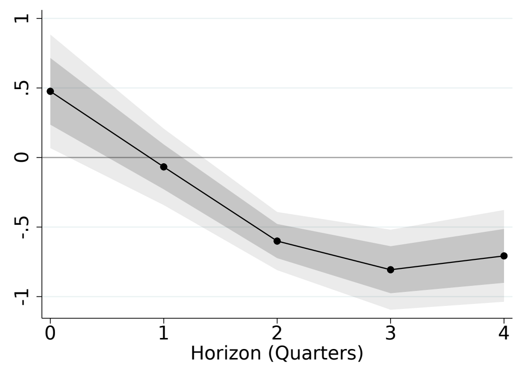
(a) Prices on GSCPI*HHI



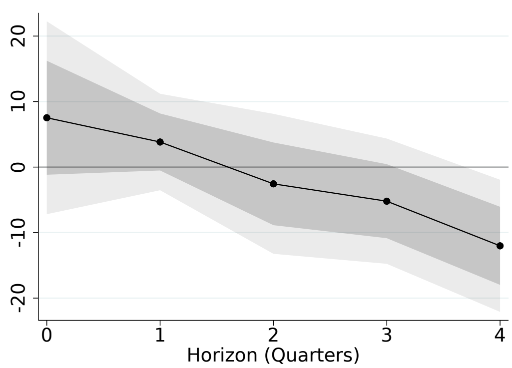
(b) Prices on Exchange Rate*HHI



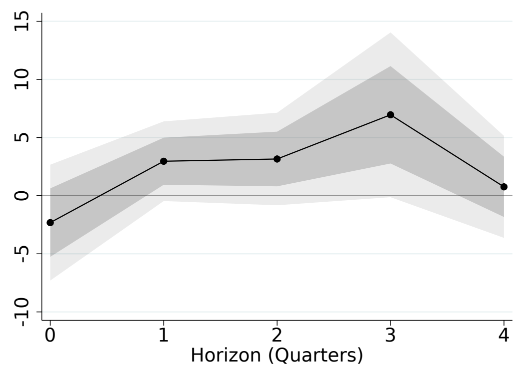
(c) Output on GSCPI*HHI



(d) Output on Exchange Rate*HHI



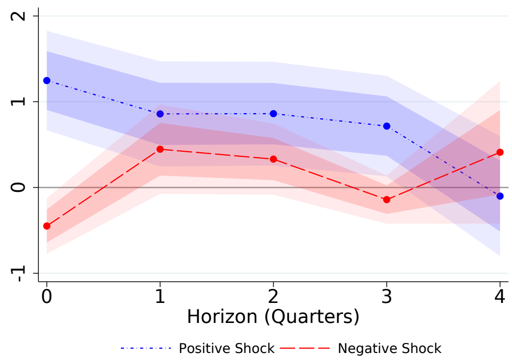
(e) Cost on GSCPI*HHI



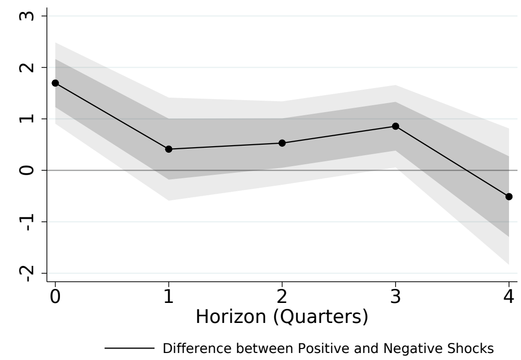
(f) Cost on Exchange Rate*HHI

Note: Robustness analysis for our main results on the role of concentration using import costs shocks instead of the GIV. Import cost shocks are either the Global Supply Chain Pressure Index (GSCPI) or the US dollar exchange rate, each multiplied by the product between the Loeontief inverse and the import shares of each sector. (When the panel shows the exchange rate rising, it means the dollar is depreciating.) *Sources*: Compustat, BLS, Federal Reserve Bank of New York's Global Supply Chain Pressure Index (`https://www.newyorkfed.org/research/gscpi.html`), and authors' calculations.

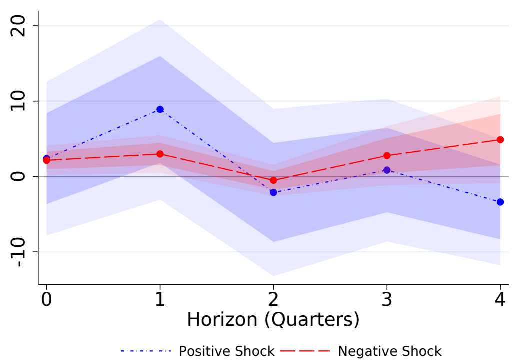
Figure C.12: Asymmetric Cost Responses



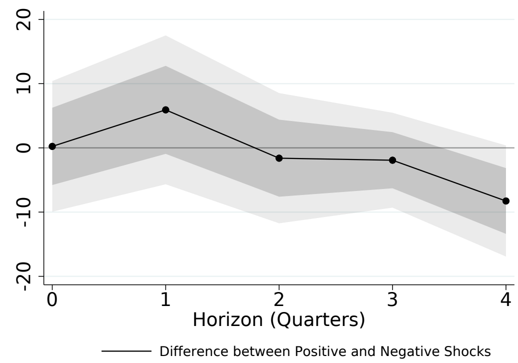
(a) Cost on GIV Level



(b) Cost on GIV Level (diff)



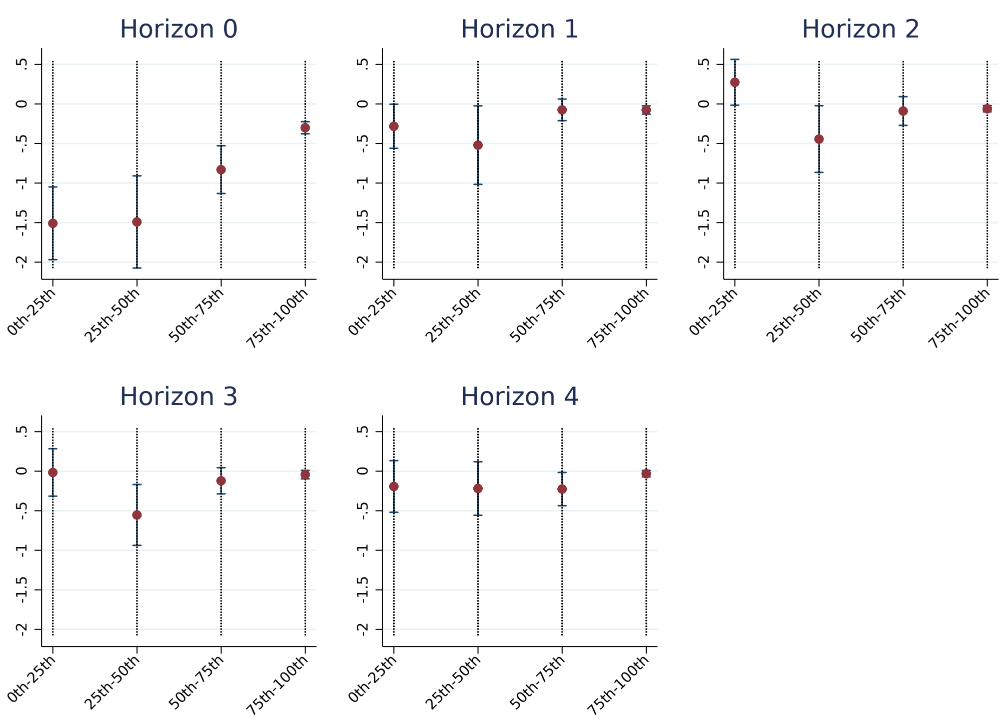
(c) Cost on GIV*HHI



(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 the cost shock and the 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. *Sources*: Compustat, BLS, and authors' calculations.

Figure C.13: The Effect of Cost Innovations on Margin by Firm Size (Quantile) Groups



Note: Quantiles are calculated using sales within an NAICS-3 quarter. Observations are dropped for NAICS-3-quarter quantiles that have fewer than five firms. *Sources*: Compustat, BLS, and authors' calculations.