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ABSTRACT

Macro evidence suggests a convex relationship between inflation and slack, but causal identification is challenging. Using large firm-panel surveys in the UK and US, we show that price responses to demand shocks are convex at the firm level, across hypothetical survey shocks, realised sales shocks, and COVID-induced demand shocks. Convexity is strongest when firms and industries face higher inflation, fades beyond two years, and applies to cost shocks. We rationalise these findings with a menu-cost model in which trend inflation moves firms closer to price-increase thresholds. We estimate that this nonlinearity explains about one quarter of the 2022 inflation overshoot.

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1 Introduction

In 2022, inflation across many advanced economies reached levels not seen for decades, with similar experiences in the US and UK. The extent of this increase in inflation was greater than most forecasters had expected, even given the increases in energy prices after the Russian invasion of Ukraine and shortages of labor and intermediate goods. Inflation rates returned close to target levels by 2025, but 2026 brought new inflation fears following the outbreak of conflict in the Middle East and the closure of the Strait of Hormuz. Understanding the dynamics of inflation following large shocks is crucial for monetary policymakers setting interest rates. But analyzing these episodes is also important from a more timeless perspective – providing identifying variation to improve our understanding of firm price-setting, and specifically to identify potential non-linearities in the response to shocks.[1]

The canonical approach to modeling aggregate inflation dynamics is the Phillips curve, which considers the relationship between measures of inflation and economic slack.[2] Cross-country macro data provide suggestive evidence of a convex relationship, but achieving identification with aggregate data is econometrically challenging. In this paper, we use data from large and representative surveys of UK and US firms to identify how prices respond to firm-level demand shocks, and, separately, cost shocks.[3] In the second part of the paper, we develop a general equilibrium model with menu costs to rationalize the micro-level estimates and analyze the implications for the aggregate Phillips curve.

We use data from the Decision Maker Panel (DMP) survey for the UK, and data from the Survey of Business Uncertainty (SBU) and the Business Inflation Expectations (BIE) survey in the US.[4] The UK DMP is a large and representative survey of CFOs in UK businesses.[5] It was established in 2016 and is run by the Bank of England in partnership with the University of Nottingham and King's College London. The survey is carried out online

[1] Other papers have also considered non-linearities in the current context, including Ball et al. (2022), Benigno and Eggertsson (2023, 2024), Boehm and Pandalai-Nayar (2022), Faber and Züllig (2025), Gitti (2025), Harding et al. (2023), and IMF (2024).

[2] The specific measures of inflation and economic slack used vary substantially in the literature. In the original 1958 paper, Phillips used monthly wage growth and unemployment, respectively.

[3] Existing papers have used regional data from the US to identify the slope of the Phillips curve. See, for example, Beraja et al. (2019), McLeay and Tenreyro (2019), Fitzgerald et al. (2020), Gitti and Cerrato (2025), and Hazell et al. (2022).

[4] Aggregate statistics from the surveys are published on a monthly basis on the DMP and SBU websites https://decisionmakerpanel.co.uk/ and https://www.atlantafed.org/research/surveys/business-uncertainty

[5] Further information on the structure of the DMP, evaluation of data quality, and how the data can be accessed are detailed in Bunn et al. (2024).

and receives close to 2,500 responses each month. The US SBU is organized in a similar manner, run by the Federal Reserve Bank of Atlanta, and collects monthly data from around 1,000 firms.[6] The Business Inflation Expectations (BIE) survey is also run by the Federal Reserve Bank of Atlanta, and collects monthly data from around 500 firms in the Federal Reserve's 6th district.

These three datasets reveal significant evidence that the response of firms' prices to demand shocks is convex; firms increase their own prices by a larger amount in response to positive shocks than they reduce them in response to negative shocks. This convexity arises using three distinct approaches.

First, we run a survey experiment that asks firms how they would adjust their prices in response to a series of hypothetical sales *volume* shocks, ranging from −20% to +20%. The size and sign of the shock that firms are presented with is randomly chosen, and each firm is then asked the same question with the same size of shock but with the sign reversed. We find strong evidence of convexity in both the US and UK, with firms raising prices in response to positive shocks, whereas the response to negative shocks is around zero.

Second, using responses from firms about their own price-setting behavior, we focus on how prices respond to developments in firms' actual sales. In the UK, we calculate firm-level sales growth forecast errors using the DMP, which are the difference between realized annual sales growth and expected year-ahead sales growth for the same period reported a year earlier. We do the same using expected and actual price growth and then assess the relationship between sales growth and price growth forecast errors, which are both scale-free. Analyzing forecast errors rather than using reported growth rates allows us to account for level differences in sales growth and price growth across firms, which could otherwise distort the results. In the US, we use the BIE to conduct a similar exercise, using data on the deviation of sales levels compared to normal. We use sales levels in place of sales forecast errors, since those are not available in the BIE. The results of both exercises again suggest significant asymmetry, with positive sales growth forecast errors and higher sales relative to normal both associated with more than two times larger price growth forecast errors.

Finally, we analyze the response of firm prices to the Covid-19 shock. The impact of Covid-19 is estimated using specific questions about the impact of the pandemic on firm

[6] See, for example, Altig et al. (2022)

sales in the UK. Once again, we find that the effect on inflation was asymmetric: positive demand shocks from Covid raised inflation at the firm level by five times more than negative Covid demand shocks reduced it.

We then present three empirical extensions to our main results, which provide additional predictions for our model to verify. Many models can predict a convex Phillips curve – for example models with menu costs, capacity constraints, financial constraints, non-linear demand curves, or wage rigidities. So, we provide three additional empirical results to help distinguish between these models.

First, we show that the convexity of the price response to demand shocks is more pronounced when inflation is high. We split the sample into high-inflation and low-inflation firms using firm average price growth across all survey months relative to the full sample average. In both the UK and the US, firms with above-average price growth exhibit a strongly non-linear response to positive versus negative shocks across all empirical exercises described above. In contrast, firms with below-average price growth do not exhibit material convexity in their price response to demand shocks.

Second, we show that our convex response is only present in shorter-run horizons. The main analysis uses survey questions asking about year-on-year price and sales changes. In the second exercise, we utilize the panel dimension of the survey to analyze longer-run responses by looking at *cumulative* price growth and sales growth changes over several years. We find evidence that the convexity of price response to sales is strongest in the first year, and declines over time, so by the third year the convexity has disappeared.

Third, we analyze the response of firm prices to *cost* shocks, which we show are also strongly convex. We run a randomized survey experiment where firms are asked about price responses to hypothetical *unit cost* shocks. The results using our randomized assignment of shock size, sign, and order, suggest a convexity in price responses. Both UK and US firms report approximately 60% cost pass-through to positive shocks in the first year after a shock, but only a 20% pass-through to negative shocks.

We combine estimates on the pass-through of demand and cost shocks with data on firm real sales growth and cost growth to quantify the importance of non-linearities for the recent rise in inflation. This quantification yields two important insights. First, cost shocks were a much more important driver of the rise in firm prices in 2022 compared to demand shocks. Second, taking non-linearities into account helps account for around one-fourth of the inflation overshoot, compared to linear pass-through of shocks. Thus, non-linearities in price-setting are not only significant in a statistical sense, but also matter quantitatively for understanding recent inflation dynamics.

These empirical results are rationalized in a model of firm price setting with menu costs, decreasing returns to scale, and positive trend inflation. Decreasing returns to scale increase firms' optimal prices when output increases relative to the aggregate. But menu costs create an (S,s) inaction region for firms in which prices do not change in response to cost or demand shocks. Positive trend inflation generates an asymmetry in the distribution of firms within the inaction zone, as positive inflation leaves more firms close to the price-increase point than firms close to their price reduction point. So, price increases are more likely to be triggered by positive shocks than reductions triggered by negative shocks of a similar size.

Simulated data from the model deliver a convex relationship between firm-level demand shocks and firm price inflation, matching our empirical results. Aggregating these responses, we find that the *aggregate* Phillips curve is also convex. Importantly, this model can also explain our empirical extensions: convexity is greater with higher trend inflation, it wanes over the longer run, and arises in response to both demand and cost shocks. A range of models, including capacity constraints, downwardly rigid wages, and quasi-kinked demand, can each reproduce some of our empirical findings. However, of the candidate models we consider, only our menu cost model matches all the empirical results. We do not claim this is the sole driver of Phillips curve convexity - more than one model mechanism could be operating in parallel - but it is a parsimonious framework consistent with our full set of facts.

The presence and implications of a non-linear Phillips curve has been a topic of keen interest among both policymakers and academics in recent years.[7] To our knowledge, our paper is the first to bring detailed empirical evidence on the response of prices to both demand and cost shocks using economy-wide firm-level data. The findings can help explain the dynamics of aggregate inflation since 2020. The demand asymmetry is key to understanding why inflation only declined modestly in the first year of the pandemic, despite a very large fall in demand. At the same time, the non-linear response to cost shocks helps

[7] Recent speeches by policymakers which reference non-linearities in the Phillips curve include Jerome Powell (2023), "Inflation: Progress and the Path Ahead"; Catherine Mann (2022), "Inflation expectations, inflation persistence, and monetary policy strategy"; Isabel Schnabel (2024), "Navigating towards neutral". Recent academic research which studies the implications on nonlinear Phillips curves for optimal monetary policy includes Ascari et al. (2025) and Karadi et al. (2024).

rationalize the sharp rise in inflation during 2022, which was largely driven by higher firm costs. Taking these asymmetries into account is particularly important in times of higher inflation and when the economy is faced with larger shocks.

Our work relates to four literature. One is on asymmetric inflation responses to shocks. The global inflation surge of 2021-2022 renewed interest in non-linear price setting. Benigno and Eggertsson (2023, 2024) derive a non-linear wage Phillips curve from labor-market frictions and downward wage rigidity, while Harding et al. (2023) use a quasi-kinked goods-demand schedule to explain both missing deflation after the Great Recession and inflation's 2022 acceleration. Convex Phillips curves also arise from industry capacity constraints (Boehm and Pandalai-Nayar, 2022), limited substitution between inputs (Juul and Jørgensen, 2025), and sectoral supply constraints (IMF, 2024). Karadi et al. (2024) study optimal monetary policy in a related model. Empirically, Ball et al. (2022) find non-linear activity effects, while Forbes et al. (2021) provide cross-country evidence.

Unlike this work, our analysis focuses on individual firms, taking aggregate conditions as given, without imposing discontinuities in wages or demand beyond a symmetric menu cost. The firm-level kink arises endogenously from menu costs, positive trend inflation, and decreasing returns to scale; its aggregate counterpart follows the same mechanism.

We also contribute to the price-setting literature. Time-dependent models, notably Calvo (1983), allow firms to reset prices randomly. State-dependent models instead link adjustment to economic conditions through menu costs (Mankiw, 1985; Ball and Mankiw, 1994, 1995) or information costs (Mankiw and Reis, 2002). Micro evidence tests these mechanisms (Bils and Klenow, 2004; Klenow and Kryvtsov, 2008; Nakamura and Steinsson, 2008), prompting refinements such as Golosov and Lucas (2007) and Midrigan (2011). Alvarez et al. (2016) show that price-change kurtosis relative to adjustment frequency is a sufficient statistic for monetary shocks' real effects. Auclert et al. (2024) find leading models behave similarly below 5% inflation, whereas Blanco et al. (2024) emphasize non-linearities in models matching price-change sizes and frequencies. Expectations also matter: Meeks and Monti (2023) show heterogeneous beliefs affect inflation dynamics, while Werning (2022) derives expectation pass-through across pricing models.

A third strand uses micro data to document asymmetric price responses. Prices respond more rapidly to positive than negative demand shocks in supermarket data (Peltzman, 2000) and New Zealand firm surveys (Buckle and Carlson, 2000). Finnish firms responded twice as strongly to VAT increases as to decreases (Benzarti et al., 2020). Karadi and Reiff (2019) model flexible, asymmetric responses to large VAT shocks using menu costs, trend inflation, and fat-tailed product shocks. Firm-level supply-curve estimates also show steeper slopes during high inflation in Sweden (Ahlander et al., 2024) and connect Danish micro responses to the aggregate Phillips curve (Hoeck and Renkin, 2025).

Finally, we extend the growing use of business surveys to evaluate major shocks (Altig et al., 2022; Bhandari et al., 2020; Candia et al., 2023, 2024). Large, high-frequency, forward-looking surveys provide timely evidence during rapidly evolving episodes; our survey also combines forward- and backward-looking measures.

The structure of this paper is as follows. In Section 2, we show cross-country evidence of convexity in the relationship between inflation and economic slack. In Section 3 we provide more information on the Decision Maker Panel, the Survey of Business Uncertainty, and the Business Inflation Expectations survey that we use. Section 4 presents three empirical tests of non-linearities in price-setting in response to demand shocks. Section 5 presents three extensions to the main results. In Section 6 we solve a general equilibrium menu cost model to rationalize our findings. Section 7 concludes.

2 Macro Data and Estimation

We first analyze the relationship between aggregate inflation and economic slack in a cross-country panel dataset, to confirm convexity in macro data. Our approach is similar to Forbes et al. (2021), who estimate the Phillips curve using data for 31 countries over 1996-2017. We build on their approach, extending the sample up to 2024 for 38 countries, collecting data from three separate sources. First, headline consumer price index (CPI) inflation data from the World Bank Global Database of Inflation (Ha et al. 2023).[8] Second, CPI inflation forecast data from the IMF World Economic Outlook (WEO) historical forecasts database.[9] For a given country-year there are two forecasts, from the Spring and Fall WEO, respectively. In the regressions we focus on five-year ahead forecasts for CPI inflation, $E_t\left[\pi_{it+5}\right]$, in order to capture long-run expectations, and we take the average of the two forecast vintages. Finally, for economic slack we use a measure of the 'output gap' based on estimates from the OECD.[10] We have data for 38 countries over the period 1990-2024

[8] Data can be accessed here: https://www.worldbank.org/en/research/brief/inflation-database
[9] Data can be accessed here: https://www.imf.org/en/Publications/WEO/weo-database/2024/April
[10] Estimated as the percentage gap between actual GDP and potential GDP, where the later is derived using a production function approach from capital, labor and productivity data

(details in Table A1). [11]

We estimate the relationship between annual CPI inflation and economic slack using the following specification, estimated for country i and year t:

$$\pi_{i,t} = \alpha_i + \beta_t + \gamma\pi_{it-1} + \theta E_t\left[\pi_{it+5}\right] +$$

$$\lambda_1 OutputGap_{it} \times 1[OG_{it} \geq 0] + \lambda_2 OutputGap_{it} \times 1[OG_{it} < 0] + \varepsilon_{it}$$

The coefficients of interest λ_1 and λ_2 capture the relationship between the output gap and inflation when the output gap is positive and negative, respectively. In addition, we include country fixed effects, α_i, which control for time-invariant differences across countries, such as different institutional frameworks or different average levels of inflation. We also control for time fixed effects to account for large shocks which affect all countries. These include, for example, the Global Financial Crisis, Covid-19, and global changes in commodity prices. Finally, we control for lagged CPI inflation and five-year ahead inflation expectations, using data from the IMF WEO forecasts.

Figure 1 presents a binned scatterplot of headline CPI inflation against the output gap over the full sample. This figure visualizes the raw data, without any controls or fixed effects. We allow the slopes of the coefficients to vary when the output gap is positive and negative. There is clear evidence of a convex relationship: the coefficient on the positive output gap side (0.34) is around three times as large as the coefficient on negative output gap out-turns (0.12). In other words, years with output above potential are associated with stronger increases in aggregate inflation than periods when output is below potential. This is consistent with a non-linear price Phillips curve in the cross-country data.

In Table 1, we provide further robustness tests for this result. Column 1 shows the linear relationship between inflation and the output gap. This is positive and significant across the full sample over 1990-2024, even after controlling for country and time fixed effects as well as controls for lagged inflation and long-term inflation expectations. In Column 2, we add a quadratic term on the output gap. This is positive and significant, consistent with the convex relationship from Figure 1. In Column 3 we test this explicitly by separating the slope coefficients depending on whether the output gap is positive or negative. We again find that the slope on the positive output gap is around three times larger (0.19)

[11] Country-year observations with annual CPI inflation greater than 15% are excluded from the sample.

than the negative output gap (0.06). The row at the bottom of the table confirms that the difference between these coefficients is statistically significant at the 5% significance level.[12]

To what extent are these results driven by the pandemic and high-inflation episode since 2020? In Columns 4 and 5, we split the sample into 1990-2019 and 2020-2024, respectively. In both time periods, we find significant evidence of a non-linearity, with positive output gaps associated with much stronger aggregate inflation. Therefore, the convex relationship between inflation and economic slack is not a phenomenon solely of the recent exceptional post-2020 period, but is also present pre-pandemic. However, the non-linearity does appear to be stronger over 2020-2024, consistent with a steepening of the Phillips curve over recent years. Finally, in Columns 6-7 we test whether the non-linearity is stronger for countries with higher average inflation rates. We define 'high inflation countries' as those with an average inflation rate above the average across all countries, 2.76%. For these countries (Column 7), there remains a highly significant non-linearity in the impact of positive vs. negative output gap outturns. In contrast, there is no significant evidence of a non-linearity for low-inflation countries (Column 6), with both positive and negative output gaps having a similar relationship with headline inflation.

It is important to emphasize that we do not make any structural or causal statements about the slope of the aggregate Phillips curve based on Table 1. There are multiple empirical challenges with estimating the Phillips curve using aggregate data, which are well-known in the literature.[13] First, the specification does not control for country-specific supply-side shocks which can affect both inflation and the output gap. Second, there is a debate about the appropriate variables to use, both on the right-hand side and the left-hand side of the specification. Different measures of inflation (e.g. headline CPI, core inflation, median CPI inflation) or slack (e.g. unemployment gap, output gap, vacancy-unemployment ratio) can lead to different conclusions. Recently, Doser et al. (2023) and Beaudry et al. (2025) show that the presence of a non-linear Phillips curve is sensitive to the inflation expectations measure used. Finally, as argued by McLeay and Tenreyro (2019), monetary policy reacts

[12] To verify that our results are not driven entirely by this specific measure of economic slack, we construct an unemployment gap measure for this sample of countries. We construct this using an HP filter for each country's unemployment series. In Figure A1, we find a similar non-linear relationship, with negative unemployment gap outturns associated with much stronger aggregate inflation than positive unemployment gap outturns.

[13] For example, Mavroeidis et al. (2014) and Hazell et al. (2022) all highlight the challenges of identifying Phillips curves in macro data while inflationary expectations, demand slack, and supply shocks are also changing. Coibion and Gorodnichenko (2015) show that the type of inflation expectations used in the estimation of the Phillips curve matters greatly for explaining inflation dynamics around the Global Financial Crisis. Coibion et al. (2018) further discuss the importance of survey expectations in Phillips curve estimation.

endogenously to changes in demand, which can mask the true slope of the Phillips curve.

Given these challenges associated with using macro data, the rest of the paper focuses on micro data from large surveys of UK and US firms to assess the impact of demand shocks on firm prices, where the effects can be more clearly identified. We then solve a general equilibrium model which matches the micro data, and use this to study the implications for the aggregate Phillips curve. Nevertheless, the macro analysis helps to motivate the micro analysis and it shows that the macro data are at least consistent with the non-linearities that we also find in our micro-level work.

3 Micro Data Sources

We use data from three large, representative surveys of UK and US firms.

The Decision Maker Panel (DMP)

The DMP is a large and representative online survey of primarily CFOs and CEOs in UK businesses with ten or more employees. The survey asks about recent developments and expectations for the year ahead in sales, prices, employment, and investment. An important advantage of the DMP survey relative to many other business surveys is the quantitative nature of the data that it collects. Bunn et al. (2024) provide a detailed overview of the survey, including the structure, quality checks against other datasets, and information on how to access the data.

The sampling frame for the DMP is the population of UK businesses with ten or more employees in the Bureau van Dijk FAME database, which itself covers all UK incorporated employee firms.[14] Firms are selected randomly from this sampling frame and invited by telephone to join the panel by a recruitment team based at the University of Nottingham. This approach helps to ensure that the survey provides a representative view of the UK economy.[15] Once firms are part of the panel, they receive monthly emails with links to a five- to ten-minute online survey. Firms that do not respond to the survey for three consecutive months are re-contacted by telephone to check whether they received the emails or have

[14]FAME is provided by Bureau Van Dijk (BVD) using data on the population of UK firms from the UK Companies House, which mandates reporting for all limited liability employee firms, numbering over one million businesses. FAME itself is part of the global AMADEUS database.

[15] Figure A3a compares the distribution of firms in the DMP to the population of firms in the UK Interdepartmental Business register. The distribution across sectors is similar (Panel A) as well as the distribution across regions (Panel B). Aggregated results are always presented weighted by industry and employment shares.

other reasons for not completing the survey. When the DMP recruitment team first contacts firms they ask to speak to the CFO, and failing that, the CEO, which is facilitated by the endorsement of the Bank of England. As a result, 78% of respondents are in these two positions (64% are CFOs and 14% are CEOs) with the remainder mostly senior finance managers. Given that the typical firm in the survey has about 75 employees, these CFOs and CEOs have a very good sense of the overall direction and performance of their business.

The DMP grew quickly after its launch and has averaged about 2,500 responses a month since 2022, covering around 5% of UK private sector employment. The surveys have a rotating three-panel structure – each member is randomized at entry into one of the three panels (A, B or C). Each panel is given one third of the questions in any given month, so that within each quarter firms rotate through all questions. This helps keep the survey short for respondents whilst yielding a regular monthly flow of data. The response rate for active respondents averages around 54% (Figure A2 shows the response rate and number of responses per month).

An advantage of the DMP survey relative to other business surveys is the quantitative nature of the data that it collects. This makes the data particularly valuable for research, especially for analyzing the impact of major economic events such as the Covid pandemic where the scale of changes is large. Many other business surveys tend to focus on questions that ask businesses to indicate whether they expect the conditions that they face to get better or worse, rather than *by how much* they expect them to get better or worse. The CFOs and CEOs the DMP targets are likely sufficiently numerate to answer quantitative questions.

Since its inception, the DMP has asked firms about how the average price that they charge has changed over the last year. This is the firm-wide average price for multi-product firms. The survey includes firms from across the economy, and therefore the pricing data are a mix of prices from consumer- and producer-facing businesses. Importantly, the DMP inflation data closely track the UK aggregate Consumer Prices Index, and in particular non-energy CPI inflation rates (Figure A4a).

The survey also asks firms about their expectations for year-ahead inflation in their own average price. Rather than ask for a point estimate, respondents are asked about the distribution of expected possible outcomes. They are asked to provide their lowest, low, medium, high, and highest expectations for year-ahead inflation, and then for the probabilities associated with each scenario, where those probabilities must sum to 100% (see Figure B1 for screenshots of how this works in the survey). From this, it is possible to calculate a mean expected outcome, a standard deviation, and a skew. The survey also contains similar questions for sales, employment, wages, unit costs, and investment, allowing comparable metrics to be calculated for these variables.

As well as the regular questions on recent and expected future outcomes, the DMP survey also includes ad-hoc questions about topical policy issues. These special questions have covered topics such as how Brexit and Covid affected businesses, firm price-setting, and monetary policy transmission, amongst others.[16]

The Survey of Business Uncertainty (SBU)

The SBU is a monthly online survey of CFOs and senior financial directors in US firms. It was established in 2014 and is organized by the Federal Reserve Bank of Atlanta in collaboration with Chicago and Stanford Universities. The SBU is representative of the US economy by size and industry. The SBU panel is smaller than the DMP. As of August 2025, the SBU had around 1,500 panel members and received around 1,100 responses each month. However, the structure of the survey and style of questions are very similar to the DMP: respondents are asked about current, past, and future outcomes for their business. They are also asked to provide subjective probability distributions for their expectations (see Altig et al. 2022 for further details).

We use data from the SBU on the response of firm prices to hypothetical sales volume shocks. These were included in the survey in June 2024 and are identical to the questions asked in the DMP for comparability. In January 2026 firms in the SBU were also asked about the response of firm prices to hypothetical unit cost shocks. However, questions on price growth have not yet featured regularly in the SBU (they were introduced in April 2025). Therefore, for the US we also use data from the Business Inflation Expectations (BIE) survey for the empirical analysis.

The Business Inflation Expectations survey (BIE)

The BIE is a monthly online survey of panelists who occupy executive and

[16] For example, Bloom et al. (2025) study the effects of Covid-19 on productivity using DMP data.

managerial positions at US firms in the Federal Reserve's 6th district.[17] This district is representative of the overall US economy by firm size and industry. The Federal Reserve Bank of Atlanta, which serves the 6th district, established the survey in 2011. As of February 2026, the BIE had around 1,100 panel members and received around 500 responses each month. Although it is geographically restricted and smaller than both the DMP and the SBU, the BIE largely tracks official statistics (see Figure A4b). Since its inception, the BIE has asked firms about their unit cost expectations and their sales levels compared to normal. In addition, the BIE introduced a price forecasting module in December 2020, allowing us to construct price growth forecast errors starting from December 2021 onward.

The structure of the BIE differs from that of the DMP and SBU. All members are in one panel. The BIE asks respondents four monthly "core" questions and one of three rotating quarterly questions. The principal core question asks firms for their year-ahead unit cost expectations. Participants are asked to assign probabilities to five fixed unit cost growth rate bins: <-1%, -1% to 1%, 1.1% to 3%, 3.1% to 5%, and >5% (see Figure B4 for screenshots of how this works in the survey). These probabilities must sum to 100%. The second question asks participants to select which similarly defined bin best reflects their realized unit cost growth over the past year. The BIE typically assigns the upper and lower bins for these questions to 6% and -2%, respectively, and the other bins to their midpoints.[18] The two quarterly questions that we use in this paper – sales level compared to normal and expected and realized price change – are simple point estimates (see Figures B5 and B6 for screenshots).

4 Micro Data Phillips Curve Estimation

In line with aggregate data, inflation within the DMP fell modestly during the first year of the Covid pandemic before picking up sharply thereafter (Figure A4a). Firm price growth also increased sharply in the US over 2022 and 2023 (Figure A4b). A key research question is whether this limited early pandemic disinflation and high subsequent inflation at least partly reflects convexities in price-setting behavior. Firms may respond in a non-linear manner to both demand shocks (such as the large fall in demand over 2020) or cost shocks

[17] The Federal Reserve's 6th district encompasses Alabama, Florida, Georgia, and parts of Louisiana, Mississippi, and Tennessee.

[18] We use the DMP's cost growth series to calculate the conditional mean unit cost expectation within each bin, and reassign values for realizations analogously. The adjusted values for unit cost expectations are -6.5%, 0.2%, 2.3%, 4.1%, and 9.1%. The adjusted values for unit cost realizations are -7.3%, 0.2%, 2.4%, 4.6%, and 11.7%.

(for example, the large energy price shock in 2022). In this section, we present three complementary results, all of which suggest firm prices are more responsive to positive versus negative demand shocks. Whilst each of these three individual exercises has some strengths and weaknesses, the common finding that prices responded in a non-linear way is robust across all three. In Section 5.3, we also test for the presence of convexities in the response to cost shocks.

4.1 Hypothetical sales volume shocks and prices

The first approach we use to assess the responsiveness of firm prices to demand shocks is a randomized survey experiment. This is the cleanest setting to identify the causal impact of demand on prices. The main limitation is that this is a hypothetical response, which is why we supplement it with evidence of how firms responded to shocks that they actually faced in the other two empirical exercises. Over five months (December 2023 to January 2024 and August to October 2024), newly designed questions asked UK firms in the DMP how their prices would respond to hypothetical sales *volume* shocks of different magnitudes. The identical question was asked to US firms in the SBU in June 2024.

The implementation took the following steps. First, firms were randomized into one of four shock scenarios: ±5%, ±10%, ±15%, and ±20%. They were then presented (at random) with the positive or the negative value of the shock and asked how they would adjust their price in response. Afterwards they were also asked about their response to an equivalent shock of the opposite sign. For example, a firm would be first asked if and how it would change prices in response to a -10% sales volume shock and then if and how it would change prices in response to a +10% sales volume shock. Figures B2 and B7 provide screenshots of the exact format of the questions in the DMP and SBU, respectively. Over the five months, 3,197 survey responses were received in the DMP, which means 6,394 observations overall (two scenarios per firm). In the SBU, we collected responses from 787 firms.

In Figure 2 Panel A, we present the main result on hypothetical sales volume shocks from the DMP. This figure plots the average price response for each of the eight shock categories, with separate lines of best fit for positive and negative shock values. In doing so, we assume that a zero sales volume shock scenario corresponds to a zero price response. The figure suggests there is a clear non-linear relationship between sales shocks and price responses. For instance, an unexpected decline in sales of 20% leads to an average price decline of 0.14%. Meanwhile, a 20% *positive* sales volume shock leads to an average price increase of 1.2%. In general, the slope of the linear fit on the negative side is 0.007, whereas on the positive side it is 0.06. In Figure 2 Panel B, we present the results from the Survey of Business Uncertainty. There is again clear evidence of a convex relationship, with positive hypothetical sales volume shocks leading to stronger positive price responses. In the regression analysis, we formally test for the significance of the difference in slopes.

In Table 2, we present the main results on the impact of sales volume shocks on prices. Columns 1-3 are the results for UK firms in the DMP. Column 1 presents the linear relationship: the coefficients suggest that a 1% increase in real sales volume would lead firms to increase prices by 0.03%. However, as suggested by Figure 2, this relationship is non-linear, with a stronger effect for positive sales shocks. In Column 2 we add a quadratic term, which is positive and highly significant, consistent with the presence of a convex relationship. In Columns 3, we explicitly test the difference in responses for negative versus positive shocks. We find that there is no significant relationship between negative shocks and prices (with a slope coefficient of 0.007). Meanwhile, the response for positive shocks is stronger (0.06), and highly significant. Below the coefficients we also test whether the difference between the two coefficients is statistically significant; indeed, we can reject the hypothesis that they are equal at the 1% significance level.[19]

Columns 4 to 6 of Table 2 present the corresponding results for US firms in the SBU. The results are very similar to those in the UK. In particular, Column 6 suggests that there is a strong and significant impact of positive sales volume shocks on prices, whereas the impact of negative shocks is not statistically different from zero. Finally, we show that we cannot reject equality of the positive and negative slopes across the UK and US samples using a Wald test, suggesting some generality to the results.[20]

Overall, the results from Figure 2 and Table 2 provide robust evidence of a convexity between sales volume shocks and prices. In the next sub-sections, we show that firms respond in a convex manner not only to hypothetical scenarios, but also in their realized price setting.

4.2 Evidence from sales shocks and price growth forecast errors

To build on our findings using hypothetical shocks, in this section we consider the

[19] Across all three empirical exercises in this section, we test for the presence of convexity using a quadratic term and also by splitting the coefficients into positive/negative slopes. The results are similar with either approach, and we also note that the explanatory power is similar in both types of specifications. For ease of presentation, in the figures we present the versions with a kink at zero.

[20] Positive test t-stat = 0.39, and negative test t-stat=0.62 using the estimates in Columns 3 and 6.

relationship between sales shocks and price growth forecast errors. This approach exploits the strong panel dimension of the survey data. In the DMP, we calculate price growth (sales growth) forecast errors as the difference between annual own-price growth (sales growth) and expected year-ahead price growth (sales growth) that firms provided in their survey responses exactly one year earlier. Thus, the sample is firms that have provided survey responses in consecutive surveys 12 months apart. It is important to note that the sales growth questions relate to the value of nominal sales rather than the volume of sales. That is one limitation of this exercise, but it would not alone account for non-linearities in the data.

Firm expectations are highly correlated with subsequent realizations in the DMP, highlighting the quality of the forecast data (Figure A5a). However, as firms experience unexpected shocks, their realizations may deviate from expectations, generating price and sales growth forecast errors.

We analyze the relationship between sales growth and price growth forecast errors, distinguishing between the effects of positive and negative sales errors. Figure 3 Panel A presents the main result. There is a strong positive relationship between the two series, with larger sales growth forecast errors (both positive and negative) associated with larger price growth forecast errors. Furthermore, there is a distinct non-linearity in this relationship, with a stronger relationship for positive rather than negative errors. The slope of this line suggests that a one percentage point larger positive sales growth error is associated with a 0.1 percentage point larger price growth. Meanwhile, the slope for negative sales growth errors is only 0.04.

We conduct a similar exercise for US firms. Because the SBU does not have a long enough price growth series, we use the BIE survey instead. We calculate price growth forecast errors in the same way, as the difference between realized annual price growth and expected year-ahead price growth reported a year earlier.[21] However, rather than asking firms about their expected and realized sales to construct forecast errors, each quarter the BIE asks firms about their sales levels as a deviation from 'normal'.[22] We use this measure in place of sales forecast errors, treating deviations from normal as a proxy for sales shocks at the firm level.

[21] Albeit with two data restrictions. The BIE's price change questions were asked infrequently from December 2020 to 2023Q1, after which these questions entered the quarterly rotation. The result is a shorter time series than the DMP. Second, the BIE asks firms to report their price change expectations as point estimates, which results in more dispersion in forecast errors than in the DMP. Nevertheless, firm expectations are highly correlated with subsequent realizations (Figure A5b)

[22] See Figure B6 for question wording.

We analyze the relationship between sales levels compared to normal and price growth forecast errors, distinguishing between the effects of positive and negative sales levels. Figure 3 Panel B presents the main results from US firms. There is a strong positive relationship for positive sales levels. Once again, there is a distinct non-linearity in this relationship. When sales are above normal, the line of best fit (based on a regression without any fixed effects) suggests that a one percentage point increase in sales levels relative to normal is associated with a 0.15 percentage point higher price growth than expected. Meanwhile, when sales are below normal, the effect on price growth forecast errors is essentially zero. Overall, both the UK and US panels provide evidence that positive sales shocks have a distinctly stronger effect on price growth compared with negative shocks. We next test the robustness of this relationship, using fixed effects specifications and sample period splits.

In Table 3, we analyze in more detail the relationship between sales shocks and price growth forecast errors. Columns 1-5 present results from UK firms in the DMP, whereas Columns 6-9 present the corresponding results from US firms in the BIE.

Column 1 confirms that there is a strong positive relationship between sales growth and price growth forecast errors, which is highly significant at 1%. However, as suggested in Figure 3, there is likely a non-linearity in this relationship across positive versus negative errors. Columns 2-4 test for the presence of a convexity in this relationship using UK firms. Column 2 adds a quadratic term to the specification from Column 1, and the coefficient is found to be positive and highly significant. Across Columns 3-4, we find that the coefficients on positive sales growth forecast errors are larger than the coefficients on negative errors, in specifications without time or firm fixed effects (Column 3), and with those included (Column 4). In Column 4 (the most demanding specification with firm and time fixed effects), the coefficient on positive errors (0.074) is more than twice as large as the one on negative errors (0.036). Furthermore, as shown by the p-values at the bottom of the table, we are able to reject the hypothesis that the coefficients are equal with a high degree of confidence. In Column 5 we examine the periods 2017-2019 finding similar evidence of non-linearities (2020-2026 also shows similar results), highlighting this is not just a Covid-era phenomenon.

Columns 6-9 replicate the same exercises for US firms. The relationship between sales in deviation from normal and price growth forecast errors is not significant across the full sample, but in Columns 8-9 we do find evidence of non-linearity. Without time or firm fixed effects (Column 8), the coefficients on positive sales levels are positive and highly significant, compared to the negligible and insignificant coefficient on negative sales levels. The difference between the coefficients is also statistically significant at the 5% level in this specification. In Column 9 we add firm and time fixed effects to the specification. This makes the coefficients less precisely estimated, although we can still reject the null that the coefficients on positive and negative sales shocks are equal at the 10% significance level.

4.3 Demand shocks and price growth during the pandemic

The final test of price responses to demand shocks uses Covid-19 as a natural experiment. Although this is only one episode, the Covid pandemic was a good example of a large and unexpected demand shock, and is therefore valuable for the study of how inflation responds to such shocks.[23] Starting in April 2020, soon after the start of the pandemic, firms in the DMP were asked to estimate how Covid-19 has affected their sales, relative to what otherwise would have happened.[24] We use this measure as a proxy of the 'Covid demand shock', conditional on other controls we can include in the regression specification. There was significant heterogeneity across industries and firms which provides us with substantial variation to estimate the effects of changes in demand on inflation. We do not have comparable data for US firms, therefore the analysis in this section is based on DMP data only.

To examine the dynamics of realized inflation we estimate a set of firm-level regressions. These include own price inflation as the dependent variable and firm-level measures of the Covid demand shock, supply side factors, and expected year-ahead inflation as explanatory variables. The equations also include firm fixed effects. The equations are estimated on a quarterly basis between 2017 Q1 and 2022 Q2 and are based on almost 35,000 individual data points for around 5,500 unique firms.

The first main result is that inflation responded asymmetrically to demand shocks during the pandemic. When sales were lowered, demand only had a small impact on

[23] Although the focus of this estimation is on the effects of Covid demand shocks, the pandemic has also affected the supply side of the economy (e.g. Brinca et al. (2021) and del Rio-Chanona et al. (2020) analyze the demand versus supply-side effects of Covid-19 in the US). In column 6 of Table 4, we control for several supply-side factors, such as the impact of Covid on firm costs, recruitment difficulties, and supply shortages, in order to test the robustness of our findings.

[24] The precise wording of the question is 'Relative to what would otherwise have happened, what is your best estimate for the impact of the spread of Covid-19 on the sales of your business in each of the following periods?'. Firms were asked about the effects in the previous quarter and their expectations for the current quarter and next two quarters ahead. Realized data are used where available, but expectations or imputed estimates based on responses from earlier quarters are used where realized data are missing.

inflation. But for the minority of firms that experienced a positive demand shock, the relationship between demand and inflation was significantly stronger. Figure 4 shows the relationship graphically.

Column 1 of Table 4 shows this result in regression form, without any additional fixed effects. The coefficient on the Covid impact on sales variable is significantly larger when the impact of Covid-19 on sales is positive than when it is negative. In column 2, we also include time fixed effects, and column 3 includes both time and firm fixed effects. The non-linearity is still clear and highly significant, although the coefficients move a little closer together than in column 1. In the last row of the table, we test for the statistical equality of the coefficients on the positive versus negative impact of Covid-19 on sales; in all cases, the difference is highly significant at the 1% level.

Columns 4 and 5 of Table 4 provide some more robustness checks on the asymmetry result. Column 4 shows how the non-linearity is not dependent on whether a control is included for whether the demand shock is positive or negative. In Column 5, instead of allowing the coefficient on the Covid impact on sales to vary according to the sign of that variable, we instead include a quadratic term. The coefficient on that squared term is positive and highly significant, meaning that the relationship between inflation and the Covid impact on sales is convex.

In Column 6 of Table 4 we introduce several supply-side factors that are likely to have affected inflation. The coefficients from all these additional controls are hidden in Table 4 for brevity but can be seen in Table A2. These variables largely represent changes in relative prices that would be likely to shift the position of the short-run Phillips curve rather than lead to movements along it. We include controls for Covid-related costs, supply and labor shortages, import intensity, energy prices, and additional costs relating to the end of the Brexit transition period.[25]

Including supply-side factors in Column 6 of Table 4 slightly reduces the coefficient on

[25] The control for Covid related costs represents the effect of Covid on the level of unit costs. This fits better than a cost growth term, implying that firms have continued to pass on higher costs in the later part of the pandemic despite cost growth turning negative. Figure A6 shows the data on Covid-related sales and costs. The additional variables that we add in column 6 are from DMP questions where data is generally not available for all quarters. Or in the case of energy intensity, we use two-digit industry level data from 2019. To address this, we calculate an average of each variable for each firm over the period in which data are available, and then allow the coefficient on that time-invariant firm average to vary over time. For brevity we only report results in Table A2 that interacted with a single time dummy (for 2021 Q2 to 2022 Q2 except for Covid-related costs, which is 2020 Q2 to 2022 Q2).

positive demand shocks, but a clear and statistically significant asymmetry in the response of inflation to positive and negative demand shocks remains. The included Covid-related costs, supply shortages, labor shortages, import prices, energy prices, and extra costs relating to the end of the Brexit transition period are all estimated to have had positive and statistically significant effects on inflation since 2021 Q2.

As well as measures of the business cycle and supply-side factors, aggregate Phillips curves also usually contain measures of expected aggregate inflation too. Ideally, we would include a firm-level measure of expected aggregate CPI inflation, but these were only added to the survey from May 2022. Instead we add measures of lagged and expected *own* price inflation in column 7 (the lagged term can help account for the fact expectations may be partially backward looking). Although the direction of causality is unclear using firms' own price expectations, it shows how our other results are robust to the inclusion of the extra variable. Some of the other coefficients become smaller, reflecting the fact these factors are also likely to be correlated with expected future inflation too.[26]

Overall, this section analyzes how firm prices respond to demand shocks using data from three separate business surveys across the US and UK. The three empirical tests we use differ in the sample periods considered, and in the precise measurement of the shock and response components. Nevertheless, we find robust evidence of a non-linearity in all three cases, with stronger price responses to positive shocks. The results are not only qualitatively but also quantitatively similar to each other. In Section 6, we show that a model with menu costs, trend inflation, and decreasing returns at the firm level can match our firm-level results. In the next section, we provide three additional empirical extensions, which also help motivate our modeling approach.

5 Micro Data Phillips Curve Extensions

In the previous section, we presented evidence that firm prices respond by much more to positive demand shocks compared with negative demand shocks using three separate empirical exercises. There are multiple mechanisms which can explain this non-linear firm-level response, including potentially capacity constraints (e.g. Boehm and

[26] In the earlier working paper version of this paper (Bunn et al. 2022), we present several additional results on the asymmetric response of price inflation to the Covid demand shock. First, we show that the non-linearity is present for both goods producers and services providers. Second, we find evidence of an asymmetric response both in the first year of the pandemic, and separately, for the second year. The asymmetry is also not driven by firm liquidity, which would be consistent with the mechanism proposed by Gilchrist et al. (2017) for the financial crisis. Finally, we also show that the asymmetry is not driven by positive shocks being perceived as more persistent by firms, which could explain the stronger price response.

Pandalai-Nayar 2022), financial constraints (e.g. Gilchrist et al. 2017), or non-linear demand functions (e.g. Harding et al. 2023). In this section, we present three extensions to our main results which will be important in the model section for identifying a menu cost channel for convex price responses. In Section 6 we outline our general equilibrium model which we will use to match the main results as well as these extensions.

5.1 High vs. low inflation

In the first extension, we consider whether the convexity that we capture is stronger in periods of higher inflation. As shown in Table 1, high-inflation countries exhibit significant non-linearity in the relationship between the output gap and inflation, whereas this convexity is absent in low-inflation countries. Likewise, our modeling framework (detailed in Section 6) would predict that when 'trend' inflation is higher, firms are more likely to pay the menu cost and increase their prices following positive demand shocks than cut prices following negative shocks.

To test this in the data, we calculate the average price growth for each firm across all survey waves. We do this for UK firms in the DMP, and separately for US firms in the SBU and BIE. We then split firms by whether their average price growth is above or below the full sample average.

In Figure 5, we present the results on the three empirical exercises from Section 4, separately for high-inflation and low-inflation UK firms. The average firm output price growth over the full sample is around 4%. High-inflation firms (those above 4%) have had an average price growth of 6.7%, whereas the average for low-inflation firms (those below 4%) is 1.6%. In all three panels, we find evidence of a clear convexity for high-inflation firms (top row). Meanwhile, for low-inflation firms (bottom row) the evidence suggests a much more linear pass-through of demand shocks to prices. We next test this formally in a regression table.

In Table 5, we provide further robustness for the results in high vs. low inflation firms. Columns 1 and 2 present the results using the hypothetical sales volume shocks. The difference between the coefficients on positive versus negative shocks is only statistically significant for high-inflation firms. Columns 3 and 4 show the results for sales and price forecast errors, also controlling for firm and time fixed effects. The convexity remains pronounced and highly significant for high-inflation firms (Column 3), whereas for low inflation firms (Column 4), the difference between the coefficients is not statistically significant. In Columns 5 and 6, we use the same sample splitting approach and show that the price response to the Covid demand shock displays significant non-linearity, but only in high-inflation firms.

We conduct the same exercise for US firms, splitting by full sample average price growth in the SBU (2.7%) or the BIE (4.5%) accordingly. In the SBU, high-inflation firms had an average price growth of 5.9%, while low-inflation firms had an average price growth of -0.6%. In the BIE, high-inflation firms averaged 8.1%, and low-inflation firms averaged 1.5%.[27] Figure 6 presents the results for high- and low-inflation US firms. Once again, we find evidence that pass-through of demand to prices is convex for high inflation firms (top row) and more linear for low-inflation firms.

Table 6 reports the robustness of the US results. Columns 1 and 2 present the results on hypothetical sales volume shocks, separately for high-inflation and low-inflation firms. The difference between the coefficients on positive versus negative shocks is only statistically significant for high-inflation firms. Columns 3 and 4 display the results from sales compared to normal and price forecast errors exercise controlling for firm and time fixed effects. Despite the much smaller sample sizes, we find evidence of a non-linearity in the sample of high-inflation firms. We cannot reject the null that the coefficients are equal among low-inflation firms (Column 4).

One concern with the above approach may be that we are splitting firms by the dependent variable when we separate into high versus low inflation. As an alternative, we measure the average price growth at the sector-year level in our UK dataset. Specifically, we use detailed SIC3 sectors, of which there are 262 in the sample. We compute this separately for each firm i, such that the sectoral average will *exclude* that firm from the calculation (a "leave-one-out" approach). We then split firms according to whether their sector is above or below the sample average in a given year. In this way, a given sector can have above-average price growth in one year, but below-average price growth in another. We again find strong evidence of a non-linearity in high-inflation sectors, while in low-inflation sectors we cannot reject the null of linear pass-through at the 5% significance level (Table A3).

Overall, we conclude from this sub-section that the inflation rate is an important

[27] The difference in time frame explains the gap between these two surveys. The BIE's price change data cover the post-pandemic inflationary period. The SBU's price change series began after this shock.

determinant for the convexity in the price response to demand shocks. This is particularly important for policymakers to consider when inflation is elevated – in such cases, prices can become much more responsive to positive shocks.

5.2 Longer-run responses

The empirical analysis so far has focused on the response of firm prices to shocks over a one-year horizon. Doing this, we find strong evidence that the response to positive shocks is stronger than the response to negative shocks. In this subsection, we explore how these responses evolve over time, again utilizing the panel dimension of the dataset. Specifically, for each firm in the DMP, we calculate the *cumulative* nominal sales growth and cumulative price growth (not the forecast errors of these quantities) over horizons from one to four years.[28] We then estimate the relationship between sales growth and price growth at each horizon, separating the coefficients by whether the *cumulative* sales growth is positive or negative. Due to sample size restrictions, we are only able to conduct this analysis using data from the DMP and not for US firms.

Figure 7 presents the main results from this exercise by plotting the coefficient estimate for positive and negative cumulative sales growth with 90% confidence intervals. The first set of coefficients plotted at the year 1 horizon is similar to our main result from Figure 3 that was based on forecast errors: positive sales growth over one year has a stronger correlation with annual price growth (roughly twice as large) than negative sales growth. However, when we consider the evolution of the coefficients by extending the horizon to 2, 3 and 4 years, we find that the coefficient estimates converge, with the effects of negative growth catching up with those on positive cumulative sales growth. Thus, negative sales growth does not lead to a *permanently* lower response in prices; rather, the path of adjustment is slower. The evidence suggests that despite the initial non-linearity, over a longer time horizon, the effects are identical. We also confirm in regressions (Table A4) that the positive and negative coefficients are significantly different in years one and two, but not by years three or four, and that these results are robust to adding firm and time fixed effects.

5.3 Prices and costs

So far, the analysis has focused on the response of prices to demand shocks, measured in several different ways. However, it is also important to consider how firms set prices in

[28] Firms are not asked about expected sales or price growth beyond the one-year horizon, therefore it is not possible to construct longer-run forecast errors in the way we construct them for the one-year horizon.

response to *cost* shocks, for at least two reasons. First, the standard New Keynesian Phillips curve models prices at the firm level as a mark-up over marginal cost. Marginal costs are notoriously difficult to measure, and the literature therefore usually focuses on average or unit costs, or estimates derived from assumed production functions. Second, the inflation episode over 2022-2026 has been driven in large part by cost shocks.

Intuitively, cost shocks should affect price decisions in a similar way to demand shocks, by moving a firm's optimal price away from its current value. In a menu cost model, positive cost shocks move firms closer to their price-increase thresholds, causing them to increase prices. Trend inflation makes the price increase and decrease thresholds asymmetric, and firms are *less* likely to lower prices following negative shocks. This should make the price response convex in response to cost shocks. In this sub-section, we empirically test the response of firm prices to unit cost shocks using a randomized survey experiment similar to the one presented in Section 4.1 for demand shocks.[29]

Hypothetical unit cost shocks

We analyze how firms respond to cost shocks using a randomized survey experiment. Similar to our setup for sales volume shocks (see Section 4.1), we randomly assign firms to one of four scenarios, which differ in the magnitude of the hypothetical unit cost shock they receive: ±5%, ±10%, ±15%, and ±20%. Firms are asked about their response to both the positive and negative unit cost shocks. Firms are also randomized into whether they first receive the positive or the negative scenario (Figures B3 and B8 show the precise questions in the DMP and SBU, respectively). This question was asked in the DMP over August to October 2024, and collected responses from 1,864 firms, which gives 3,728 observations in total (two scenarios per firm). The identical question was asked in January 2026 in the SBU, and received responses from 895 firms.

Figure 8 plots the average (unweighted) response to these unit cost shock scenarios for both UK (Panel A) and US (Panel B) firms. We estimate the lines of best fit using a regression with no constant, so that a 0% unit cost shock corresponds to a 0% average price response. Firms respond significantly to both positive and negative shocks, but we again note significant non-linearity. The response to positive shocks is around 0.6, or a 60% pass-through. Meanwhile, the response to negative shocks is only 0.2, meaning 20%

[29] In related work, Cavallo et al. (2024) use a state-dependent pricing model to show that large cost shocks lead to large increases in the frequency of price adjustment and faster corresponding pass-through to prices.

pass-through.[30]

Overall, this provides evidence that cost shocks are passed through in a non-linear fashion to firm prices. This is important to bear in mind, especially when an economy is hit by large shocks. On the one hand, assuming a linear pass-through of shocks can underestimate how quickly prices will rise following cost increases. Equally, a linear pass-through would over-estimate how quickly price growth declines as cost shocks unwind.[31]

Quantifying the importance of non-linearity

The previous two sections have shown significant evidence of non-linearities in the response of firm prices to both demand and cost shocks, estimated using several different methodologies. How important is the non-linearity for understanding recent inflation dynamics in the UK? To estimate this, we combine data on demand shocks and cost shocks with the empirical estimates of pass-through, in both linear and non-linear specifications. For 'demand shocks', we compare the average real sales growth forecast errors in 2018 versus 2022. Figure A8, Panel A shows the distribution of these data for the two respective periods. The two distributions are similar, although demand shocks in 2022 are more dispersed. To estimate unit cost shocks in the pre-pandemic period, we use unit cost growth forecast errors in 2018 (comparing realized unit cost growth in 2018 to expectations from 2017). Meanwhile, for 2022, we calculate the *difference* between realized cost growth in 2022 and expected unit cost growth in 2018 (and 2017 if missing) for the same firms and use this as a proxy for the cost shock. This is because questions on unit cost growth were not asked in 2021, preventing us from calculating forecast errors in a comparable way. Looking at the distribution of these unit cost shocks in the two periods there is a clear shift to the right in 2022 consistent with the rapid increase in firm costs during this period (Figure A8, Panel B).

We combine these data on demand and cost shocks with the estimates on average price responses from hypothetical sales volume shocks (Table 2) and unit cost shocks (Table

[30] Table A5 confirms this convexity in a regression specification for the UK and US. We also test whether the price responses to positive and negative unit cost shocks are equal across countries using a Wald test across independent samples, and cannot reject the equality between the UK and the US of the slopes on positive unit cost shocks (t-stat = 1.16) or the equality of the slopes on negative unit cost shocks (t-stat=0.66).
[31] There is also evidence from the US that firm prices respond asymmetrically to cost shocks. In a blog post from 2013, Mike Bryan, Brent Meyer and Nicholas Parker show qualitative evidence that firms in the Atlanta Fed Business Inflation Expectations (BIE) survey are more likely to increase prices following rises to raw material costs than they are to decrease prices following declines in costs. When costs decline, firms indicate that they are more likely to increase profit margins.

A5). In Table 7, we calculate the contribution of these shocks to the increase in inflation. On average, inflation among DMP firms increased by 4.4 percentage points over 2018-2022. Under linear shock pass-through, cost shocks can account for around 2.7pp of this increase, whereas demand shocks can account for close to zero (Column 1). However, once we take into account the non-linear responses to shocks in Column 2, cost shocks can account for 3.8pp of the increase in inflation, and demand shock can account for around 0.1pp. This quantification yields two important insights. First, cost shocks were a much more important driver of the rise in firm price growth in 2022 compared to demand shocks. Second, non-linearities in the pass-through of shocks can help explain close to one-fourth (1.2pp out of 4.4pp) of the total increase in inflation. Thus, non-linearities in price-setting are not only significant in a statistical sense, but also quantitatively for understanding recent inflation dynamics. In the next section, we solve a general equilibrium menu cost model to rationalize our findings and analyze the implications for aggregate inflation dynamics.

6 DSGE Menu Cost Model

The empirical work so far has presented evidence consistent with a convex aggregate Phillips curve (Section 2) and significant evidence of non-linear pass-through of demand and cost shocks to prices using survey data from UK and US firms (Sections 4 and 5). In this section, we set out a state-dependent menu cost model that rationalizes our main firm-level findings and use it to study the implications for the aggregate Phillips curve. State-dependent pricing models are particularly relevant in times of high inflation and large shocks, due to their ability to capture changes in both the frequency and magnitude of price adjustments (e.g. Ascari et al. 2025, Cavallo et al. 2024, Gagliardone et al. 2025, Gagnon 2009).[32] More generally, using a model is crucial, as general equilibrium effects can affect how individual firm responses aggregate to the macro level (see, for example, Hazell et al. 2022, on the importance of taking general equilibrium effects into account).

As a summary Table 8 assesses alternative mechanisms for Phillips curve convexity against the key empirical findings we document. Capacity or financial constraints, downward wage rigidity, and quasi-kinked demand can each generate a convex aggregate Phillips curve, and several mechanisms can match some individual firm-level facts. However, a menu cost model with positive trend inflation, decreasing returns to scale and firm level demand shocks appears to be the only mechanism able to match all five facts. We do not claim other

[32] In related work, Gödl and Gödl-Hanisch (2024) study the state-dependence of wage setting using firm-level and union-level data.

mechanisms play no role - several may be in operation at once - but among the candidate models, the menu cost framework offers the most parsimonious account of our results. Appendix A discusses Table 8 in greater detail.

6.1 Model structure

Our model is based closely on Nakamura and Steinsson (2010).[33] We make two modifications. First, firms are subject to idiosyncratic demand shocks, in addition to the idiosyncratic productivity shocks and aggregate demand shocks in the original Nakamura and Steinsson (2010) model. This modification enables us to trace out a Phillips curve at the firm level, while partialling out the aggregate state as we do in our empirical exercises.

Second, the production technology of firms exhibits decreasing returns to scale at the firm level, but constant returns to scale at the aggregate level. We make this modification in order to give firms a reason to raise prices when they are hit by idiosyncratic demand shocks. Firms in standard New Keynesian models typically have constant returns to scale and face CES demand. This means that an idiosyncratic shock does not affect their costs or their desired markups, and hence gives them no reason to raise prices. In contrast, with decreasing returns to scale, firms' costs and hence their desired prices rise if they increase output, even if aggregate variables, such as the wage, remain unchanged.

There is a continuum of firms indexed by z, each of which produces a single differentiated good $y_t(z)$ using a diminishing returns to scale (DRS) production technology using labor $L_t(z)$ and an index of intermediates $M_t(z)$, and λ indexes the degree of decreasing returns:

$$y_t(z) = \widetilde{A}_t(z)\left[L_t^{1-s_m}(z)M_t^{s_m}(z)\right]^{\lambda}$$

$\widetilde{A}_t(z)$ is labor productivity defined as

$$\widetilde{A}_t(z) = A_t(z)\left(\int_0^1 L_t(j)dj\right)^{1-\lambda}$$

where $A(z)$ denotes firm-level productivity. This formulation ensures returns to scale are

[33] We choose to adopt a menu cost price-setting model from the literature based on answers to survey questions in the DMP. Over 2023-2025, firms have been asked whether they usually set prices at fixed intervals (i.e. 'time-dependent' price setting) or in response to events (i.e. 'state-dependent'). On average, the majority of firms selected state-dependent price-setting, as shown in Figure A9. See Bunn et al. (2026) for further details.

decreasing at the firm level but constant at the aggregate level.

Products are both intermediates and final goods in roundabout production as in Nakamura and Steinsson (2010). Productivity is an AR(1) process, independent and mean zero across firms:

$$\log(A_t(z)) = \rho_A \log(A_{t-1}(z)) + \varepsilon_t^A(z)$$

Consumers maximize utility over composite consumption C and labor supply L:

$$E_t \sum_{\tau=0}^{\infty} \beta^{\tau}\left[\frac{1}{1-\gamma}C_{t+\tau}^{1-\gamma} - \frac{\omega}{\psi+1}L_{t+\tau}^{1+\psi}\right]$$

Consumers have isoelastic preferences over each of the varieties, such that firms face the following demand curve:

$$c_t(z) = C_t\left(\frac{p_t(z)}{P_t}\right)^{-\theta} d_t(z)$$

where $d_t(z)$ is an idiosyncratic demand wedge that generates variation in demand at the firm level, and where $p_t(z)$ and P_t are the firm's price and the aggregate price level, respectively. Firms can change their nominal price if they hire κ units of labor, such that their per-period profits are given by:

$$\pi_t(z) = p_t(z)y_t(z) - W_t\left(L_t(z) + \kappa I_t(z)\right) - P_t M_t(z)$$

Firms maximize the present discounted value of these profits, discounted at the consumers' stochastic discount factor. The firm-level idiosyncratic demand shock $d_t(z)$ follows an AR(1) process:

$$\log d_t(z) = \rho_d \log d_{t-1}(z) + \varepsilon_t^d(z)$$

The monetary authority targets nominal output. Let, $S_t \equiv \log(P_t C_t)$ denote log nominal aggregate demand, and aggregate S_t which follows a random walk with drift:

$$S_t = \mu + S_{t-1} + \eta_t$$

There is no long-run growth in productivity or labor supply in the model, so μ equals the average inflation rate. The firm's objective is to maximize the present discounted value of profits. The recursive value function is given by:

$$V_t\Big(A_t(z), d_t(z), p_{t-1}(z), S_t\Big) = \max_{p_t(z)} \Big\{\pi_t(z) + E_t\Big[D_{t,t+1} V_{t+1}(A_{t+1}(z), d_{t+1}(z), p_t(z), S_{t+1})\Big]\Big\}$$

The model is closed with market clearing for goods and labor, with roundabout production. Further details are given in Appendix B.

6.2 Calibration, solution, and simulation method

Where possible, and except where stated otherwise, our calibration follows that of the one-sector menu-cost model in Nakamura and Steinsson (2010). Table 9 summarizes all the model parameters. We calibrate demand shocks to have the same persistence and baseline variance as productivity shocks in Nakamura and Steinsson (2010). To solve the model, the state and choice spaces are discretized on grids. We solve the firm's decision problem by iterating the value function based on a guess of the aggregate law of motion $E_t\Big[\log\ P_{t+1}\Big] = \Gamma\Big[S_t\ -\ \log P_t\Big]$. We then update this guess for Γ based on the aggregate dynamics that result from our solution to the firm's problem. We iterate this procedure until convergence, checking that the final solution Γ is accurate and unbiased. To produce our simulated data, we simulate 1000 firms for 100 years (1200 periods of one month).

6.3 Baseline results

In this subsection of the paper, we perform the same empirical exercises on our simulated data as we did on the DMP data. First, we analyze the firm-level price responses to positive versus negative demand shocks.

The results from the firm-level simulated data are presented in Figure 9, Panel A, which shows the impact of a change in the firm's idiosyncratic demand level on subsequent inflation. As with the empirical results presented in Section 4, we find evidence of a distinct non-linearity. Positive demand shocks lead to stronger price inflation at the firm level; negative demand shocks decrease price growth by much less. The response to positive shocks is roughly triple the response to negative shocks.

In Figure 9, Panel B we aggregate the firm-level responses to generate the standard Phillips curve relationship. The difference between aggregate real output and the flex-price level of output (the level which maximizes per-period profits) – i.e. the standard measure of the output gap - is on the horizontal axis. The figure shows that the aggregate Phillips curve is also convex. The non-linearity we observe at the firm level therefore survives aggregation and the incorporation of general equilibrium effects.

The intuition for this result is that menu cost models generate an endogenous inaction zone as shown in Figure 10. Firms do not change prices between their left 'raise prices' point and their right 'cut prices' point. Positive trend inflation causes firms generally to drift leftward on this diagram, towards the price increase point, generating a left-tilted density of firms on the $\log(P_{it}/P_t)$ support. When these firms are hit by a positive demand shock those next to the 'increase prices' point put up prices. So, the response to a small demand increase is proportional to the density of firms at this 'increase prices' point. In contrast the response to a small negative shock is proportional to the density of firms at the 'cut prices' point to the right. This density is much lower due to trend inflation, generating a convex price response to demand shocks.

We can illustrate this mechanism by decomposing the mapping between firm-level price responses and demand shocks into extensive- and intensive-margin components. The extensive-margin contribution is the deviation of the frequency of price changes from its average, multiplied by the average size of price changes conditional on adjustment. The intensive-margin contribution captures the corresponding role of variation in the size of price changes, holding the adjustment frequency fixed. A residual interaction term reflects the fact that both the frequency and size of price changes vary jointly across demand states. Figure A10 shows that the convexity of the Phillips curve is driven primarily by the extensive margin. Firms facing larger positive demand shocks are more likely to raise prices, while the size of those price changes remains relatively stable. Conversely, firms facing larger negative demand shocks are less likely to raise prices, generating a negative extensive-margin contribution.

6.4 Extension results

The kinks that we observe in the firm-level and aggregate Phillips curves arise from the interaction of menu costs, trend inflation, and (for the firm-level curves) decreasing returns to scale. To highlight this, Figure 11 shows how the shape of the firm-level Phillips curve depends on the rate of trend inflation. There are three panels – the left has trend inflation of -2%, the center has trend inflation of 0%, and the right has trend inflation of 2%.

Starting with the right panel, this is the standard model with positive trend inflation displaying a convex Phillips curve. The left-hand panel of Figure 11 shows that the curve becomes concave when inflation is negative. This is because negative trend inflation causes firms to bunch near the upper 'cut prices' boundary of the inaction zone. Finally, the center panel plots this relationship at zero inflation, which is almost a straight line.[34]

A second extension of the model is to examine the Phillips curve in 'long differences' and show how the slope coefficients in response to positive and negative shocks converge over the long run as in our empirical results. Figure 12 shows the analog in our simulated data of the empirical exercise, highlighting how the asymmetry disappears over longer horizons. The intuition for this result is that over longer time periods the distribution of firms within the Ss bands is ergodic – it returns on average to its steady state – so that all shocks pass through into prices. Thus, over longer time periods the slope coefficients for positive and negative demand shocks converge, aligning the model with the empirical results from Figure 7.

Finally, we model cost shocks as idiosyncratic productivity shocks following the process described in Section 6.1. The model can generate a convex response of prices to cost shocks in a similar manner to demand shocks because firms focus on their markups (see Figure 13). As a result, the model aligns with the empirical data to generate a convex response of inflation to demand and cost shocks. The intuition for how firm prices should respond to demand and cost shocks is similar; they both change a firm's optimal price, leading to a similar process of adjustment.

So, in summary, our Ss menu cost model can match both the micro data and macro convex Phillips curve. It can also match the extension results of stronger convexity at higher inflation rates, of convergent responses of prices to positive and negative demand shocks, and convexity of responses to cost as well as demand shocks.

7 Conclusion

Inflation rates across many advanced economies reached levels not seen for decades following the exceptional economic shocks of the Covid-19 pandemic and the war in Ukraine in 2022. In 2026, concerns about inflation re-emerged following the conflict in the Middle East and the sharp increase in energy prices. These episodes have stimulated a renewed interest in studying price-setting behavior and potential convexities in the Phillips curve. Convexities in the relationship between inflation and economic slack are present in

[34] It is not totally straight because the revenue function is not linear. In particular, pricing too low is more costly than pricing too high (as the pricing error is scaled by a large quantity). This generates mild convexity.

cross-country macro data, although identification in these settings is an empirical challenge. In this paper, we use firm-level data from large representative surveys of US and UK firms to test for non-linearities in the response of firm prices to shocks.

We carry out three different empirical exercises which all show that prices respond in a non-linear way to demand shocks. First, we use a randomized survey experiment where firms indicate their price responses to a series of hypothetical sales volume shocks. The effect of positive shocks is estimated to be significantly stronger than the response to negative shocks. To substantiate these findings using data on real price-setting, we test the relationship between sales shocks and price growth forecast errors, leveraging the strong panel dimension of these surveys. The results again suggest significant convexity, with positive sales growth forecast errors associated with price growth forecast errors which are at least twice as large. Finally, we use Covid-19 as a natural experiment and show that inflation was five times more sensitive to demand when demand was growing than when it was falling.

Many models can generate convex responses of prices to demand shocks at the firm level, including menu costs, capacity constraints, financial constraints, and non-linear demand curves. To make progress identifying between these, we extend our results in three ways. First, we show that the convex response to demand shocks is pronounced when inflation is high. Second, we show that the non-linearities are a short-term phenomenon: over longer time horizons (more than three years), the responses to positive and negative sales growth converge. Thirdly, we show that firms also respond in a non-linear fashion to cost shocks, with stronger pass-through for increases in costs as for reductions in costs.

Finally, we build a model of price-setting behavior which features menu costs, trend inflation, and diminishing returns at the firm level. Simulated data from the model are able to replicate the main firm-level convexity in prices and produce a convex *aggregate* Phillips curve in response to demand shocks. Furthermore, the model can match our additional empirical results. The model generates greater convexity at higher levels of inflation, linearity over long-run horizons, and convex response to cost shocks.

Taken together, our results can help explain the dynamics of inflation since 2020. Indeed, empirically taking non-linearities into account helps account for around one-fourth of the 2022 increase in firm price growth. Accurate modeling of inflation dynamics should take these non-linearities into account, particularly in times of high inflation and when the shocks to the economy are large.

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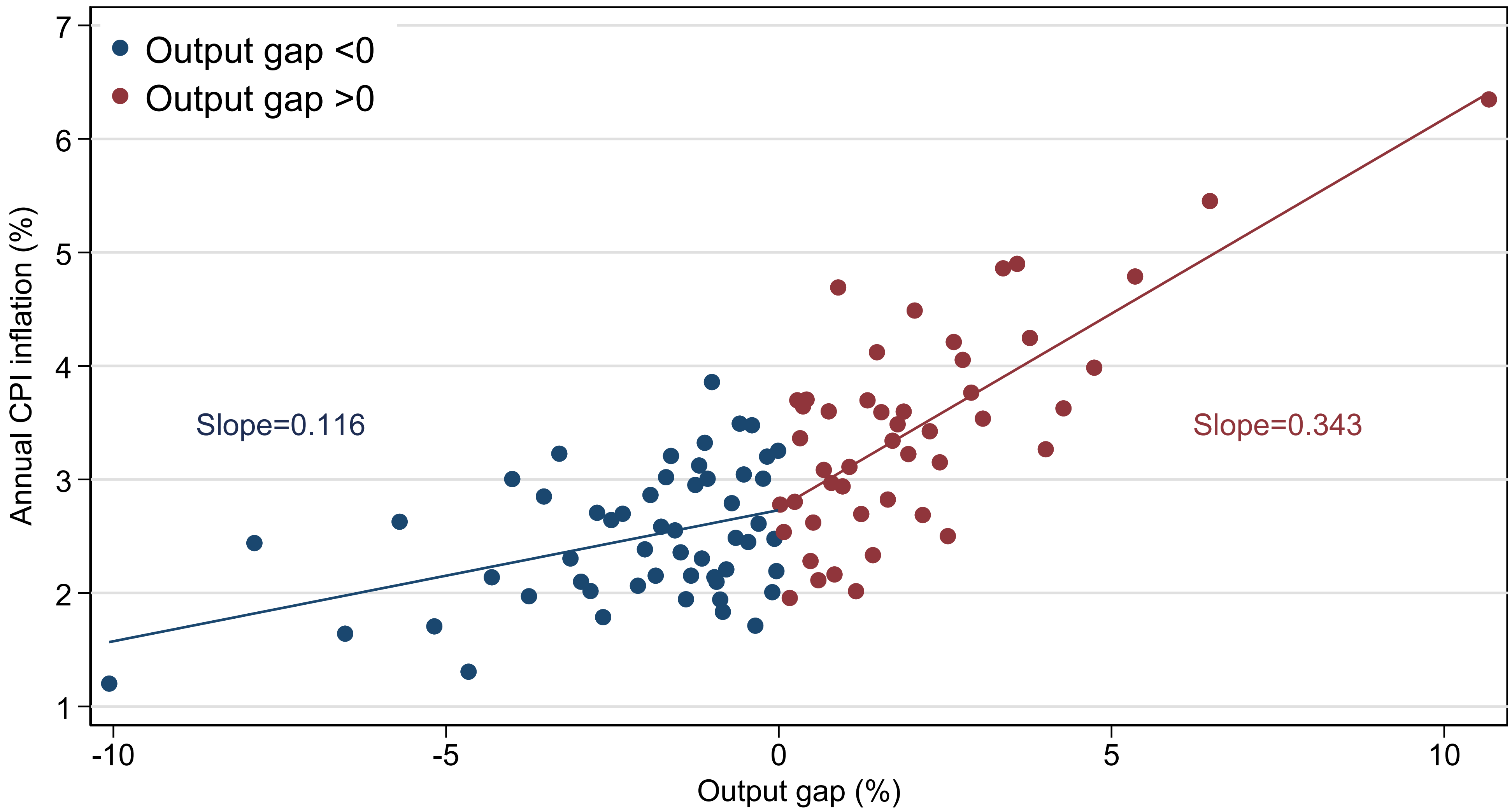
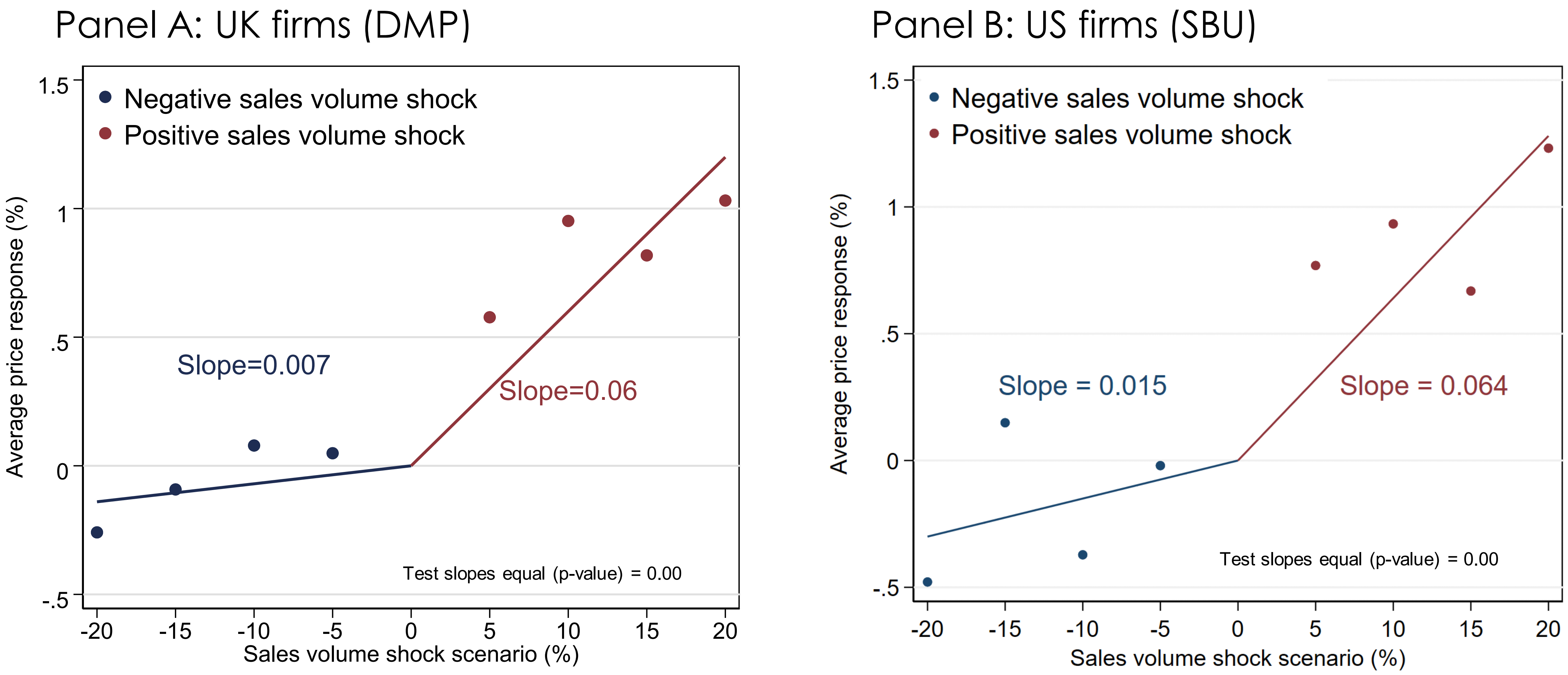
Figure 1: Macro evidence on inflation and output gap



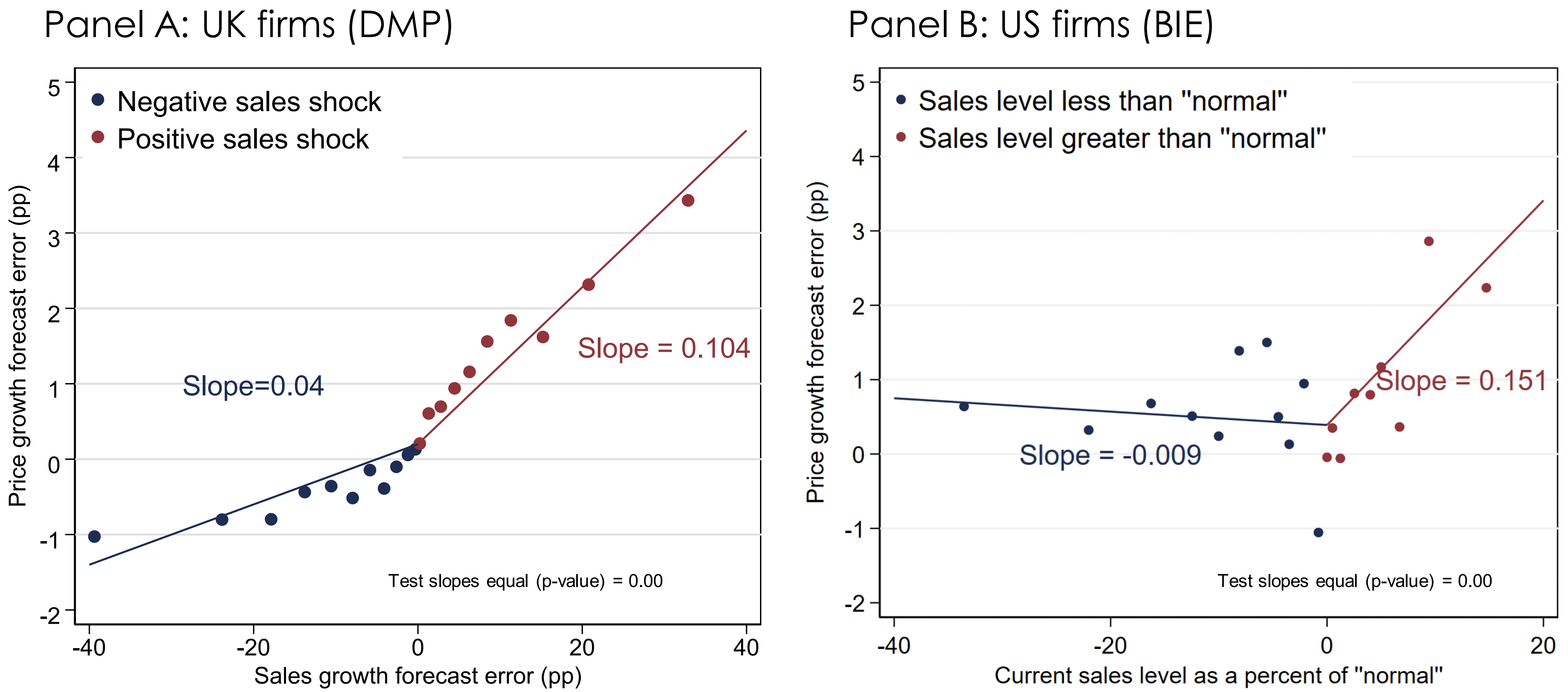
Notes: This figure is a binned scatterplot of annual CPI inflation rates on output gap estimates for 38 countries over the period 1990-2024. Data on annual inflation rates is taken from the World Bank cross-country database of inflation (Ha et al. 2023). Data on output gap estimates is obtained from the OECD. The total number of country-year observations in the figure is 1,205.

Figure 2: Price response to hypothetical sales volume shocks



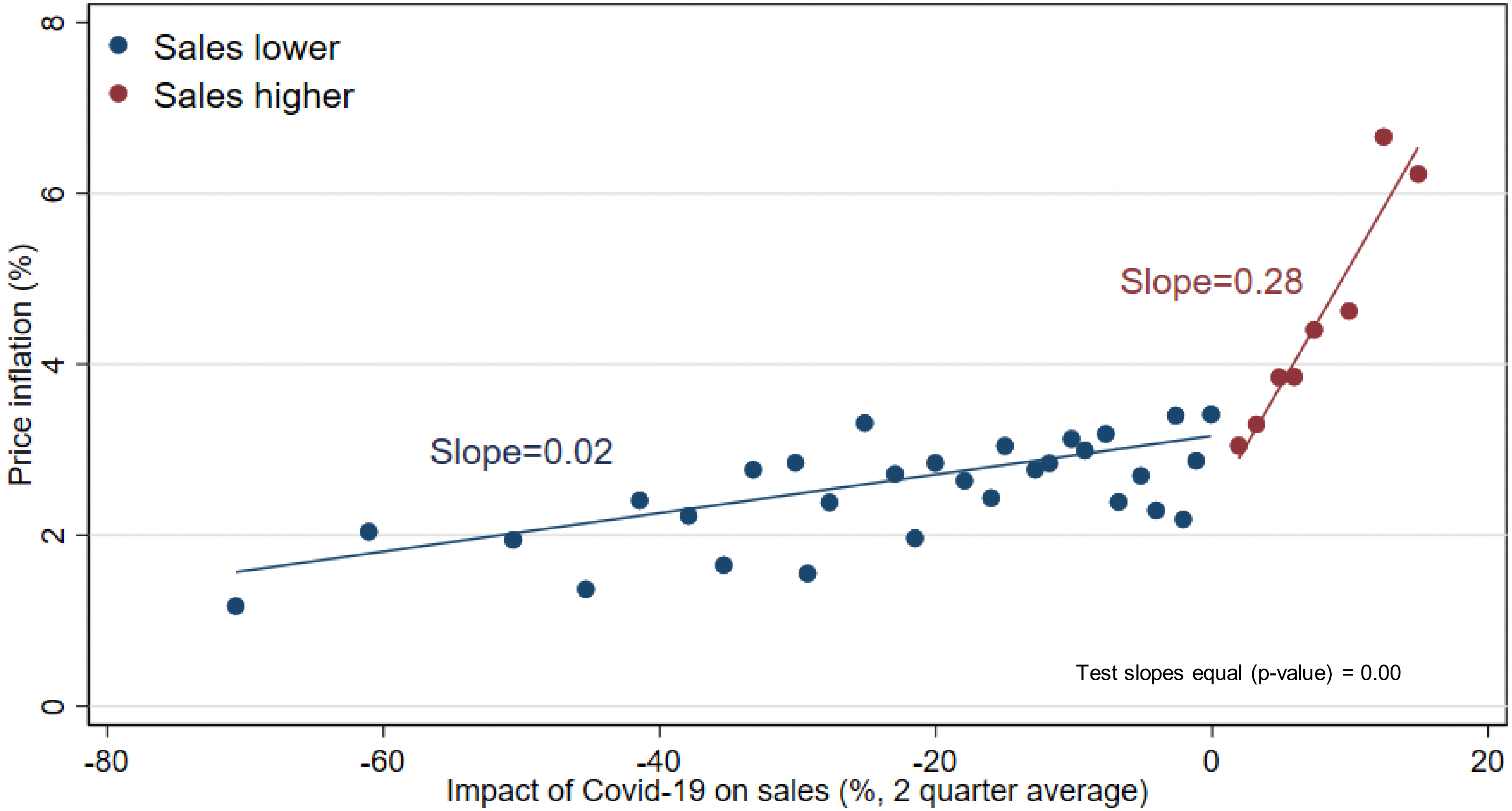
Notes: This figure reports responses to the question "Suppose that your business's sales volume over the next 12 months is X per cent higher/lower than you currently expect. How would that affect the average price you charge, relative to what you currently expect?" Firms are randomised into one of four scenarios for sales volume: ±5%, ±10%, ±15%, ±20%. Firms are presented with both the positive and negative values for a given scenario. Panel A is based on 6,394 observations from 2,486 UK firms in the Decision Maker Panel. Panel B is based on 1,570 observations from 787 US firms in the June 2024 survey wave of the Survey of Business Uncertainty. Across the two panels, we cannot reject the equality of the slopes on positive sales volume shocks (t-stat = 0.39) or the equality of the slopes on negative sales volume shocks (t-stat=0.62).

Figure 3: Relationship between sales shocks and price forecast errors



Notes: **Panel A** shows the relationship between nominal sales growth forecast errors and annual price growth forecast errors. Each dot represents 5% of the sample between January 2018 and March 2026. Sales forecast errors are trimmed at the 5th and 95th percentiles by quarter. Price forecast errors are winsorised at the 1st and 99th percentiles. The scatter plot is based on 24,920 observations for 4,579 UK firms in the Decision Maker Panel. **Panel B** shows the relationship between sales levels “compared to normal” and annual price growth forecast errors based on 1,260 observations for 339 firms in the Business Inflation Expectations survey from December 2021 to February 2026. Sales compared to normal responses are trimmed at the 5th and 95th percentiles by quarter. Price growth forecast errors are winsorised at the 5th and 95th percentiles. Each dot represents 5% of the sample.

Figure 4: Realized inflation and impact of Covid-19 on sales (UK Firms)

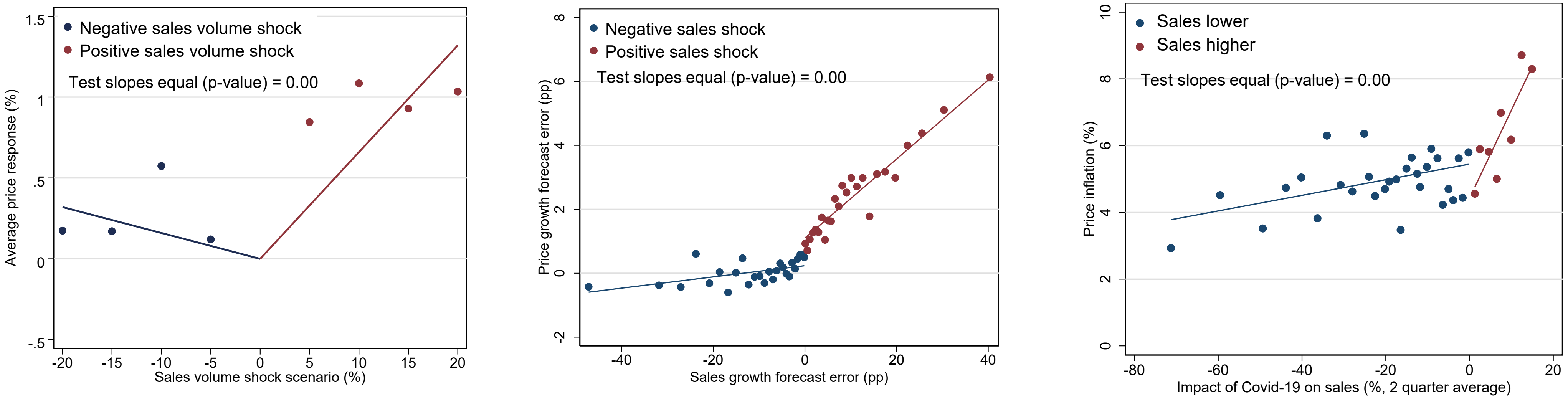


Notes: Each dot represents 2% of observations (during the pandemic, 2020 Q2 to 2022 Q2), grouped by impact of Covid-19 on sales. Zero responses are excluded. The scatterplot is based on 11,343 observations from 3,694 UK firms in the Decision Maker Panel. Due to lack of comparable data on the impact of Covid-19 on firm sales in the US, this figure is only presented for UK firms.

Figure 5: Response to demand shocks: High vs. low inflation (UK firms)

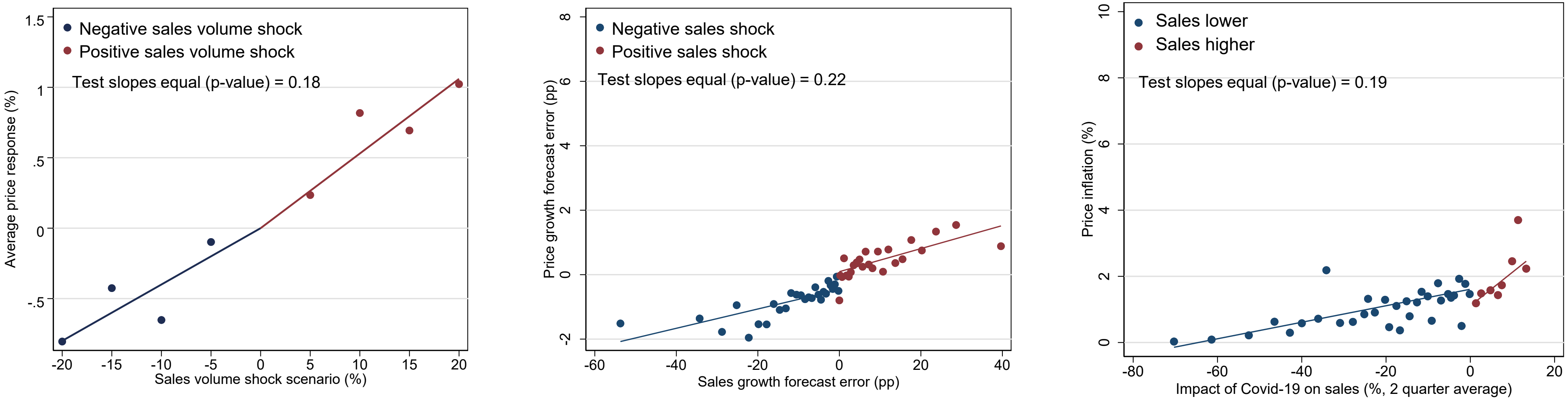
Panel A: Hypothetical shocks | *Panel B: Forecast errors* | *Panel C: Covid demand shocks*

High Inflation Firms



Average price growth: 6.7%

Low Inflation Firms



Average price growth: 1.6%

Notes: High-inflation firms are firms with average price growth across the full sample above 4% (sample average). Low-inflation firms are firms with average price growth across full sample below 4%. All figures are based on data from UK firms in the Decision Maker Panel.

Figure 6: Response to demand shocks: High vs. low inflation (US firms)

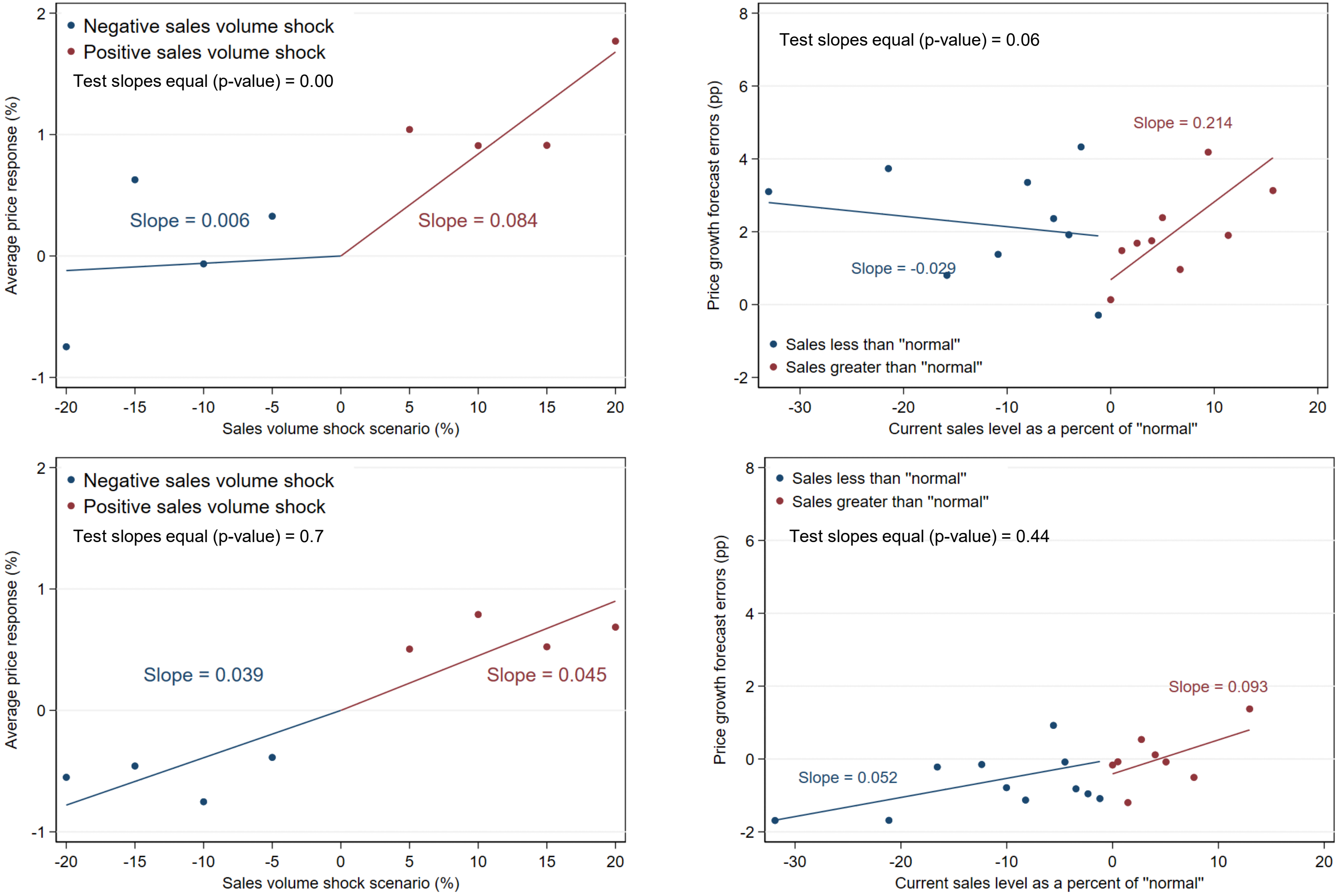
Panel A: Hypothetical shocks (SBU) *Panel B: Sales shocks and price forecast errors (BIE)*

High Inflation Firms

Average price growth: 8.1% (BIE) 5.9% (SBU)

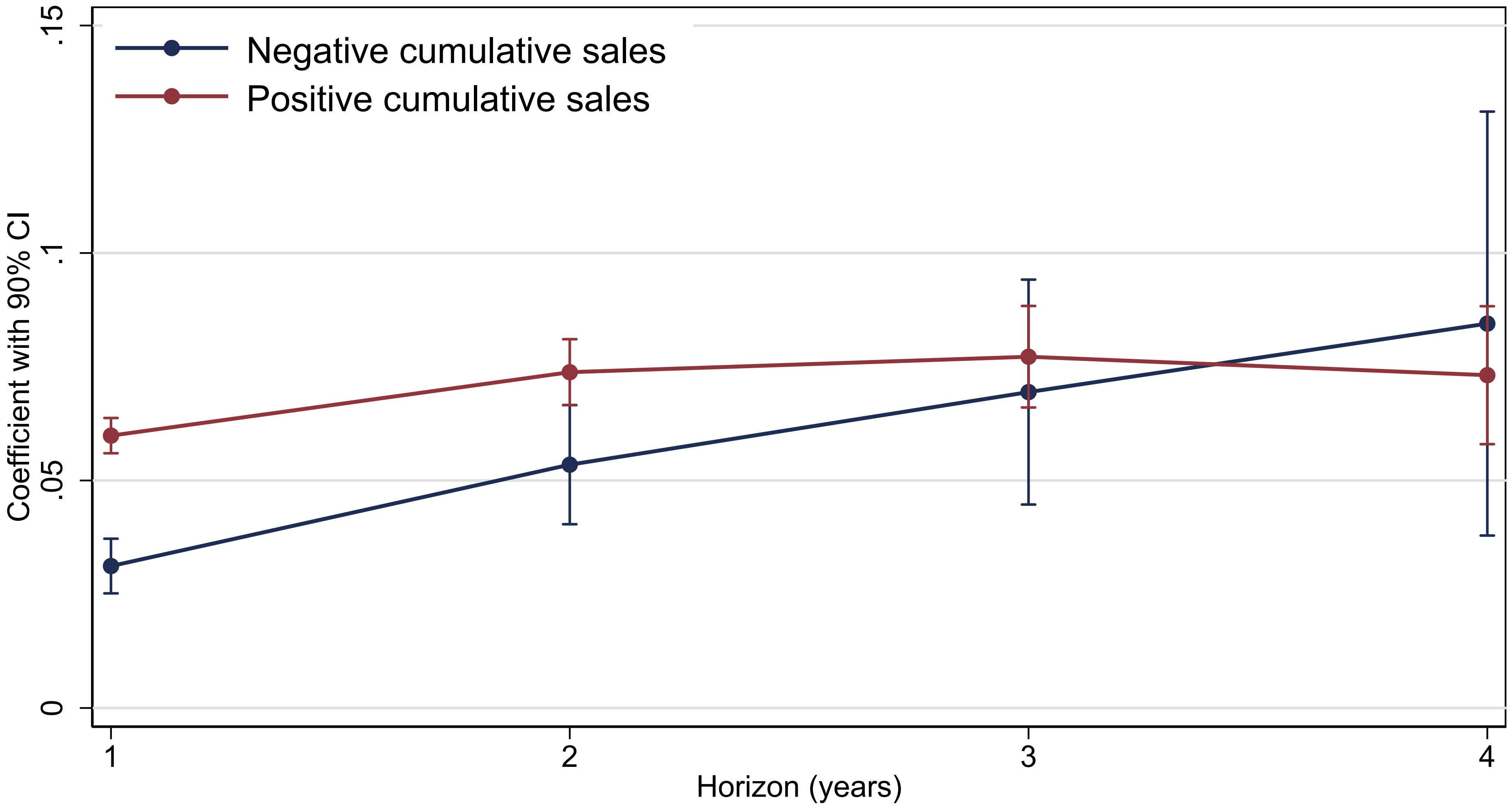
Low Inflation Firms

Average price growth: 1.5% (BIE) -0.6% (SBU)



Notes: High inflation firms are firms with average price growth across the full sample above BIE or SBU sample averages. Low-inflation firms are firms with average price growth across the full sample below the sample average. All figures are based on data from US firms in the Survey of Business Uncertainty (Panel A) and the Business Inflation Expectations survey (Panel B).

Figure 7: Relationship between sales and price growth: Longer-run responses (UK Firms)

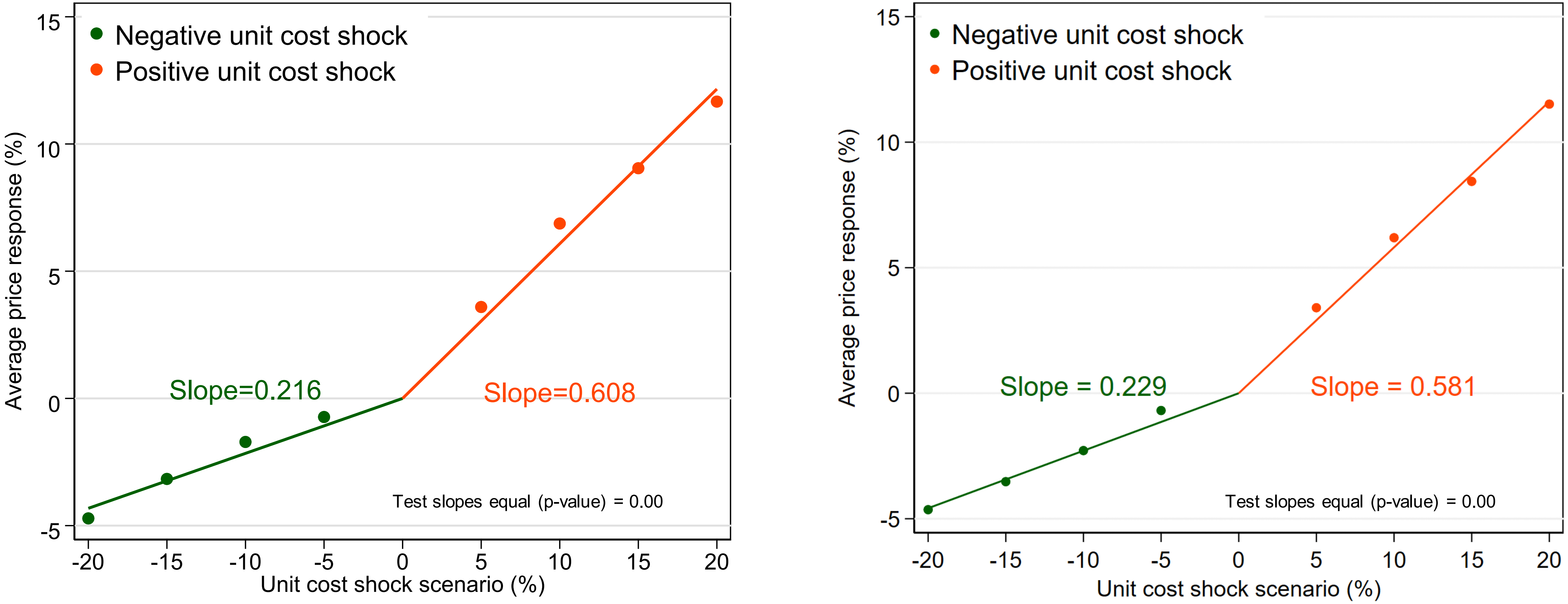


Notes: This figure presents the coefficients on regressions of cumulative own-price growth on cumulative nominal sales growth over horizons from one to four years. The coefficients on each horizon are based on separate regressions. Standard errors are clustered at the firm level and 90% confidence intervals are reported. This figure is based on data from UK firms in the Decision Maker Panel. This analysis is not shown for US firms, because price growth data over a long enough time period is not available.

Figure 8: Price response to hypothetical unit cost shocks

Panel A: UK Firms (DMP)

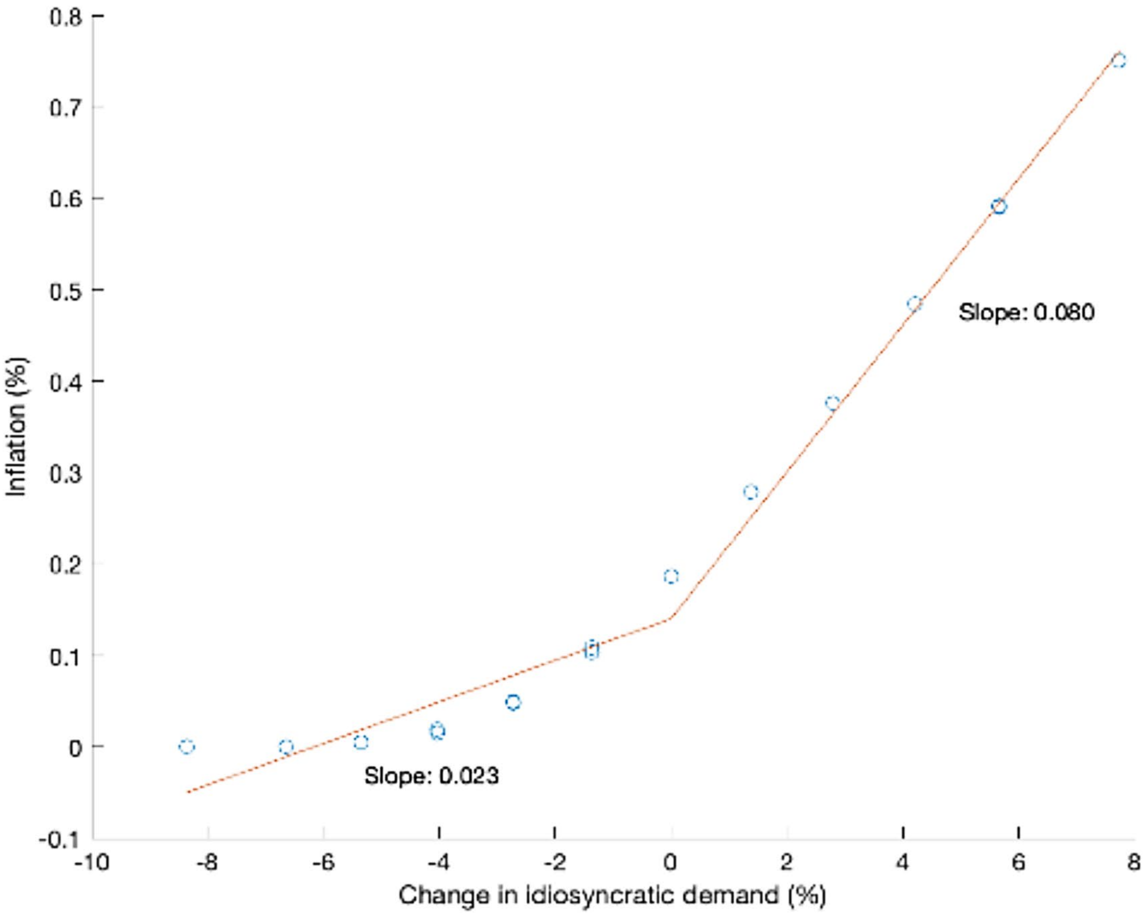
Panel B: US Firms (SBU)



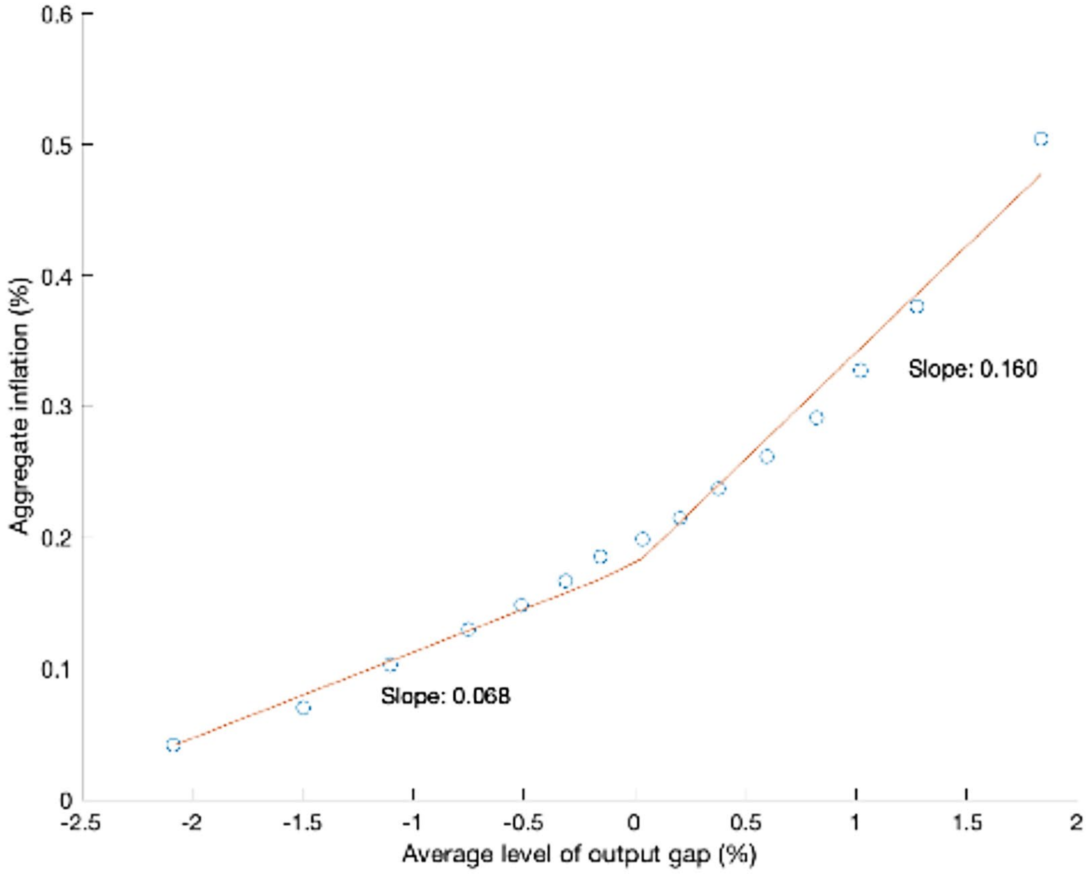
Notes: This figure reports responses to the question "Suppose that your business's unit costs over the next 12 months are X per cent higher/lower than you currently expect. How would that affect the average price you charge, relative to what you currently expect?" Firms are randomised into one of four scenarios for unit costs: ±5%, ±10%, ±15%, ±20%. Firms are presented with both the positive and negative values for a given scenario. **Panel A** is based on 3,728 observations from 1,864 UK firms in the Decision Maker Panel. **Panel B** is based on 1,787 observations from 895 firms in the Survey of Business Uncertainty. Across the two panels, we cannot reject the equality of the slopes on positive unit cost shocks (t-stat = 1.16) or the equality of the slopes on negative unit cost shocks (t-stat=0.66).

Figure 9: Simulated Phillips curves from menu cost model

Panel A: Firm simulated data



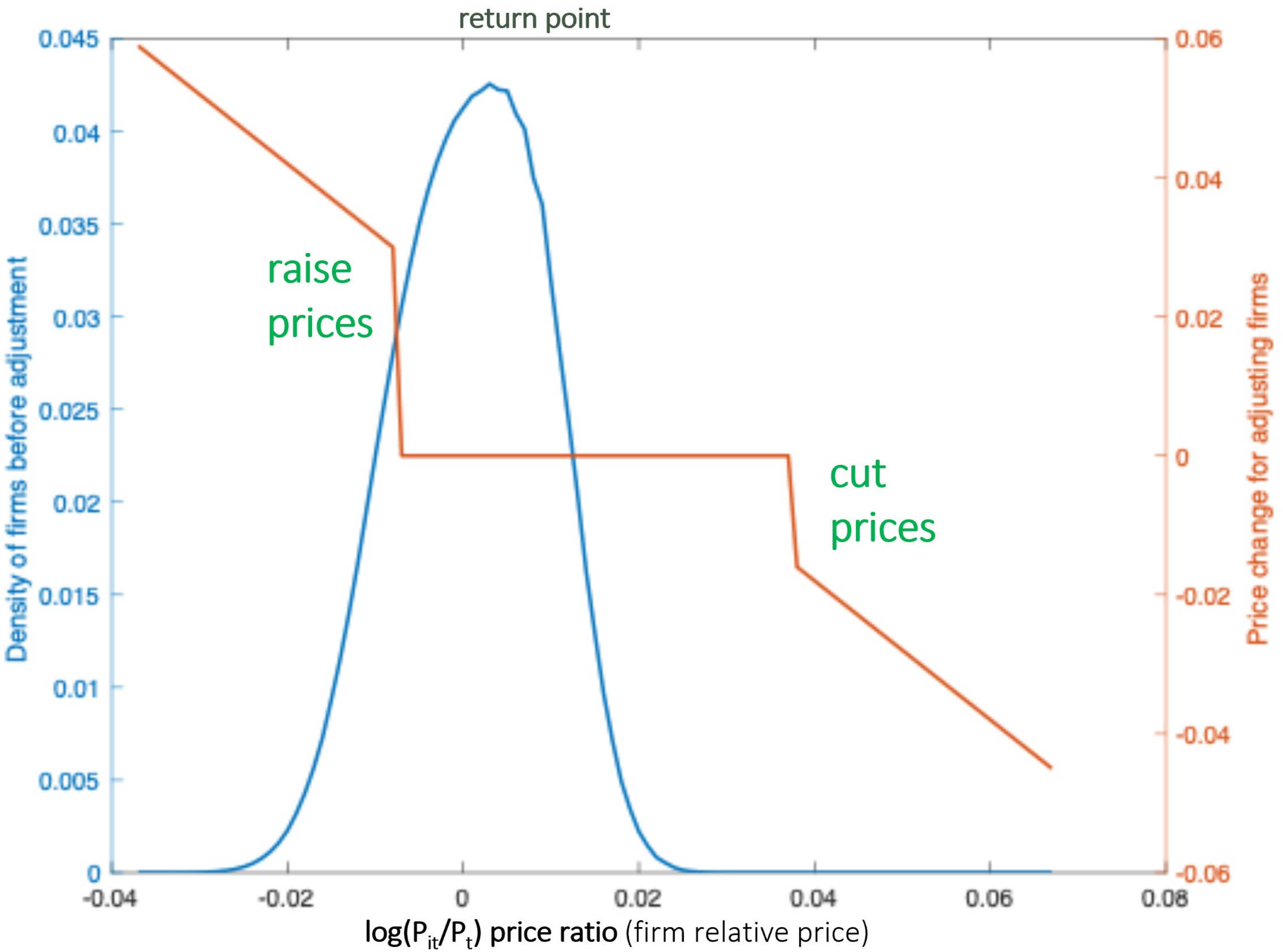
Panel B: Macro simulated data



Notes: : The left-hand figure presents simulated firm-level data from the model outlined in Section 6. The x-axis is the one-month change in idiosyncratic demand and the y-axis is the one-month inflation rate. The scatter plot uses 100 quantile bins. The right-hand figure presents simulated aggregate-level data from the model outlined in Section 6. The x-axis is the average level of the output gap calculated over twelve months and the y-axis is the twelve-month inflation rate. The scatter plot uses 15 quantile bins.

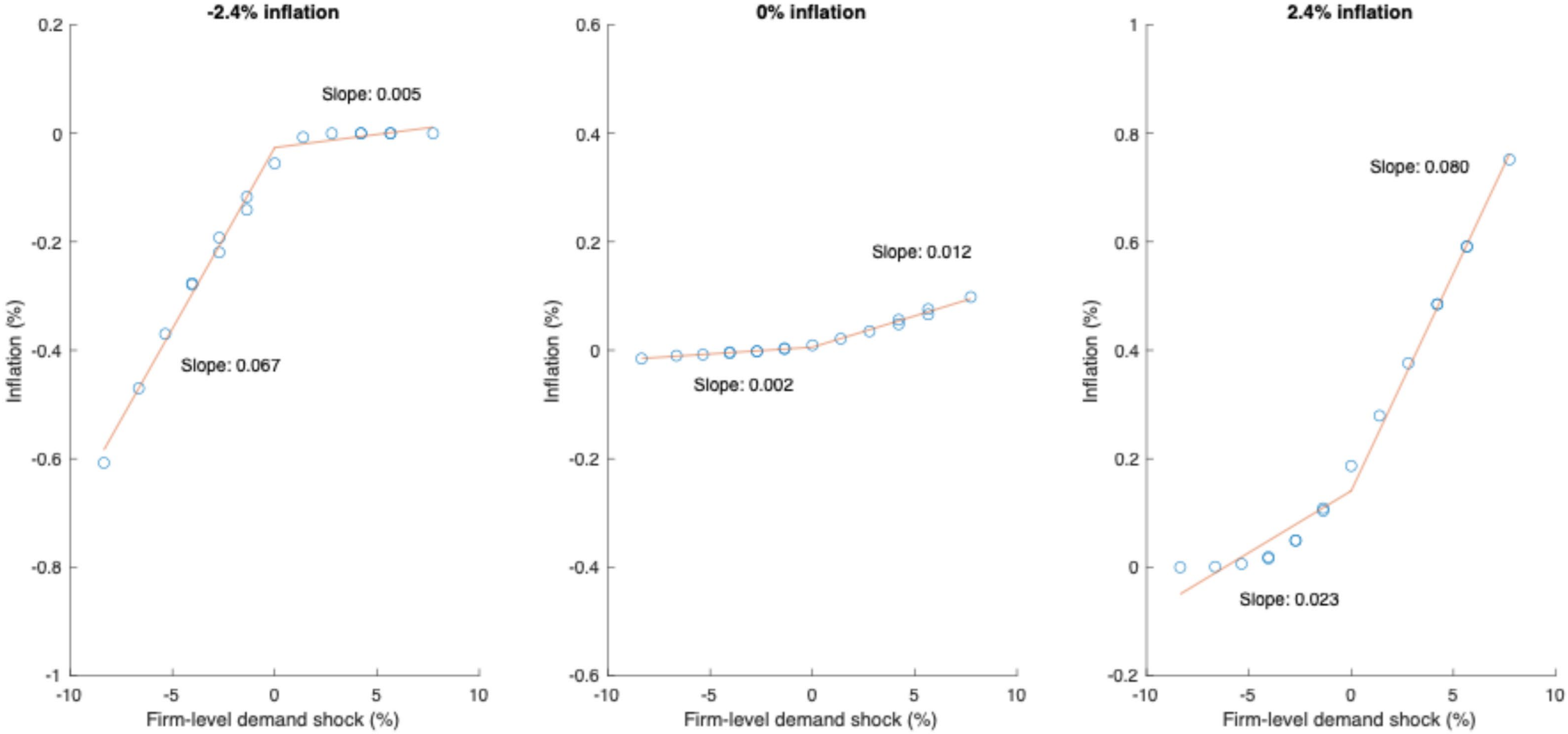
Figure 10: Distribution of firms in inaction zone

For median value of aggregate demand and idiosyncratic demand



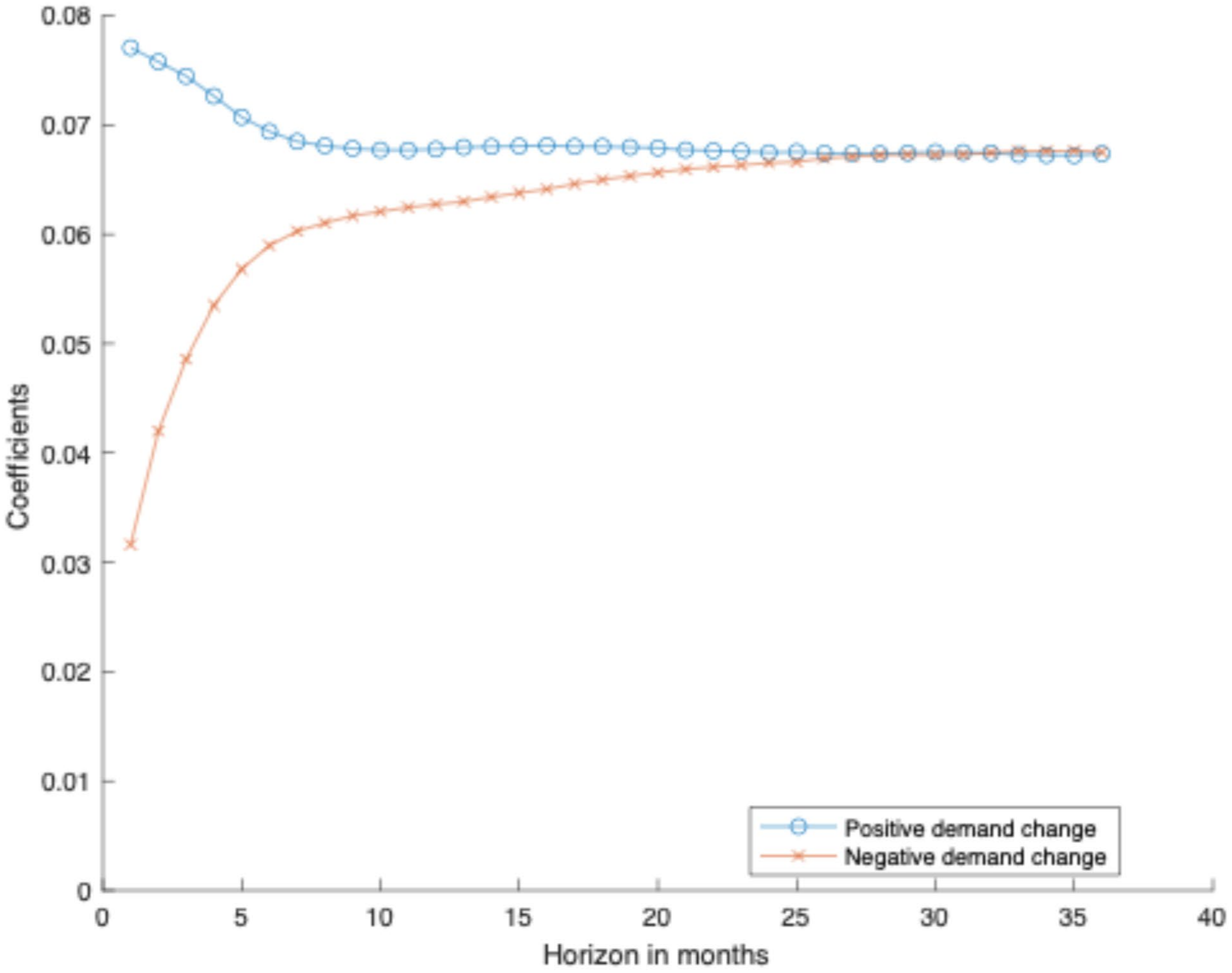
Notes: This figure presents simulated firm-level data from the model outlined in Section 6. It shows the density of firms within the zone of inaction (blue line) and the price changes that firms do conditional on changing prices (red line). It is drawn at the median value of aggregate and idiosyncratic demand.

Figure 11: Simulated firm-level Phillips curves at negative, zero, and positive inflation rates



Notes: This figure presents simulated firm-level data from the model outlined in Section 6. Panel A shows a simulation with -2.4% trend inflation in the model, Panel B shows a simulation with 0% trend inflation in the model, and Panel C shows a simulation with 2.4% trend inflation in the model (our baseline setup). In each panel, the x-axis is the one-month change in idiosyncratic demand and the y-axis is the one-month inflation rate. While the scale is different on the y-axis across subplots, the range of approximately 1.2pp is held constant so the gradients have the same interpretation. The scatter plots use 20 quantile bins.

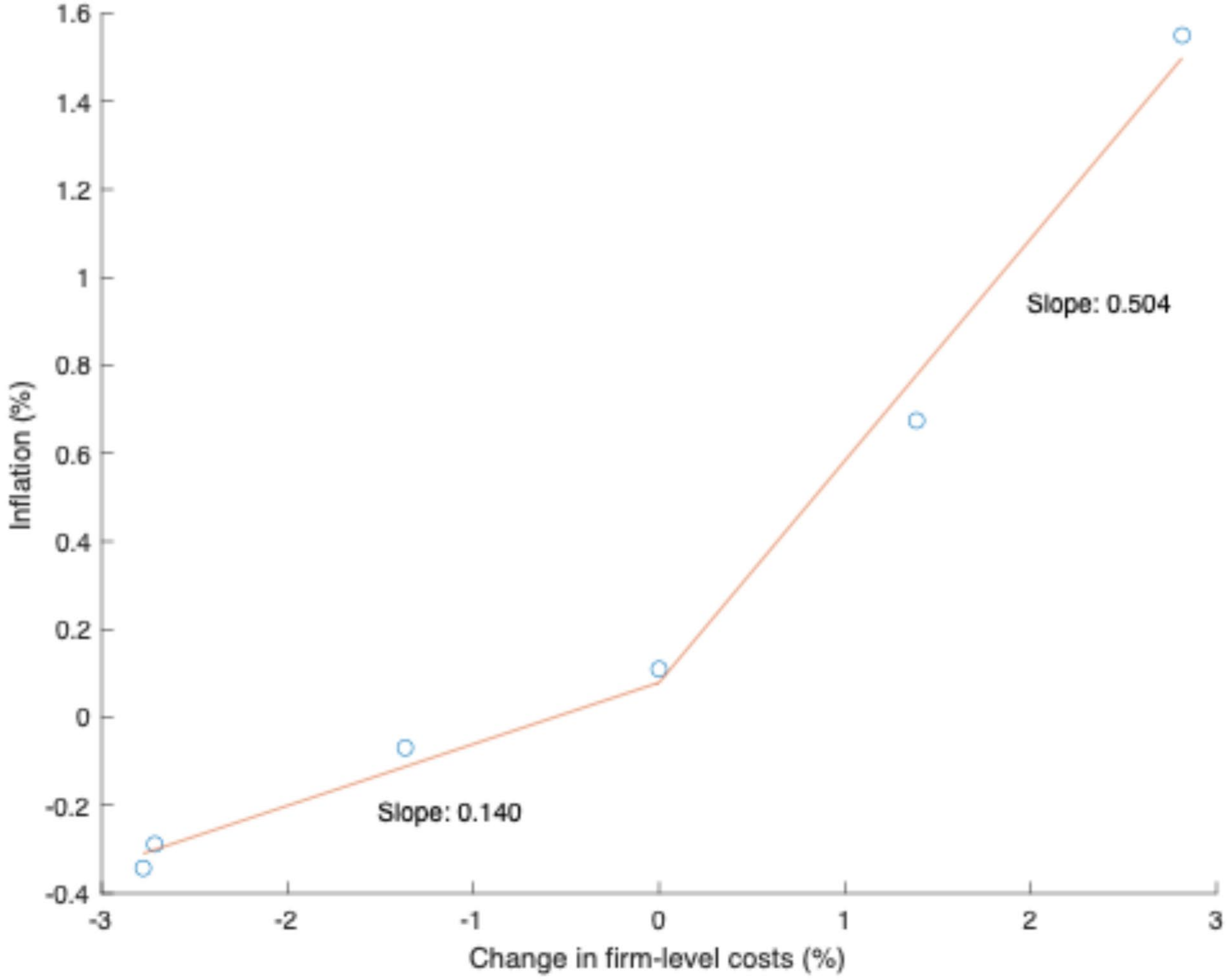
Figure 12: Simulated firm-level responses over different horizons to positive and negative demand shocks



Notes: This figure shows that the asymmetry in the slope of the two sides of the Phillips curve disappears in the model, as it does in the DMP data. We are showing the β_+^h, β_-^h from the regression below, where x_t^i is idiosyncratic demand.

$$p_{t+h}^i - p_t^i = \alpha_o^h + \alpha_i^h + \alpha_t^h + \beta_+^h \left(x_{t+h}^i - x_t^i\right) I\left[x_{t+h}^i - x_t^i > 0\right] + \beta_-^h \left(x_{t+h}^i - x_t^i\right) I\left[x_{t+h}^i - x_t^i < 0\right] + \varepsilon_{it}$$

Figure 13: Simulated firm-level price responses to cost shocks



Notes: This figure presents simulated firm-level data from the model outlined in Section 6, adapted to have cost shocks in place of demand shocks. Cost shocks are set to have 10% of the variance of demand shocks in order to keep the y-axis on a similar scale. The x-axis is the one-month change in idiosyncratic costs and the y-axis is the one-month inflation rate. The scatter plot uses 100 quantile bins.

Table 1: Macro evidence on inflation and output gap

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable:	Average Headline CPI Inflation (%)						
Sample:	1990-2024			1990-2019	2020-2024	Low-Inflation Countries	High-Inflation Countries
Output Gap_{it}	0.1167^{***}	0.1182^{***}					
	(0.0217)	(0.0209)					
Output Gap^2_{it}		0.0067^{***}					
		(0.0022)					
Output Gap_{it} X OG > 0			0.1909^{***}	0.1938^{***}	0.3885^{***}	0.0884^{*}	0.1981^{***}
			(0.0408)	(0.0627)	(0.1405)	(0.0438)	(0.0459)
Output Gap_{it} X OG < 0			0.0558	-0.0059	-0.0124	0.1030^{***}	0.0409
			(0.0350)	(0.0616)	(0.0721)	(0.0267)	(0.0436)
$Inflation_{it-1}$	0.4863^{***}	0.4816^{***}	0.4831^{***}			0.3869^{***}	0.4899^{***}
	(0.0289)	(0.0311)	(0.0309)			(0.0453)	(0.0403)
$E_t[Inflation_{it+5}]$	0.6538^{***}	0.6673^{***}	0.6716^{***}	1.6412^{***}	0.9495	0.5597^{***}	0.6434^{***}
	(0.0901)	(0.0916)	(0.0940)	(0.1277)	(0.7979)	(0.1165)	(0.1190)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.773	0.775	0.775	0.635	0.857	0.786	0.767
Number of observations	1,159	1,159	1,159	1,021	184	569	590
Test coefficients equal (p-value)			0.036	0.049	0.020	0.774	0.043
Average inflation rate	2.761	2.761	2.761	2.721	4.108	2.018	3.477

Notes: Data on annual inflation rates is taken from the World Bank cross-country database of inflation (Ha et al. 2023). Data on output gap estimates is obtained from the OECD. Data on inflation expectations is taken from the IMF World Economic Outlook. Country-years with inflation above 15% are dropped from the sample. 'High inflation countries' are countries with an average inflation rate above the sample average (2.76%). Standard errors are clustered at the country level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 2: Price response to hypothetical sales volume shocks

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	Average Price Response (%)			Average price response (%)		
Sample:	UK Firms (DMP)			US Firms (SBU)		
Sample period:	Dec-2023, Jan-2024, Aug-2024 to Oct-2024			June 2024		
Sales volume shock	0.0338***	0.0338***		0.0393***	0.0392***	
	(0.0048)	(0.0048)		(0.0067)	(0.0067)	
Sales volume shock^2		0.0013***			0.0013***	
		(0.0002)			(0.0003)	
Sales volume shock X Shock > 0			0.0601***			0.0638***
			(0.0050)			(0.0080)
Sales volume shock X Shock < 0			0.0074			0.0147
			(0.0072)			(0.0092)
R^2	0.013	0.019	0.021	0.030	0.039	0.041
Number of observations	6,394	6,394	6,394	1570	1570	1570
Test coefficients equal (p-value)			0.000			0.000

Notes: This table reports results from the question "Suppose that your business's sales volume over the next 12 months is X per cent higher/lower than you currently expect. How would that affect the average price you charge, relative to what you currently expect?" Firms are randomised into one of four scenarios for sales volume: ±5%, ±10%, ±15%, ±20%. Firms are presented with both the positive and negative values for a given scenario. The results in all columns are unweighted. US data are from Meyer et al. (2024). Standard errors are clustered at the firm level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Across Columns 3 and 6, we cannot reject the equality of the slopes on positive sales volume shocks (t-stat = 0.39) or the equality of the slopes on negative sales volume shocks (t-stat=0.62).

Table 3: Relationship between sales shock and price forecast errors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable:	Price Growth Forecast Error (pp)					Price Growth Forecast Error (pp)			
Sample:	UK Firms (DMP)					US Firms (BIE)			
Sample Period:	Nov-2017 to Mar-2026				2017-2019	Dec-2021 to Feb-2026			
Sales Shock	0.0532^{***}	0.0563^{***}				-0.0185	0.0058		
	(0.0035)	(0.0037)				(0.0333)	(0.0362)		
Sales Shock^2		0.0005^{***}					0.0018		
		(0.0001)					(0.0014)		
Sales Shock X Shock≥0			0.1036^{***}	0.0743^{***}	0.0517^{***}			0.1511^{***}	0.0835
			(0.0064)	(0.0064)	(0.0126)			(0.0569)	(0.0656)
Sales Shock X Shock<0			0.0386^{***}	0.0355^{***}	0.0240^{*}			-0.0089	-0.0686
			(0.0043)	(0.0051)	(0.0127)			(0.0270)	(0.0470)
Firm fixed effects	Yes	Yes	No	Yes	Yes	Yes	Yes	No	Yes
Time fixed effects	Yes	Yes	No	Yes	Yes	Yes	Yes	No	Yes
R2	0.340	0.342	0.045	0.341	0.453	0.365	0.366	0.008	0.367
Number of observations	23,643	23,643	24,920	23,643	3,340	1169	1169	1260	1169
Test coefficients equal (p-value)			0.000	0.000	0.174			0.026	0.096

Notes: **Columns 1-5** show the relationship between nominal sales growth forecast errors and annual price growth forecast errors based on data from UK firms in the Decision Maker Panel. Sales forecast errors are trimmed at the 5th and 95th percentiles by quarter. Price forecast errors are winsorised at the 1st and 99th percentiles. **Columns 6-9** show the relationship between sales levels compared to normal and annual price growth forecast errors based on data from US firms in the Business Inflation Expectations survey. Sales compared to normal are trimmed at the 5th and 95th percentiles by quarter. Price forecast errors are winsorised at the 5th and 95th percentiles. The constant of the regressions are also estimated but not reported. Standard errors are clustered at the firm level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Response of price growth to Covid demand shock (UK Firms)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable: Realized price inflation							
Sample period: 2017Q1 to 2022Q2 (quarterly data)							
Covid impact on $sales_{it}$#sales impact $positive_{it}$	0.2614***	0.2440***	0.1247***	0.0832***		0.1038***	0.0900***
	(0.0322)	(0.0311)	(0.0256)	(0.0163)		(0.0251)	(0.0245)
Covid impact on $sales_{it}$#sales impact $negative_{it}$	0.0131***	0.0055	0.0165***	0.0153***		0.0186***	0.0172***
	(0.0026)	(0.0035)	(0.0034)	(0.0034)		(0.0034)	(0.0034)
Dummy for Covid impact on sales $positive_{it}$	-0.2439	-0.7020***	-0.4119**			-0.3979**	-0.3966**
	(0.2172)	(0.2123)	(0.1776)			(0.1723)	(0.1678)
Covid impact on $sales_{it}$					0.0382***		
					(0.0060)		
(Covid impact on $sales_{it})^2$					0.0004***		
					(0.0001)		
Realized price inflation a year ago_{it} (firm level)							0.0818***
							(0.0157)
Expected price inflation a year $ahead_{it}$ (firm level)							0.3132***
							(0.0166)
Supply-side controls	No	No	No	No	No	Yes	Yes
Firm fixed effects	No	No	Yes	Yes	Yes	Yes	Yes
Time fixed effects	No	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.019	0.138	0.546	0.546	0.546	0.560	0.582
Number of observations	34,076	34,076	34,076	34,076	34,076	34,076	34,076
Test coefficients equal (p-value)	0.000	0.000	0.000	0.000		0.001	0.004

Notes: Standard errors are clustered at the firm level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Impact of Covid on sales is an average of the current and previous quarter. Data is not available for all variables for all firms. Where data are missing for a particular variable, a dummy variable is included to account for that (results not reported), except for the impact of Covid on sales where all observations included in the regressions have data. All columns are based on data from UK firms in the Decision Maker Panel. Supply-side controls used in Columns 6 and 7 include: the impact of Covid on unit costs; share of non-labour inputs disrupted; a measure of recruitment difficulties; firm import intensity; the impact of Brexit on unit costs; energy costs in production. See Table A2 for the full specification.

Table 5: Price growth and demand shocks: High vs. low inflation (UK Firms)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	Average Price Response (%)		Price Growth Forecast Error (pp)		Price Growth (%)	
Firm Inflation:	High	Low	High	Low	High	Low
Sales volume shock X Shock>0	0.0663***	0.0533***				
	(0.0069)	(0.0071)				
Sales volume shock X Shock<0	-0.0163	0.0390***				
	(0.0100)	(0.0105)				
Sales growth forecast error X Error ≥0			0.0992***	0.0414***		
			(0.0101)	(0.0068)		
Sales growth forecast error X Error <0			0.0389***	0.0327***		
			(0.0089)	(0.0055)		
Covid impact on sales X sales impact ≥0					0.1445***	0.0659**
					(0.0366)	(0.0288)
Covid impact on sales X sales impact <0					0.0105*	0.0199***
					(0.0060)	(0.0038)
Firm fixed effects	No	No	Yes	Yes	Yes	Yes
Time fixed effects	No	No	Yes	Yes	Yes	Yes
R2	0.024	0.031	0.355	0.308	0.487	0.380
Number of observations	3,626	2,566	11,705	11,938	12,889	21,171
Test coefficients equal (p-value)	0.000	0.184	0.000	0.362	0.000	0.115
Difference coefficients positive/negative	0.083	0.014	0.060	0.009	0.134	0.046
Average firm price growth in sample (%)	7.445	2.663	6.322	2.012	5.262	1.469

Notes: Columns 1-2 are based on price responses to hypothetical sales volume shocks (Section 4.1). Columns 3-4 are based on price growth and sales growth forecast errors (Section 4.2). Columns 5-6 are based on price responses to the Covid demand shock (Section 4.3). High-inflation firms are firms with average price growth across the full sample above 4% (sample average). Low-inflation firms are firms with average price growth across full sample below 4%. All columns are based on data from UK firms in the Decision Maker Panel. Standard errors are clustered at the firm level and reported in parentheses, with *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Price growth and demand shocks: High vs. low inflation (US Firms)

	(1)	(2)	(3)	(4)
Dependent Variable:	Average Price Response (%)		Price Growth Forecast Error (pp)	
Sample:	US Firms (SBU)		US Firms (BIE)	
Firm Inflation:	High	Low	High	Low
Sales volume shock X Shock>0	0.0841***	0.0449***		
	(0.0132)	(0.0107)		
Sales volume shock X Shock<0	0.0064	0.0388***		
	(0.0143)	(0.0130)		
Sales Shock X Shock≥0			0.0830	-0.0200
			(0.0733)	(0.0715)
Sales Shock X Shock<0			-0.1484**	0.0533
			(0.0707)	(0.0418)
Firm fixed effects	No	No	Yes	Yes
Time fixed effects	No	No	Yes	Yes
R2	0.061	0.038	0.379	0.415
Number of observations	684	711	510	545
Test coefficients equal (p-value)	0.000	0.696	0.060	0.440
Difference coefficients positive/negative	0.078	0.006	0.231	-0.073
Average firm price growth in sample (%)	5.911	-0.701	6.909	2.048

Notes: High-inflation firms are firms with average price growth across the full sample above the sample average (2.7% SBU and 4.5% BIE). Low-inflation firms are firms with average price growth across full sample below the sample averages. Columns 1-2 are based on data from US firms in the Survey of Business Uncertainty. Columns 3-4 are based on data from US firms in the Business Inflation Expectations survey. Standard errors are clustered at the firm level and reported in parentheses, with *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Contributions to rise in inflation between 2018 and 2022 from changes in cost and demand shock distributions (UK firms)

	Linear response to shocks	Non-linear response to shocks	Net impact of non-linearity
Increase in inflation among DMP firms 2018-2022 (pp):	4.4	4.4	
Contribution of cost shocks to increase in inflation (pp):	2.7	3.8	1.1
Contribution of demand shocks to increase in inflation (pp)	0.0	0.1	0.1
Unexplained (pp):	1.7	0.5	
Total additional contribution of non-linearity (pp):			1.2

Notes: This table shows the contributions to rise in inflation between 2018 and 2022 from changes in cost and demand shock distributions. Cost shock and demand shock distributions are presented in Figure A11. Estimates of the impact of demand shocks on firm prices are taken from Columns 1 and 3 of Table 2, for linear responses and non-linear responses, respectively. Estimates of the impact of unit cost shocks on firm prices are taken from Columns 1 and 3 of Table A5, for linear responses and non-linear responses, respectively.

Table 8: Model comparisons

Feature:	Convex aggregate Phillips curve	Convex price response to demand shocks	Greater convexity for high inflation firms	Convexity fades at long horizons	Convex price response to cost shocks
Level:	Macro	Micro	Micro	Micro	Micro
Data	✓ (Figure 2)	✓ (Figures 3-5)	✓ (Figures 6-7)	✓ (Figure 8)	✓ (Figure 9)
Augmented menu-cost model	✓ (Figure 10)	✓ (Figures 10-11)	✓ (Figure 12)	✓ (Figure 13)	✓ (Figure 14)
Baseline menu-cost model	✓	X	X	X	X
Downward wage rigidity	✓	X	X	X	X
Capacity or financial constraints	✓	✓	X	X	X
Quasi-kinked demand	✓	✓	~	~	~

Notes: ✓ Yes, ~ Partial, X Not in standard model. The augmented menu-cost model has decreasing returns to scale, positive trend inflation, and idiosyncratic demand shocks. Baseline menu-cost model just has trend inflation.

Table 9: Model parameters

Symbol	Parameter meaning	Baseline value	Source/rationale
β	Discount factor	0.96	Nakamura and Steinsson (2010)
θ	Elasticity of substitution between varieties	4	Nakamura and Steinsson (2010)
γ	Coefficient of relative risk aversion	1	Nakamura and Steinsson (2010)
λ	Returns to scale in production function	0.9	Khan and Thomas (2008)
K	Fixed cost of changing prices in labour units	0.015	To hit median frequency of price change in Nakamura and Steinsson (2010)
μ	Trend inflation rate	2.4% per year	Average inflation during 1992-2022
σ_η	Standard deviation of nominal demand shocks	0.011 (quarterly)	Std dev of HP-filtered UK nominal GDP during 1992-2022
ρ_d	Persistence of demand shocks	0.9 per month	-
σ_d	Standard deviation of demand shocks	0.03	Analogue of Nakamura and Steinsson (2010)
ω	Scale of disutility of labour	Normalised	To match steady-state labour supply of one third
s_m	Intermediate input share in production	0.70	Nakamura and Steinsson (2010)
ψ	Labour supply elasticity	0	Nakamura and Steinsson (2010)

Notes: The model is solved at monthly frequency. β and μ are reported as annual values, the per-period values used are $\beta^{(1/12)}$ and $\mu/12$ respectively. σ_η is the quarterly standard deviation of nominal demand shocks, the per-period value used is $\sigma_\eta/\sqrt{3}$.

Appendix A – model comparison table details

This appendix sets out the reasoning behind each cell of the model comparison table in Section 6. The table assesses whether each of the leading alternative explanations for Phillips curve convexity can reproduce the five empirical facts we document: a convex aggregate Phillips curve, a convex firm-level price response to demand shocks, stronger firm-level convexity at high inflation, convexity that fades at longer horizons, and a convex firm-level price response to cost shocks. We grade each model as published, rather than appealing to extensions we might construct. A grade of Yes (✓) indicates that the model produces the result through its core mechanism as it stands. A grade of Partial (~) indicates that the model produces a related result, but only at the aggregate rather than the firm level, or only conditionally on the state of the economy, so that it does not match the result as we document it. A grade of No (X) indicates that the model is silent on the result, or that reproducing it would require an extension beyond the published framework.

Model: Standard Menu-Cost Models, e.g. Ball & Mankiw (1994, 1995), Golosov & Lucas (2007), Gertler & Leahy (2008), Nakamura & Steinsson (2010), Blanco et al. (2024), Karadi et al. (2024)

Convex aggregate Phillips curve [Yes]. Ball and Mankiw (1994, 1995) show that with positive trend inflation, menu cost pricing generates an asymmetric aggregate response in which firms raise prices more readily than they cut them, delivering a convex aggregate Phillips curve. This result is driven by trend inflation, which is not a feature of these other standard menu-cost models.

Convex price response to demand shocks (firm-level) [No]. In the menu-cost models solved with constant returns and CES demand, an idiosyncratic demand shock leaves a firm's marginal cost and desired markup unchanged, so it does not move the firm's optimal price and triggers no adjustment. There is therefore no firm-level demand response for convexity to arise from. Ball and Mankiw (1994, 1995) have trend inflation but no cross section of firms in which a firm-level response could be measured. Our model adds decreasing returns, which makes a firm's optimal price rise when idiosyncratic demand pushes up its output.

Greater convexity for high inflation firms [No]. None of these models produces a firm-level demand response that varies with the inflation rate. The quantitative models solved at low or zero trend inflation have a symmetric firm distribution and no firm-level convexity for inflation to strengthen. Ball and Mankiw (1994, 1995) have trend inflation but no firm-level cross section. Our model combines decreasing returns with positive trend inflation.

Convexity fades at long horizons (firm-level) [No]. For the same reason, these models do not produce a short-run asymmetry between positive and negative shocks at the firm level, so there is nothing to fade over longer horizons.

Convex price response to cost shocks (firm-level) [No]. None of these models combines a firm-level Ss distribution with the features our model uses to make cost pass-through asymmetric. In the quantitative models solved at low or zero trend inflation the firm distribution is roughly symmetric, so positive and negative cost shocks pass through equally. In Ball and Mankiw (1994, 1995), trend inflation delivers aggregate convexity but the model has no firm-level cross section in which a within-firm cost asymmetry could arise.

Model: Capacity Constraints or Financial Constraints, e.g. Gilchrist et al. (2017), Boehm & Pandalai-Nayar (2022), Juul & Jørgensen (2025)

Convex aggregate Phillips curve [Yes]. This is a main result of capacity constraint models. Financial constraints partially achieve this result: Gilchrist et al. (2017) document that distressed firms raise prices during downturns which attenuates aggregate inflation's response to negative demand shocks. This is consistent with some aggregate convexity but the mechanism predicts price increases in downturns regardless of demand conditions rather than steeper responses to positive shocks specifically.

Convex price response to demand shocks (firm-level) [Yes]. Firm-level capacity constraints generate a convex supply curve. Near the capacity ceiling, a positive demand shock causes a sharp price rise because marginal costs are steep. A negative shock to a firm with slack capacity has little price effect because the supply curve is flat, so firm-level price asymmetry does emerge. The mechanism is a physical constraint, not a nominal one, so the convexity is about the level of capacity utilisation rather than price-setting frictions per se. In models with financial constraints, a cash-flow floor limits price reductions in response to negative demand shocks, though this depends on the severity of financial distress rather than being a general prediction.

Greater convexity for high inflation firms **[No].** The mechanism is driven entirely by the level of capacity utilisation, which is a real variable. Trend inflation has no direct bearing on where firms sit relative to their capacity ceiling, as that depends on demand conditions. There is therefore no channel through which higher trend inflation would systematically strengthen the convexity of price responses to demand shocks. Financial constraints are similarly determined by real debt-service obligations and offer no additional channel from trend inflation to pricing asymmetry.

Convexity fades at long horizons (firm-level) [No]. This is a putty-clay model in which firms fix capacity ex ante, and the model has no endogenous capital accumulation, so it does not produce our horizon-fading result. An extension allowing investment to relax the capacity constraint over time could plausibly generate fading convexity in the long run, but the convergence would run opposite to our result: the asymmetry would close because the positive-shock response weakens as capacity expands (convergence from above), whereas in our data it closes because the negative-shock response strengthens as delayed downward pass-through completes (convergence from below, Figure 14). Financial constraints produce an attenuated negative-shock response from the outset and there is no force which would cause it to strengthen and converge to the positive-shock response from below.

Convex price response to cost shocks (firm-level) [No]. The capacity constraint mechanism generates convex responses to demand shocks because demand pushes firms against a capacity ceiling. A cost shock shifts marginal cost regardless of the firm's position relative to that ceiling, so the mechanism does not generate asymmetry between positive and negative cost shocks. Any utilisation-related variation in pass-through would be cross-firm heterogeneity rather than the within-firm convexity we document. Financial constraints similarly predict cross-firm variation in cost pass-through rather than the within-firm asymmetry that we document.

Model: Downward Wage Rigidity, e.g. Daly & Hobijn (2014), Schmitt-Grohé & Uribe (2023), Benigno & Eggertsson (2024)

Convex aggregate Phillips curve [Yes]. This is a central contribution of the model.

Convex price response to demand shocks (firm-level) [No]. The model has no firm-level price-setting mechanism and no idiosyncratic firm-level shocks, so there is no cross-sectional dimension from which a firm-level Phillips curve could be constructed. All firms are identical and occupy the same point, so the model cannot speak to this result.

Greater convexity for high inflation firms **[No].** The model has no firm-level heterogeneity in price growth and no channel from trend inflation to firm-level convexity. The result has no counterpart in a framework where all nonlinearity is aggregate and labour-market-driven.

Convexity fades at long horizons (firm-level) [No]. The slanted-L is a static aggregate relationship. The wage norm is backward-looking by one period, but this does not generate horizon-dependent convergence of firm-level price responses.

Convex price response to cost shocks (firm-level) [No]. Supply shocks have larger aggregate inflation effects in the tight-labour-market regime, but this is a regime-dependent amplification of all supply shocks rather than an asymmetry between positive and negative cost shocks at the firm level.Model: Quasi-Kinked Demand, e.g. Ilut, Valchev & Vincent (2020), Harding, Lindé & Trabandt (2022, 2023), Dupraz (2024)

Convex aggregate Phillips curve [Yes]. This is a main result of the paper.

Convex price response to demand shocks (firm-level) [Yes]. The Kimball aggregator implies that marginal revenue is a concave function of price, so firms' optimal pricing schedule is convex in marginal cost (Figure 1 of Harding, Lindé and Trabandt (2023)). Since demand shocks feed through to marginal cost via the output gap, this generates within-firm asymmetry: a representative firm raises prices more in response to a positive demand shock than it cuts them for a negative shock of equal size.

Greater convexity for high inflation firms **[Partial].** Figure 2 of Harding, Lindé and Trabandt (2023) shows the banana-shaped Phillips curve is more convex at higher inflation levels, which is consistent with this result. However, it is an aggregate relationship rather than a firm-level cross-sectional split, and adding cross-sectional variation in firm-level price growth would likely be required to reproduce the firm-level version.

Convexity fades at long horizons (firm-level) [Partial]. Section 4.4 of Harding, Lindé and Trabandt (2023) states that inflation risk in the nonlinear model is mostly a near-term phenomenon, with most of the difference from the linearized solution dissipating within two years. While the model produces fading convexity at long horizons, this is a different exercise to the one in our paper, and it is not clear that it would match our empirical finding of convergence driven by the negative slope increasing to catch up with the positive one. This catch-up pattern is not the natural prediction of a mechanism that generates fading through reversion to steady state.

Convex price response to cost shocks (firm-level) [Partial]. Figure 1 of Harding, Lindé and Trabandt (2023) shows the representative firm's optimal price is a convex function of marginal cost, which does imply within-firm asymmetry since the firm raises prices more in response to a cost increase than it cuts them for a decrease of equal size. However, the asymmetry in this model is state-dependent: it is meaningful only when the firm is already in a high-inflation state and is weak near the low-inflation steady state, so it is not an unconditional prediction of the model.

Appendix B – model details

Household Behavior

The households in the economy maximize discounted expected utility, given by

$$E_t \sum_{\tau=0}^{\infty} \beta^{\tau}\left[\frac{1}{1-\gamma}C_{t+\tau}^{1-\gamma} - \frac{\omega}{\psi+1}L_{t+\tau}^{1+\psi}\right],$$

where E_t denotes the expectations operator conditional on information known at time t, C_t denotes household consumption of a composite consumption good, and L_t denotes household supply of labor. Households discount future utility by a factor β per period; they have constant relative risk aversion equal to γ; and the level and convexity of their disutility of labor are determined by the parameters ω and ψ, respectively.

Households consume a continuum of differentiated products indexed by z. The composite consumption good C_t is a Dixit–Stiglitz index of these differentiated goods:

$$C_t = \left[\int_0^1 c_t(z)^{\frac{\theta-1}{\theta}} dz\right]^{\frac{\theta}{\theta-1}},$$

where $c_t(z)$ denotes household consumption of good z at time t, and θ denotes the elasticity of substitution between the differentiated goods.

The households must decide each period how much to consume of each of the differentiated products. For any given level of spending in time t, the households choose the consumption bundle that yields the highest level of the consumption index C_t. This implies that household demand for differentiated good z is:

$$c_t(z) = C_t\left(\frac{p_t(z)}{P_t}\right)^{-\theta} d_t(z),$$

where $p_t(z)$ denotes the price of good z in period t, $d_t(z)$ is an idiosyncratic demand shock, and P_t is the price level in period t, given by:

$$P_t = \left[\int_0^1 p_t(z)^{1-\theta} dz\right]^{\frac{1}{1-\theta}}.$$

The price level P_t has the property that P_tC_t is the minimum cost for which the household can purchase the amount C_t of the composite consumption good. We treat $d_t(z)$ as an exogenous demand wedge rather than a preference parameter, so it does not enter the price index.

A complete set of Arrow–Debreu contingent claims is traded in the economy. The budget constraint of the households may therefore be written as:

$$P_tC_t + E_t\left[D_{t,t+1}B_{t+1}\right] \leq B_t + W_tL_t + \int_0^1 \pi_t(z)dz,$$

where B_{t+1} is a random variable that denotes the state-contingent payoffs of the portfolio of financial assets purchased by the households in period t and sold in period $t + 1$; $D_{t,t+1}$ denotes the unique stochastic discount factor that prices these payoffs in period t; W_t denotes the wage rate in the economy at time t; and $\pi_t(z)$ denotes the profits of firm z in period t. To rule out 'Ponzi schemes', we assume that household financial wealth must always be large enough so that future income suffices to avert default.

The first-order conditions of the household's maximization problem are:

$$D_{t,T} = \beta^{T-t}\left(\frac{C_T}{C_t}\right)^{-\gamma}\frac{P_t}{P_T},$$

$$\frac{W_t}{P_t} = \omega L_t^{\psi} C_t^{\gamma},$$

and a transversality condition. Equation (6) describes the relationship between asset prices and the time path of consumption, whereas Equation (7) describes labor supply.

Firm Behavior

There is a continuum of firms in the economy indexed by z. The production function of firm z incorporates diminishing returns to scale as:

$$y_t(z) = \widetilde{A}_t(z)\left[L_t(z)^{1-s_m} M_t(z)^{s_m}\right]^{\lambda},$$

where $y_t(z)$ denotes the output of firm z in period t, $L_t(z)$ denotes the quantity of labor firm z employs for production purposes in period t, $M_t(z)$ denotes an index of intermediate inputs used in the production of product z in period t, s_m denotes the materials share in production, $\widetilde{A}_t(z)$ denotes the productivity of firm z at time t, and λ indexes the degree of decreasing returns to scale. Products are both intermediates and final goods in roundabout production as in Nakamura and Steinsson (2010). Importantly, returns to scale are decreasing at the firm level but constant at the aggregate level:

$$\widetilde{A}_t(z) = A_t(z)\left(\int_0^1 L_t(j)dj\right)^{1-\lambda}$$

The intermediate input index is:

$$M_t(z) = \left[\int_0^1 m_t\left(z, z'\right)^{\frac{\theta-1}{\theta}} dz'\right]^{\frac{\theta}{\theta-1}},$$

where $m_t(z, z')$ denotes the quantity of the z'th intermediate input used by firm z.

In turn, the demand of firm z for product z' is given by:

$$m_t\left(z, z'\right) = M_t(z)\left(\frac{p_t\left(z'\right)}{P_t}\right)^{-\theta}$$

Firms maximize the discounted value of expected profits:

$$E_t \sum_{\tau=0}^{\infty} D_{t,t+\tau}\pi_{t+\tau}(z),$$

where profits in period t are:

$$\pi_t(z) = p_t(z)y_t(z) - W_t\left[L_t(z) + \kappa I_t(z)\right] - P_t M_t(z)$$

and κ is the menu cost payable in labor units. The indicator variable $I_t(z)$ equals 1 if the firm changes its price in period t and 0 otherwise.

Productivity shocks follow an AR(1) process:

$$logA_t(z) \ = \rho_A logA_{t-1}(z) + \varepsilon_t^A(z),$$

The firm-level idiosyncratic demand shock $d_t(z)$ follows an AR(1) process:

$$\log d_t(z) = \rho_d \log \ d_{t-1}(z) + \varepsilon_t^d(z)$$

Both $\varepsilon_t^A(z)$ and $\varepsilon_t^d(z)$ are i.i.d. shocks.

The monetary authority targets nominal output. Let$S_t \equiv log(P_t C_t)$ denote log nominal aggregate demand which follows a random walk with drift:

$$S_t = \ \mu + S_{t-1} + \eta_t$$

The firm's objective is to maximize the present discounted value of profits. The recursive value function is given by:

$$V_t\left(A_t(z), d_t(z), p_{t-1}(z), S_t\right) = \ \max_{p_t(z)} \left\{\pi_t(z) + E_t\left[D_{t,t+1}V_{t+1}(A_{t+1}(z), d_{t+1}(z), p_t(z), S_{t+1})\right]\right\}$$

The presence of intermediate inputs creates strategic complementarities in pricing decisions, amplifying the effects of nominal shocks. This structure, combined with state-dependent pricing and idiosyncratic shocks, generates heterogeneity in firm-level price adjustment behavior.

Appendix References

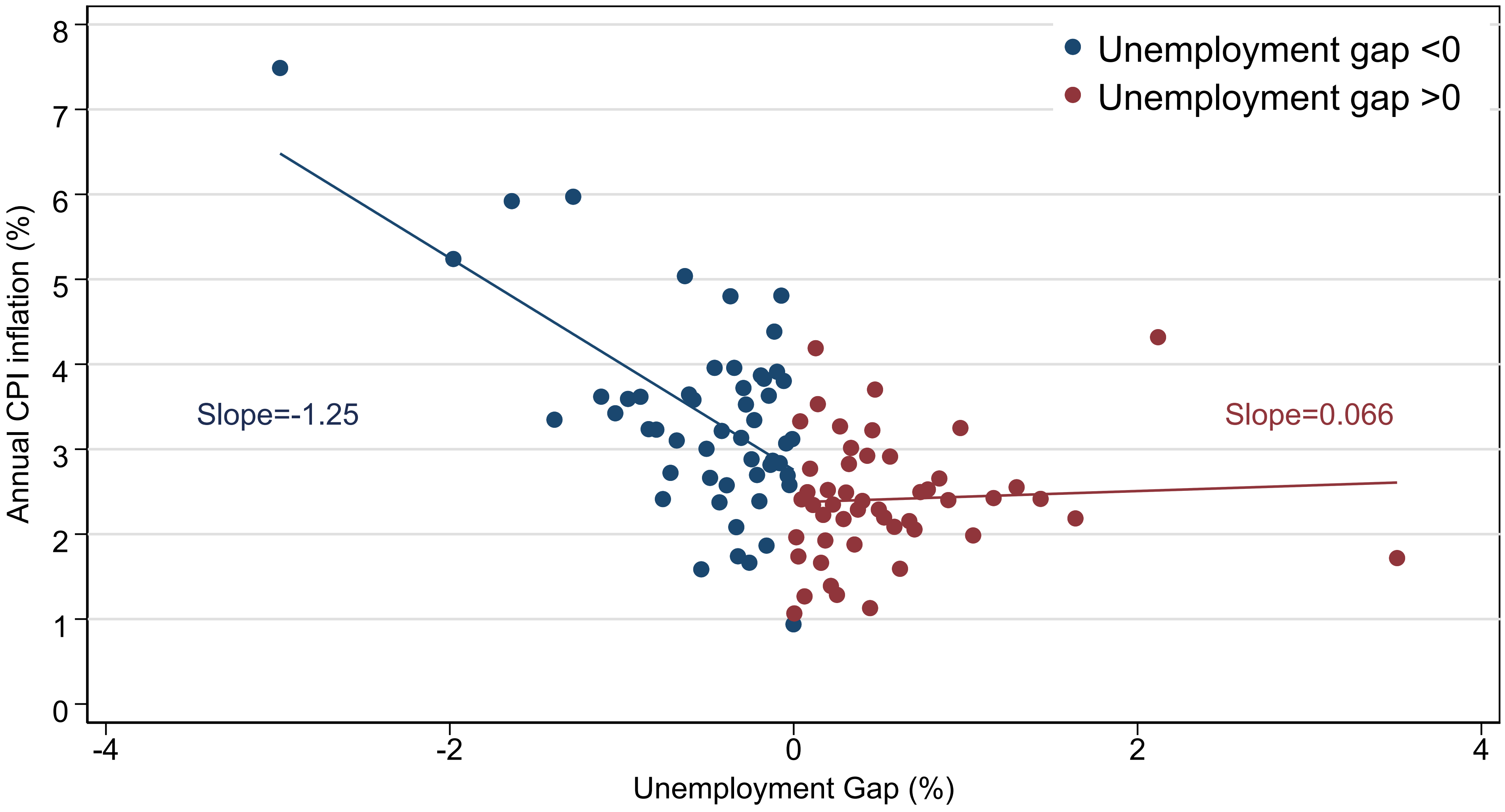
Daly, M C and B Hobijn (2014), "Downward Nominal Wage Rigidities Bend the Phillips Curve", *Journal of Money, Credit and Banking* 46(S2): 51-93.

Dupraz, S (2024) "A Kinked-Demand Theory of Price Rigidity", *Journal of Money, Credit and Banking* 56: 325-363.

Gertler, M and J Leahy (2008), "A Phillips Curve with an Ss Foundation", *Journal of Political Economy* 116(3): 533-572.

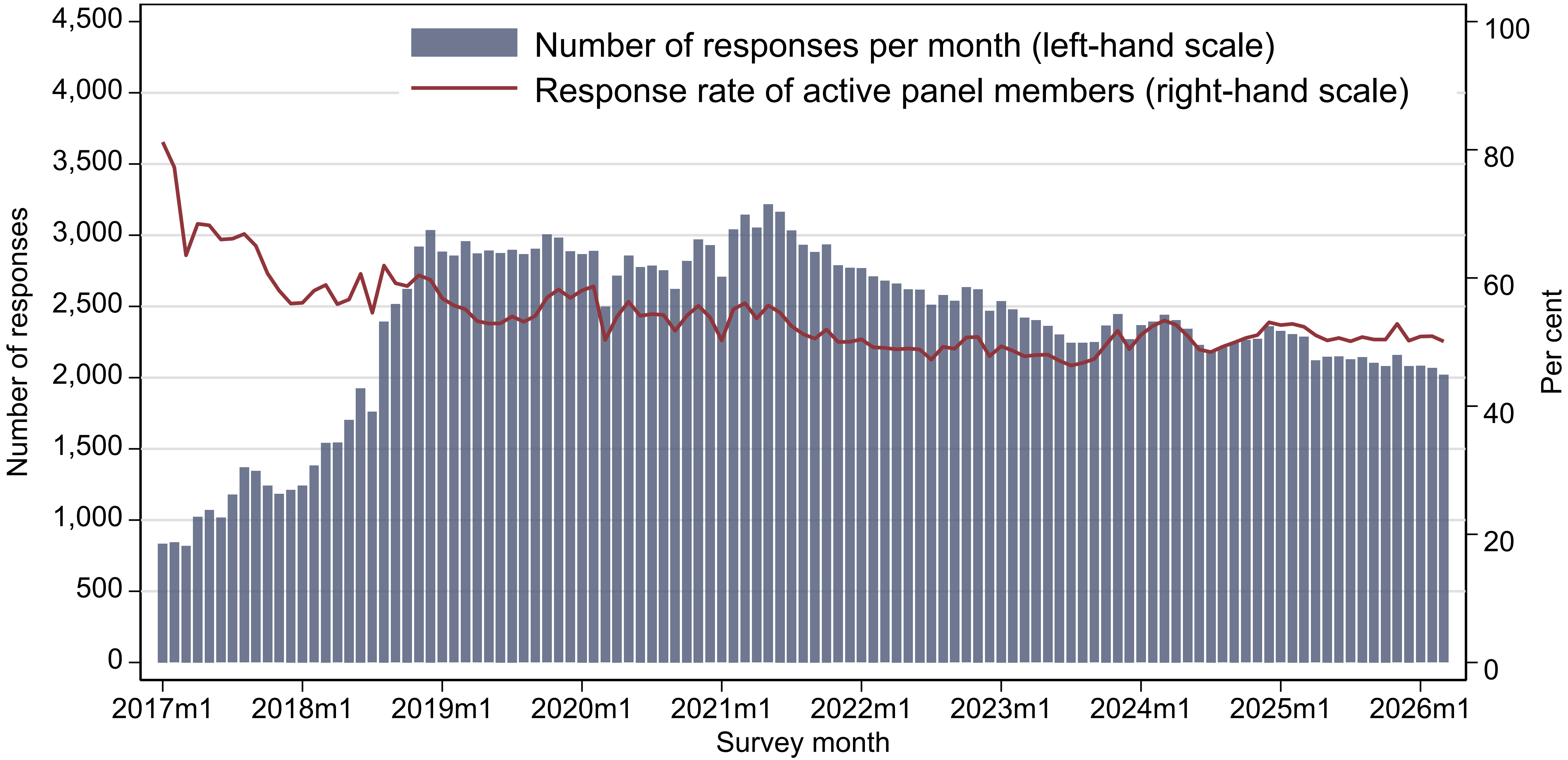
Ilut, C, R Valchev and N Vincent (2020) "Paralyzed by Fear: Rigid and Discrete Price Under Demand Uncertainty" *Econometrica* 88(5): 1899-1939.

Figure A1: Macro evidence on inflation and unemployment gap



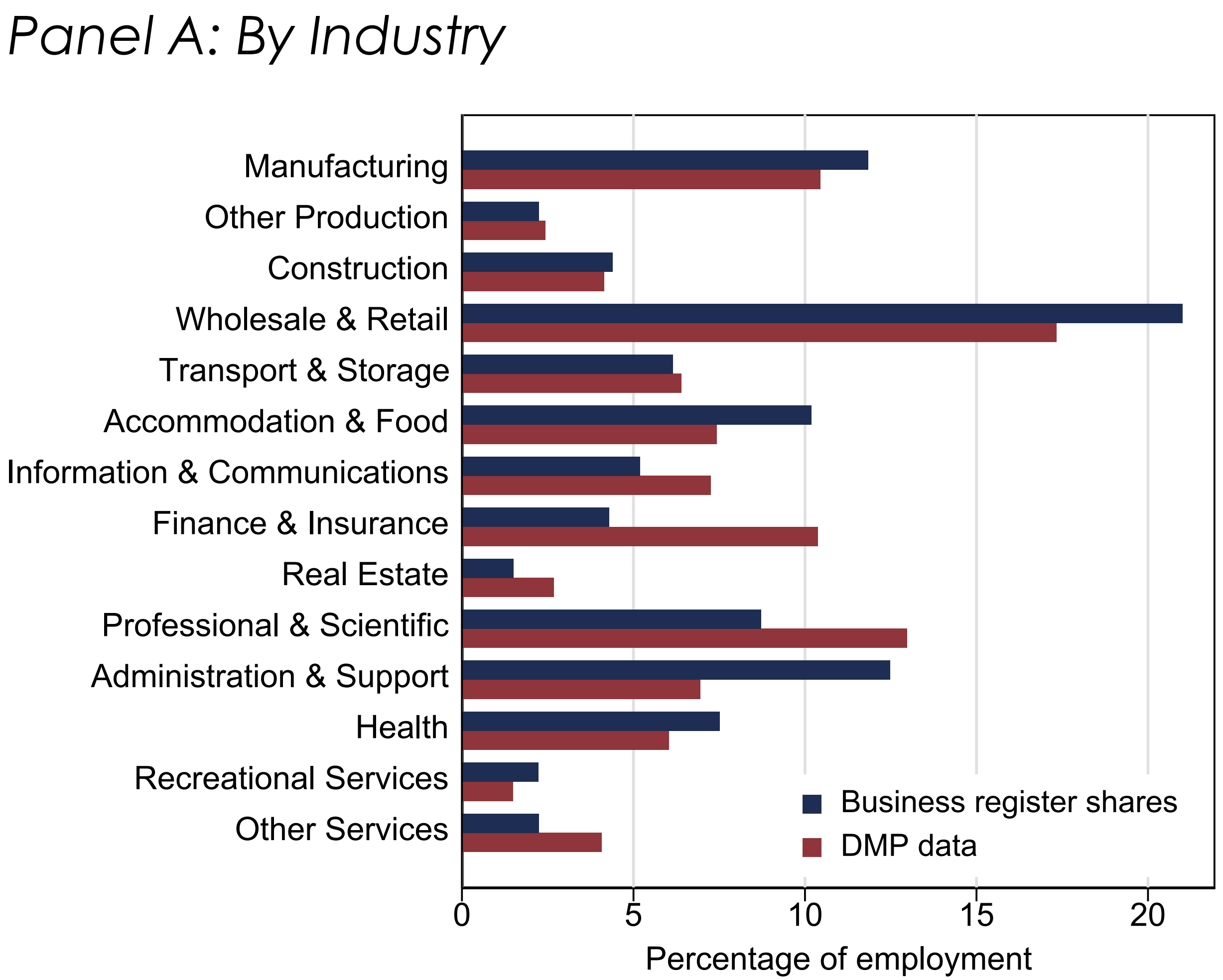
Notes: This figure presents a binned scatterplot of the relationship between aggregate inflation and the unemployment gap for the sample of countries in Figure 2. Each point represents roughly 1% of observations. Data on annual inflation rates are taken from the World Bank cross-country database of inflation (Ha et al. 2023). Data on unemployment are taken from the OECD. The unemployment gap is constructed using an HP filter for each country series. Country-years with inflation above 15% are dropped from the sample.

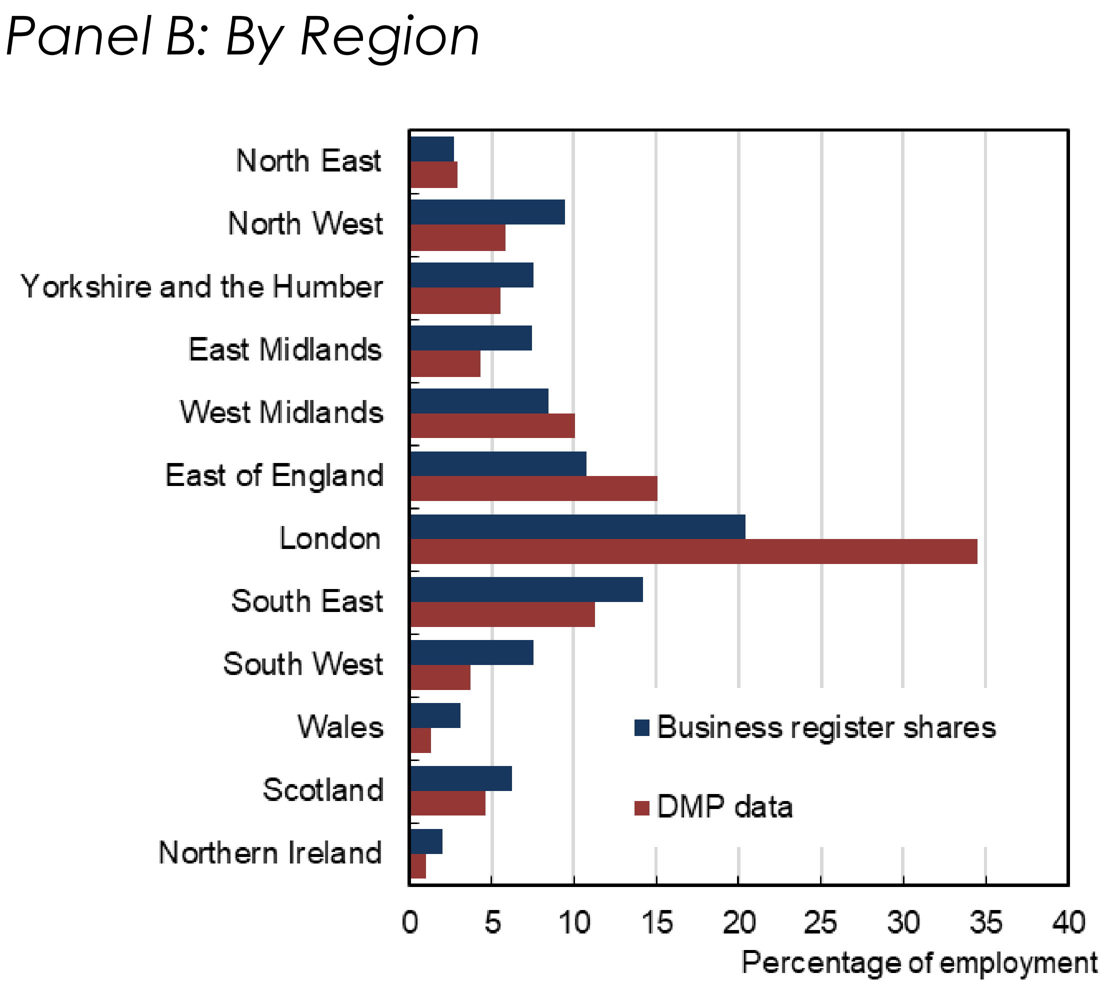
Figure A2: DMP Response rate



Notes: The response rate of active panel members in the Decision Maker Panel is calculated as the percentage of panel members who had completed at least one survey over the last twelve months who responded to the survey in a given month.

Figure A3a: DMP vs. UK industrial and regional distribution

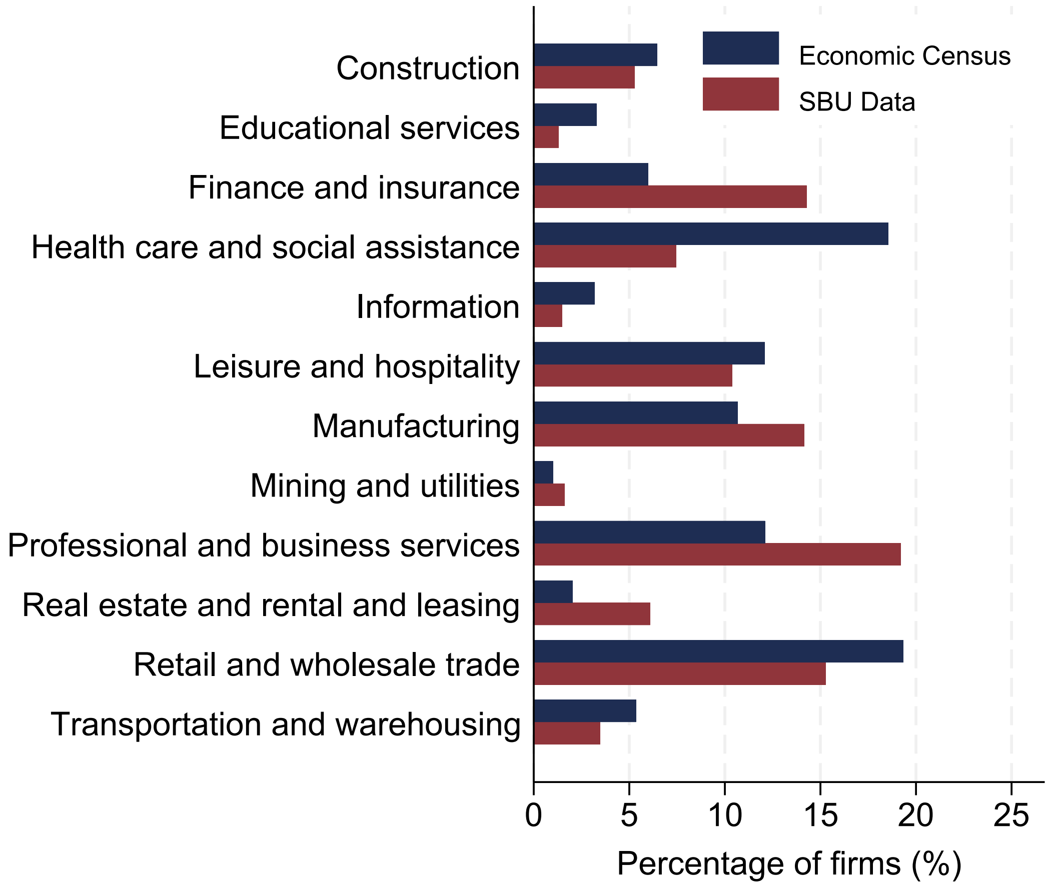




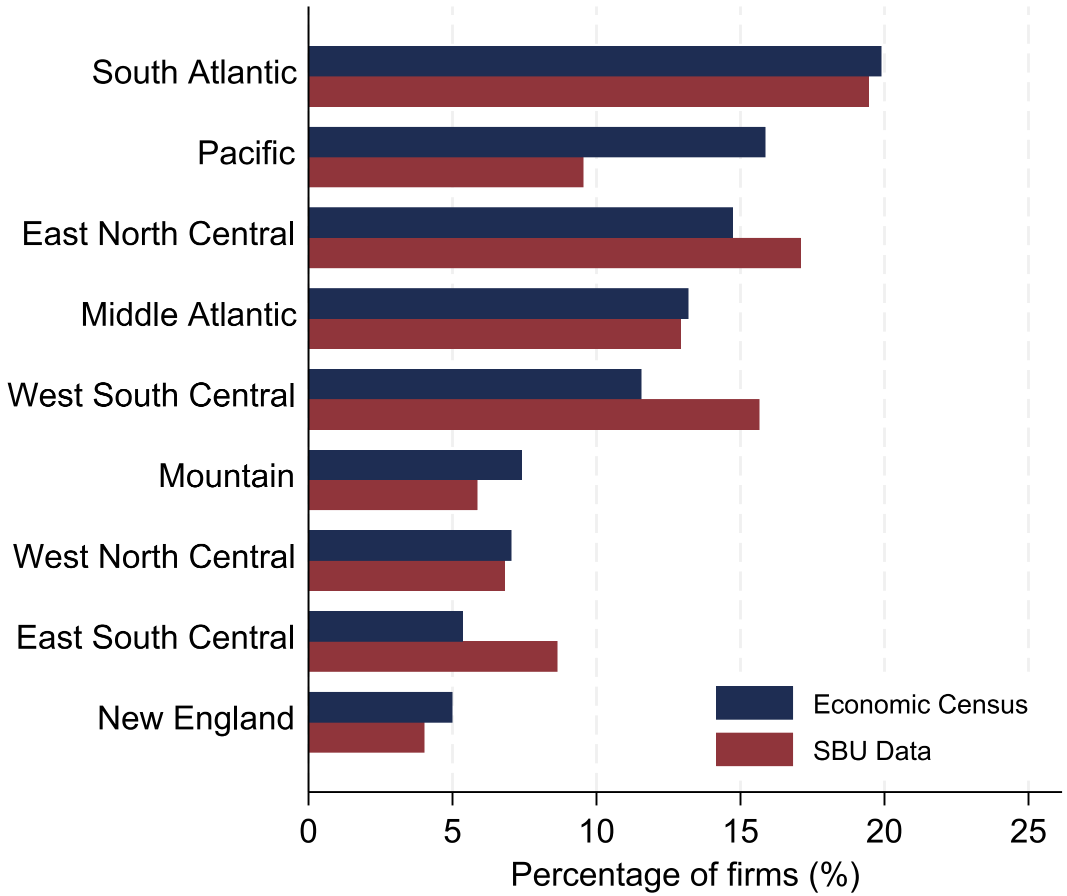
***Notes**: Other production includes agriculture; forestry & fishing; mining & quarrying; electricity, gas & air conditioning supply; water supply; and sewerage, waste management & remediation activities. Data are averages from 2017 to 2025.*

Figure A3b: SBU vs. US industrial and regional distribution

Panel A: By Industry

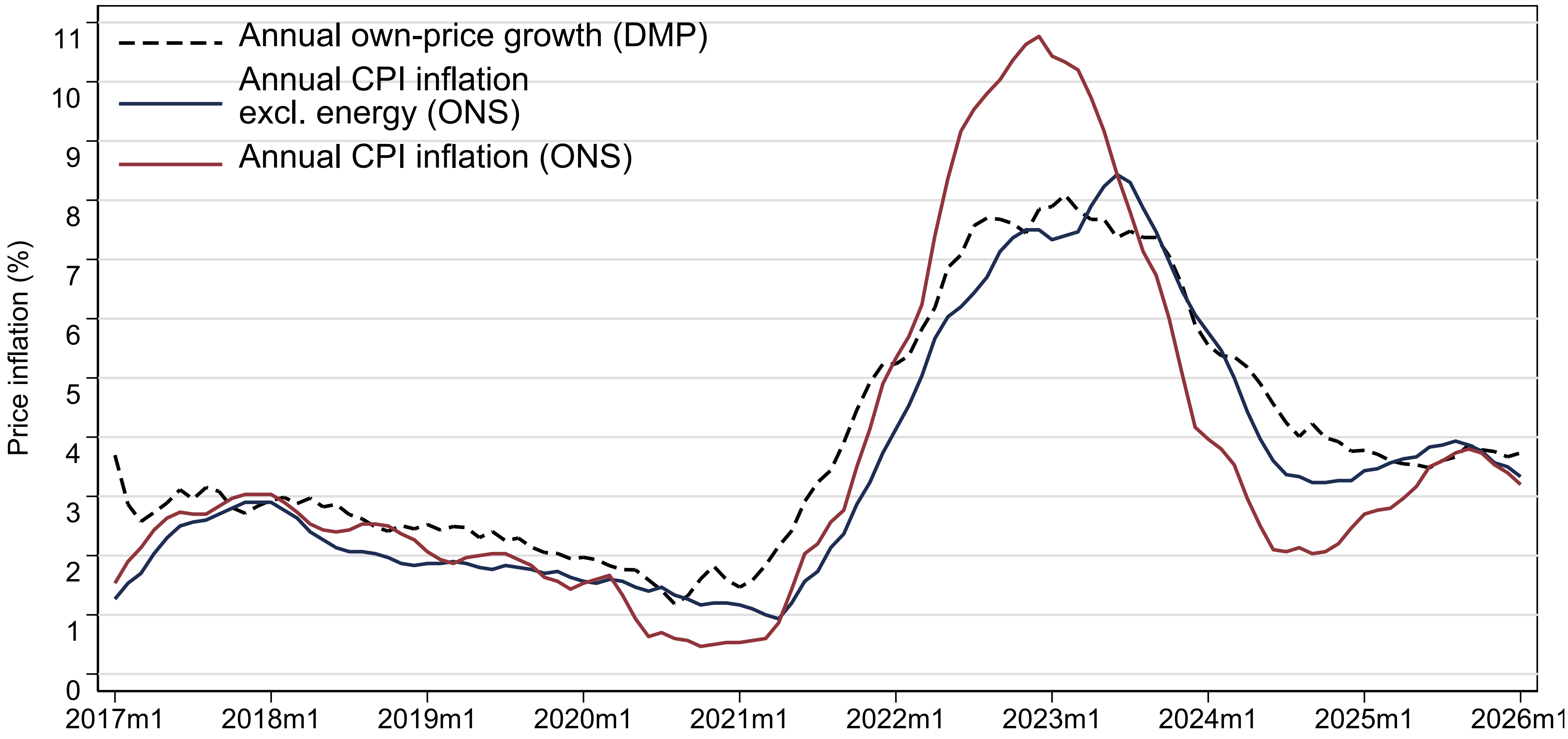


Panel B: By Region



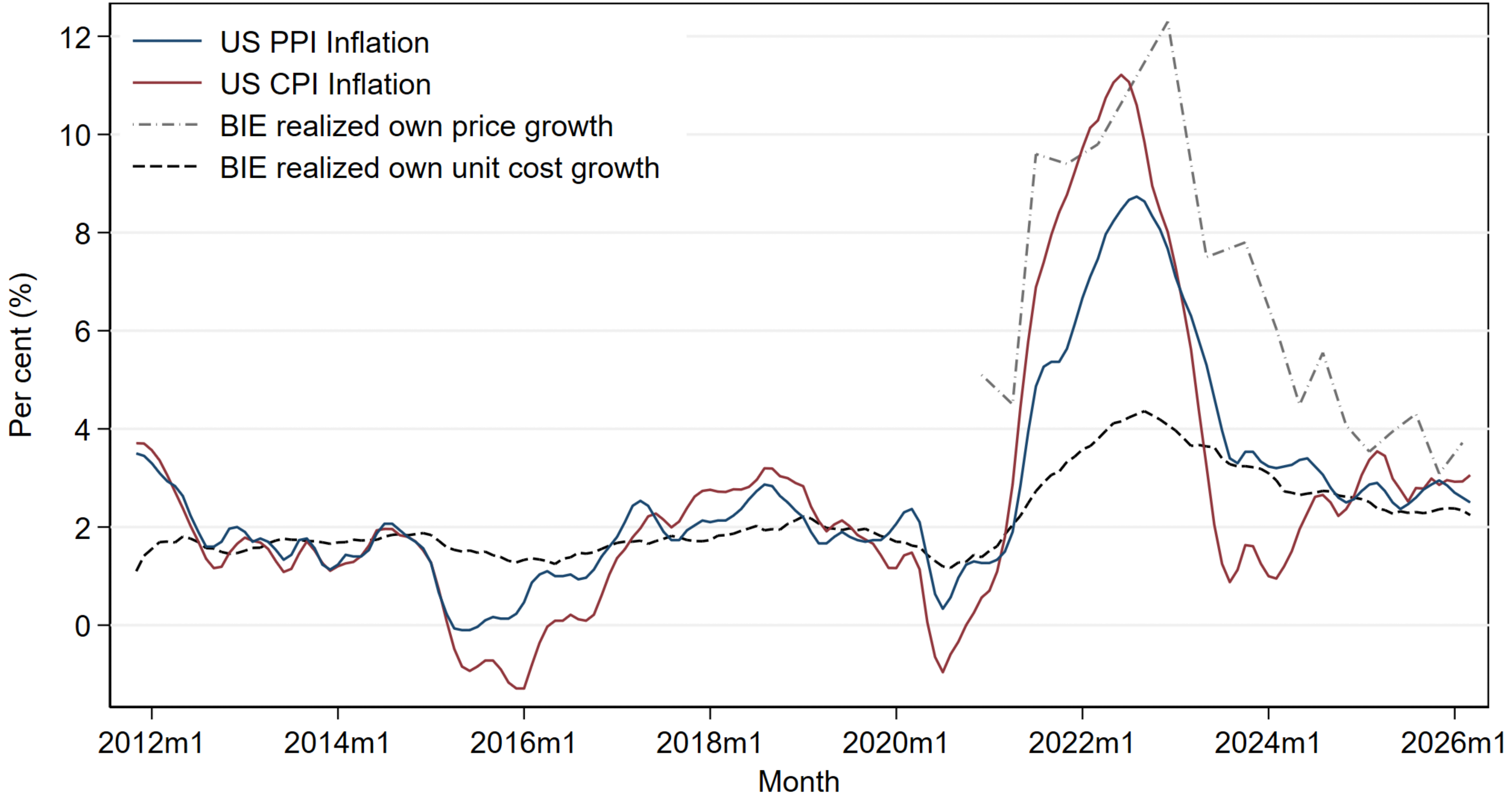
***Notes**: This figure compares the percentage of firms by industry (Panel A) and region (Panel B) in the US Survey of Business Uncertainty against the 2022 Economic Census. The shares are employment-weighted. Panel A is based on 6835 firms in the SBU. Panel B is based on 6995 firms in the SBU.*

Figure A4a: UK CPI inflation, UK CPI inflation excluding energy, and DMP price growth



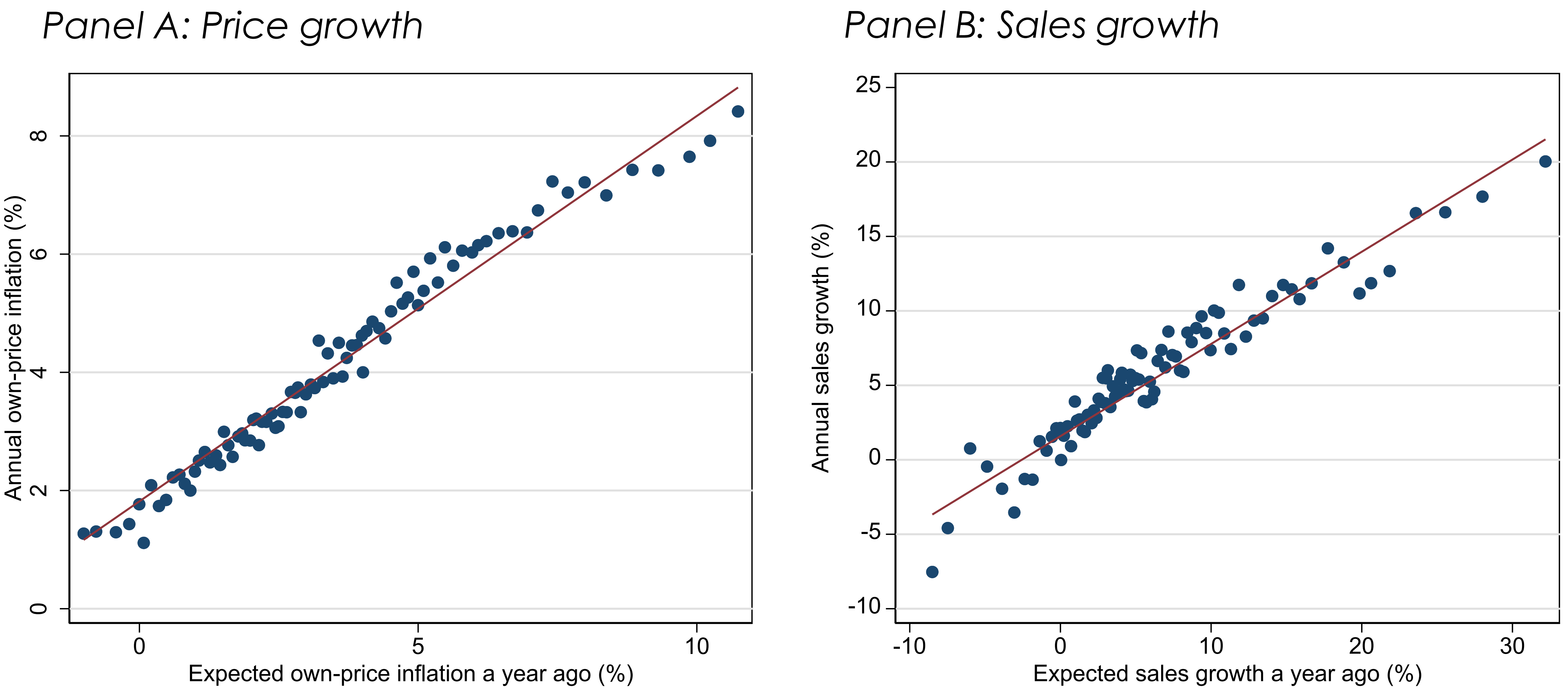
Notes: Data are three-month moving averages. Sources: DMP, UK Office for National Statistics.

Figure A4b: US CPI inflation, US PPI inflation, and BIE price and cost growth



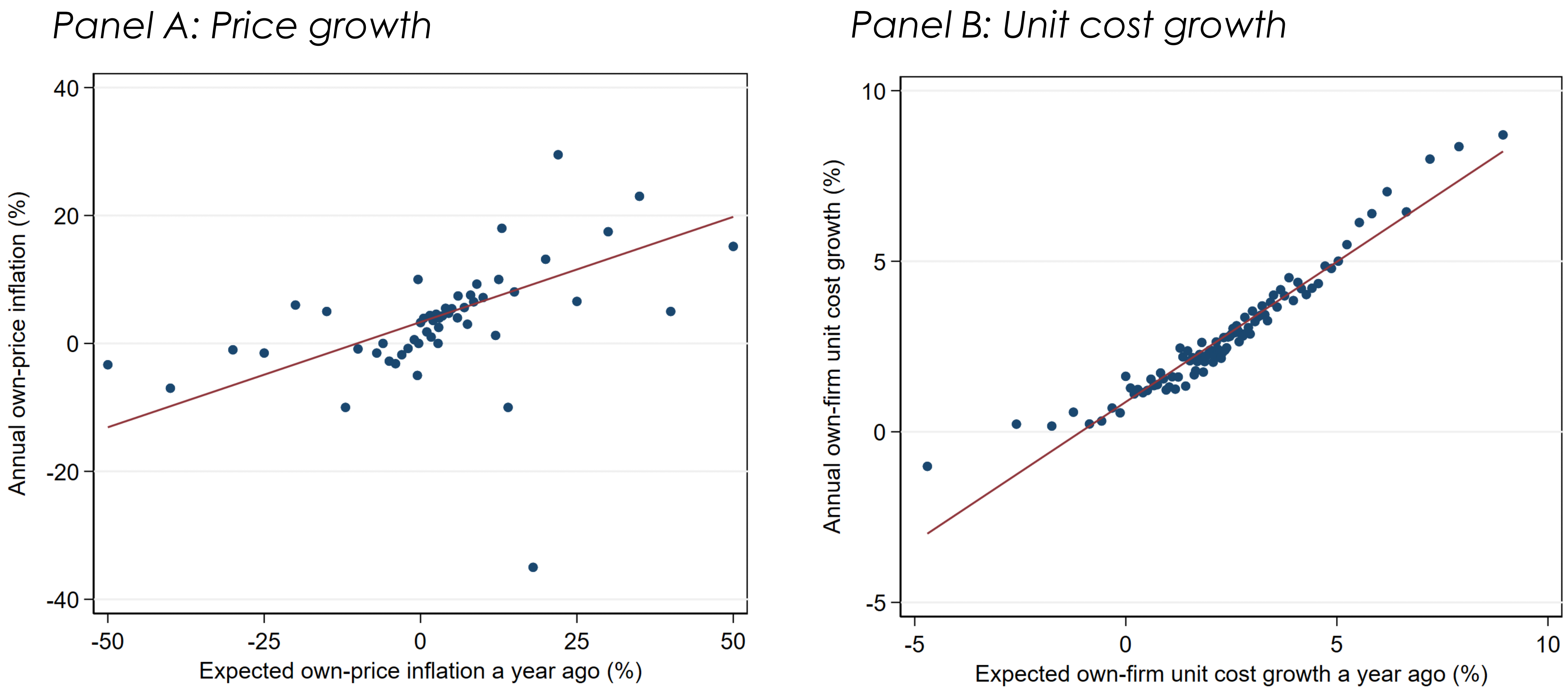
Notes: Data for PPI, CPI, and own unit cost growth are three-month moving averages. Sources: BIE, US Bureau of Labor Statistics. The publication of the CPI series by the BLS was temporarily paused in October 2025 due to the government shutdown.

Figure A5a: Comparison of firm year-ahead expectations with realizations (UK Firms)



Notes: This figure presents binned scatter plots comparing year-ahead expectations for price growth (Panel A) and sales growth (Panel B) with realisations for the respective variables a year later. Each dot represents 1% of the sample. The figures are based on data from UK firms in the Decision Maker Panel over the period November 2017 to March 2026.

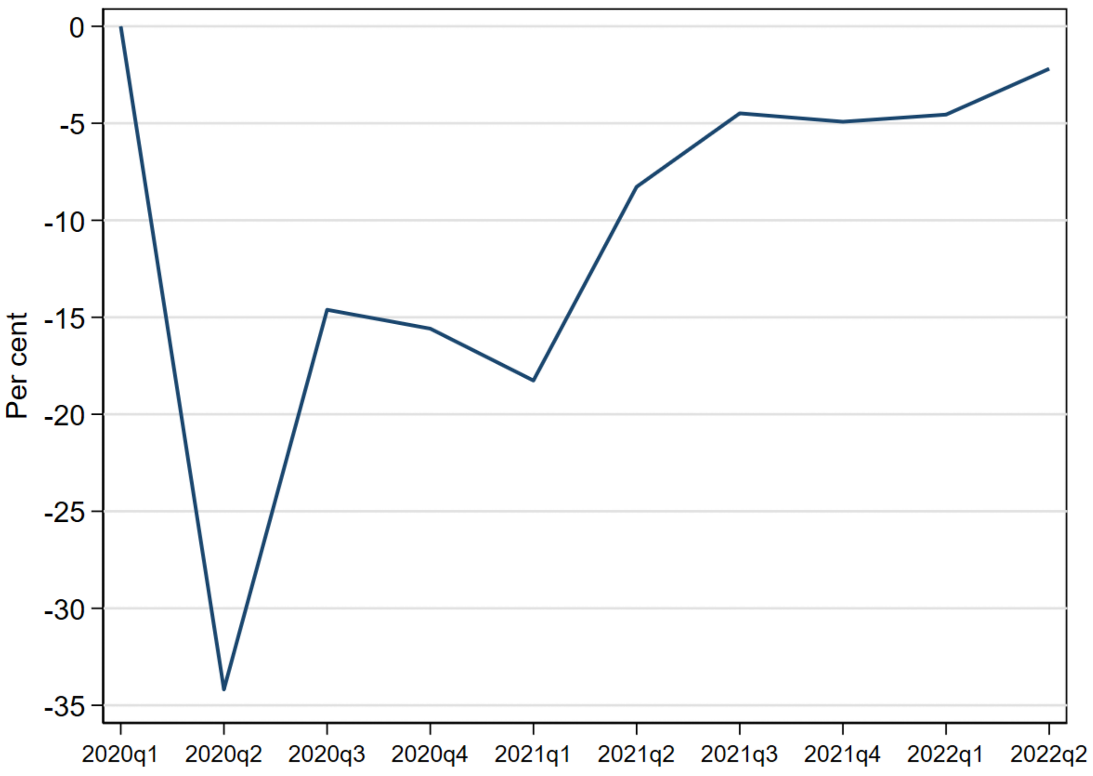
Figure A5b: Comparison of firm year-ahead expectations with realizations (US Firms)



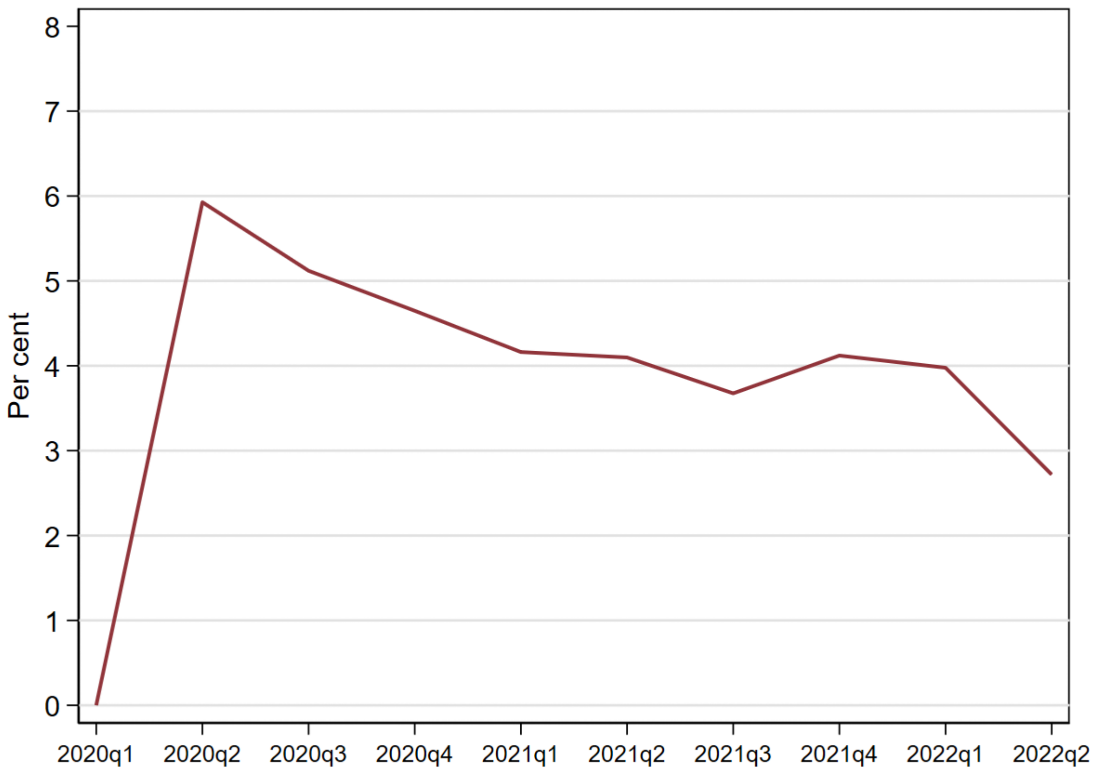
Notes: This figure presents binned scatter plots comparing year-ahead expectations for price growth (Panel A) and unit cost growth (Panel B) with realisations for the respective variables a year later. Each dot represents 1% of the sample. The figures are based on data from US firms in the Business Inflation Expectations survey over the period December 2021 to February 2026 (Panel A) and October 2011 to February 2026 (Panel B).

Figure A6: Impact of Covid-19 on sales and unit costs

Panel A: Sales



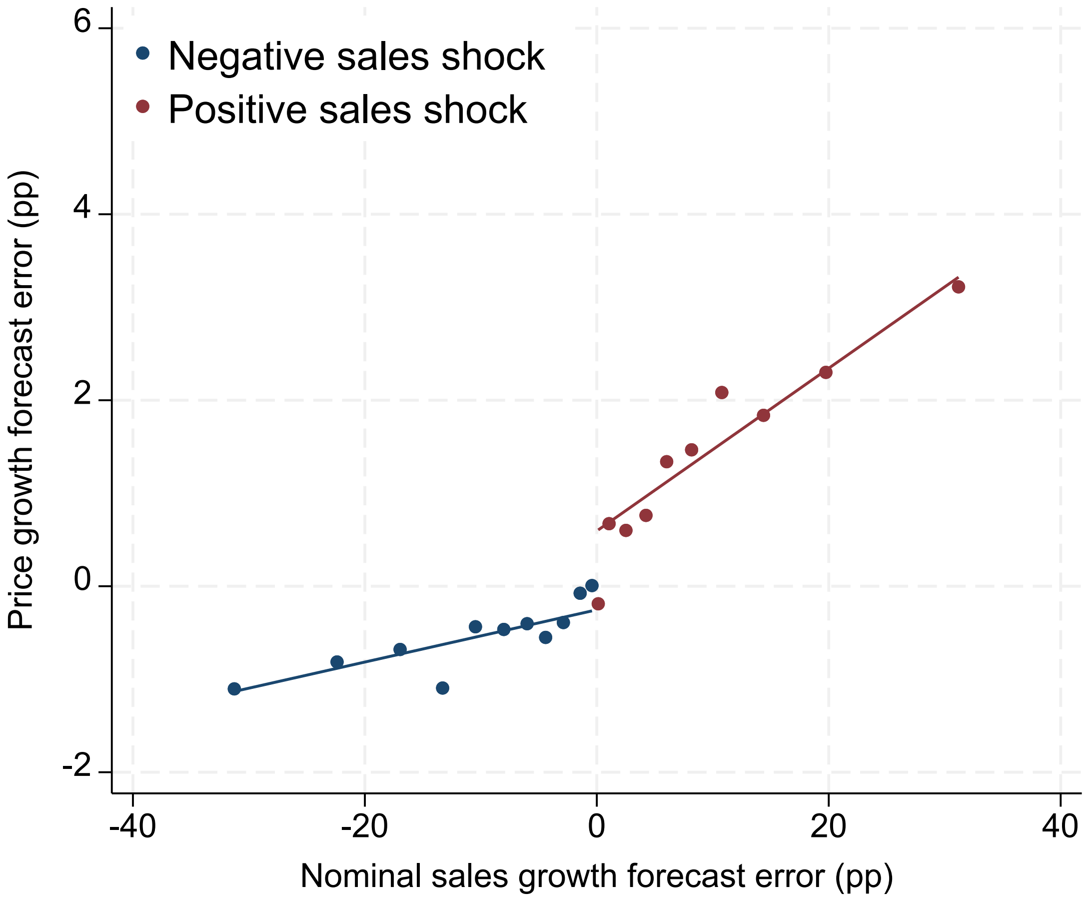
Panel B: Unit costs



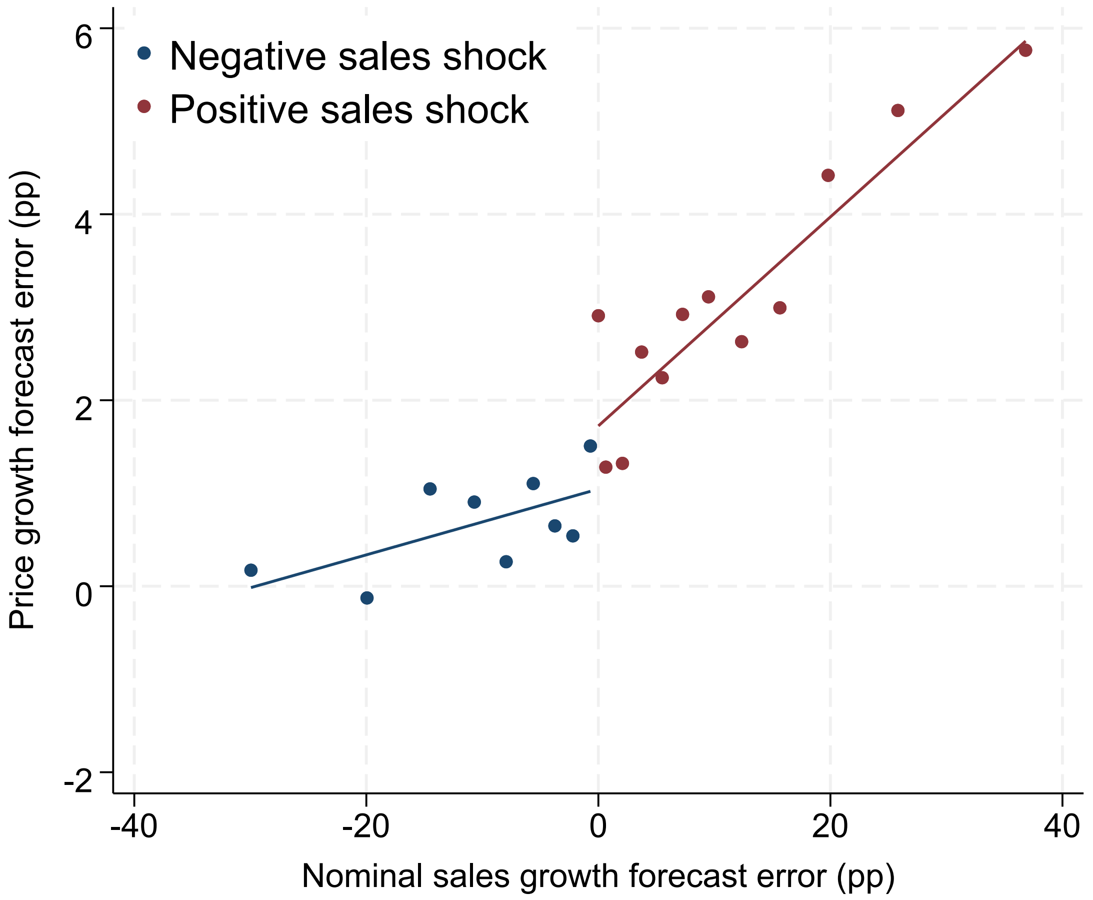
Notes: The results are based on the questions: 'Relative to what would otherwise have happened, what is your best estimate for the impact of the spread of Covid-19 on the sales of your business in each of the following periods?'; 'Relative to what would otherwise have happened, what is your best estimate for the impact of measures to contain coronavirus (social distancing, hand washing, masks and other measures) on the average unit costs of your business in each of the following periods?' The results are based on data from the DMP.

Figure A7: Relationship between sales and price forecast errors: Heterogeneity by recruitment difficulty

Panel A: Low recruitment difficulty



Panel B: High recruitment difficulty

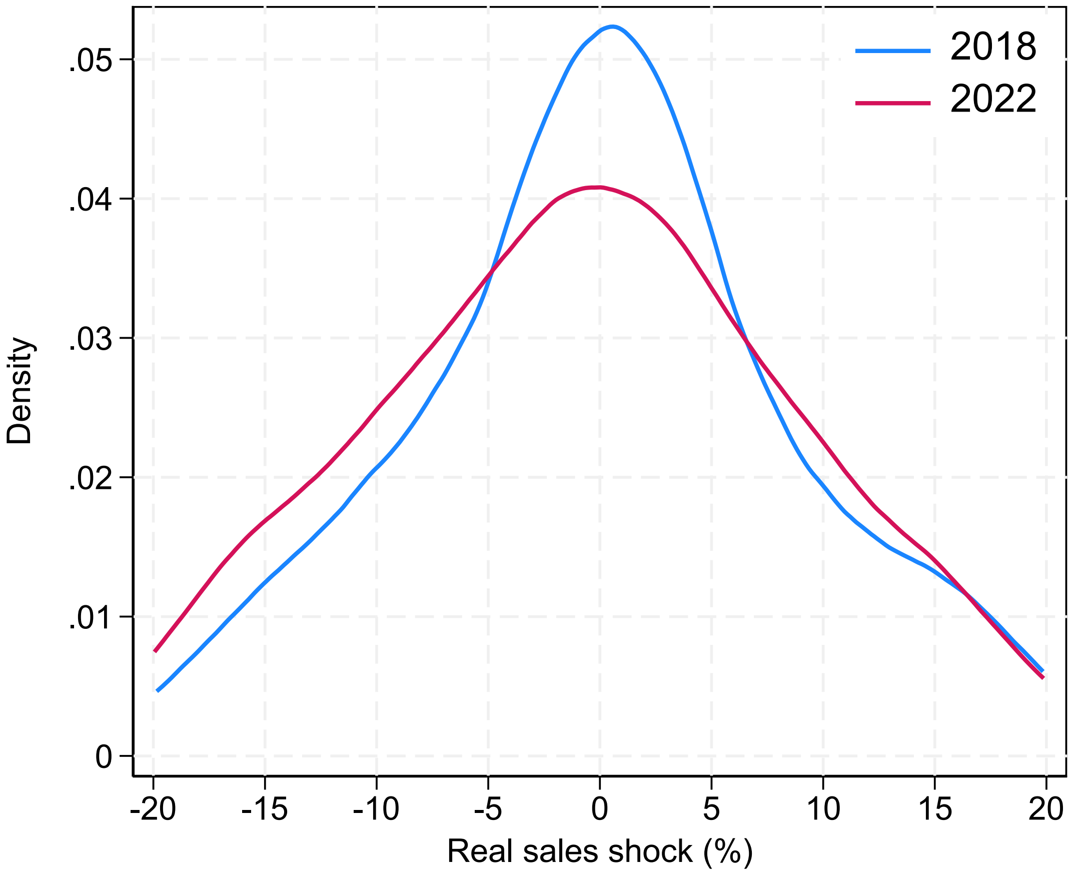


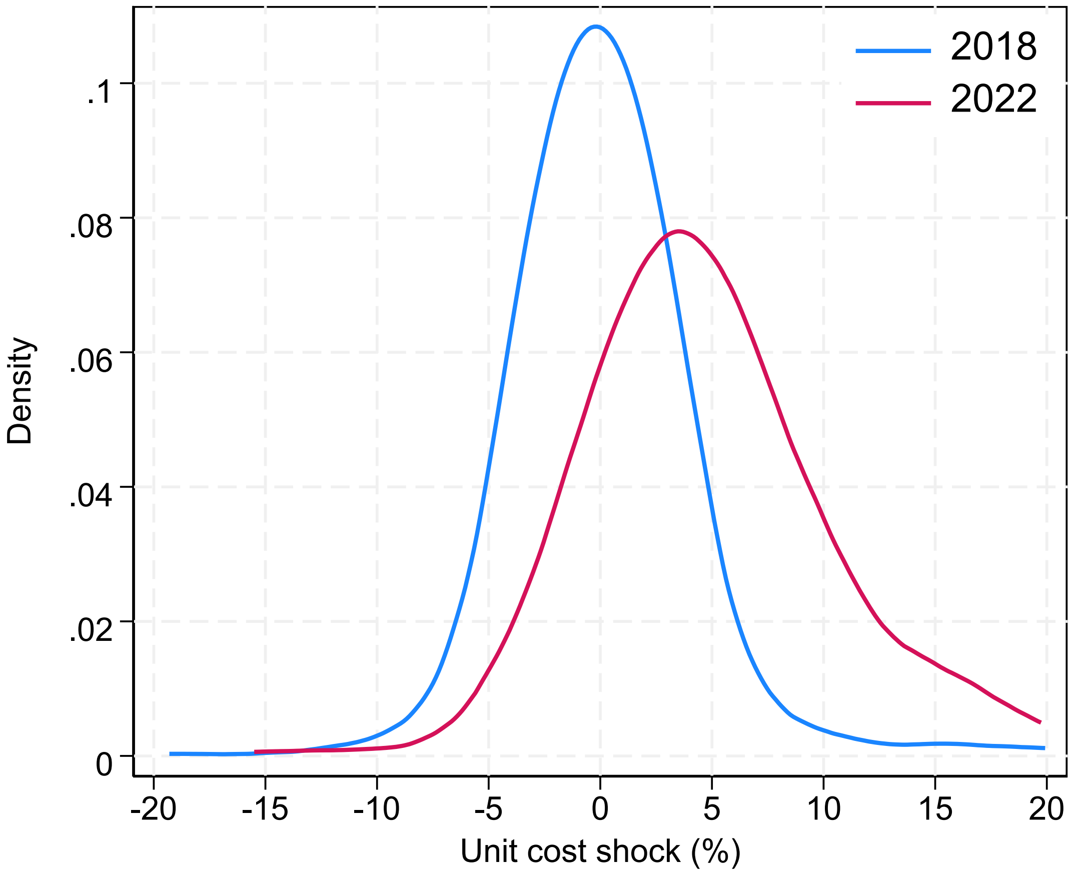
Notes: This figure shows the relationship between nominal sales growth forecast errors and annual price growth forecast errors. Each dot represents 5% of the sample between January 2018 and August 2025. Sales forecast errors are trimmed at the 5th and 95th percentiles by quarter. Price forecast errors are winsorised at the 1st and 99th percentiles. Recruitment difficulties are based on responses to the question: “Are you finding it easier or harder than normal to recruit new employees at the moment?”

Figure A8: Distributions of demand and cost shocks

Panel A: Demand shocks

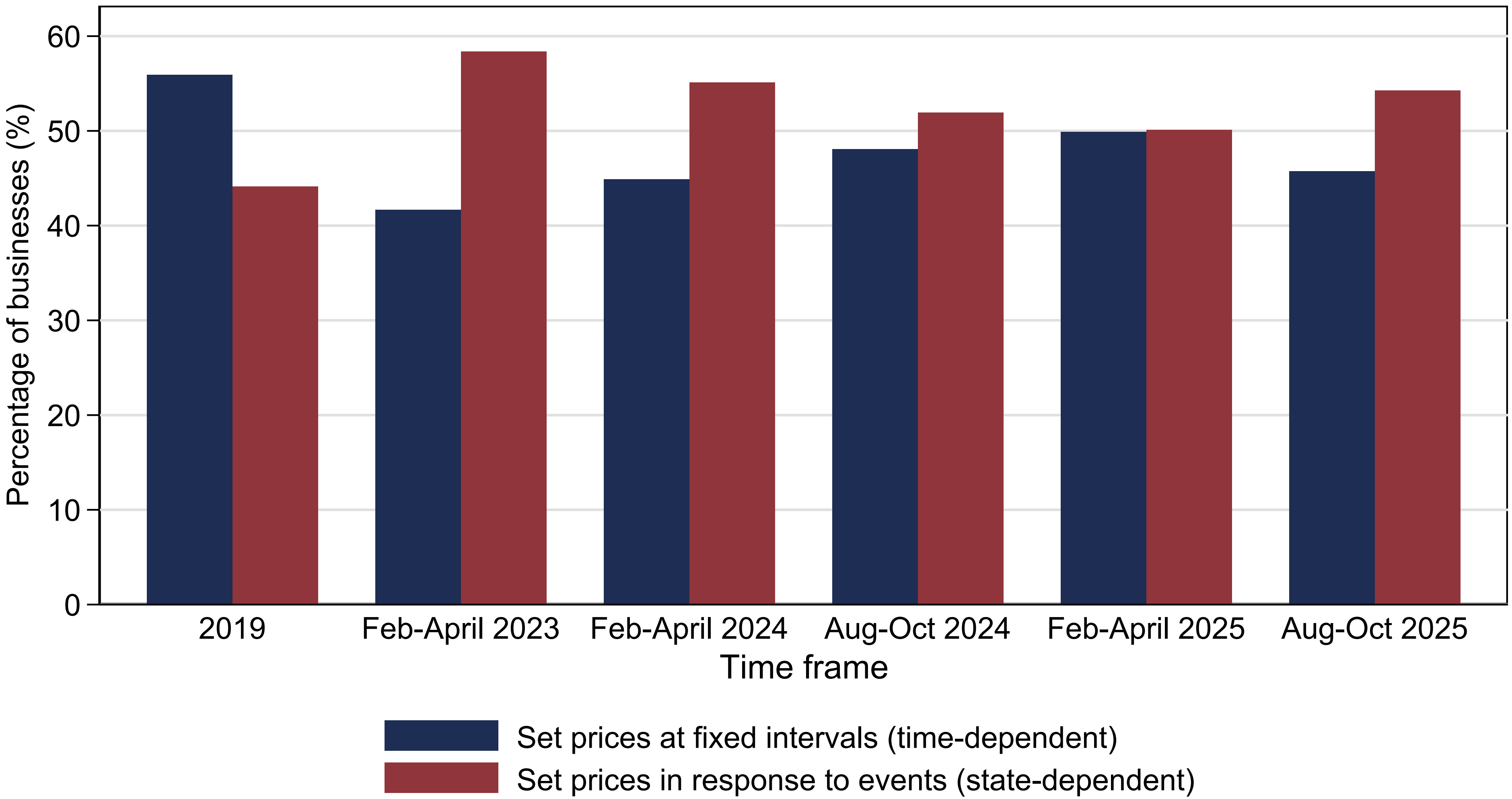
Panel B: Unit cost shocks





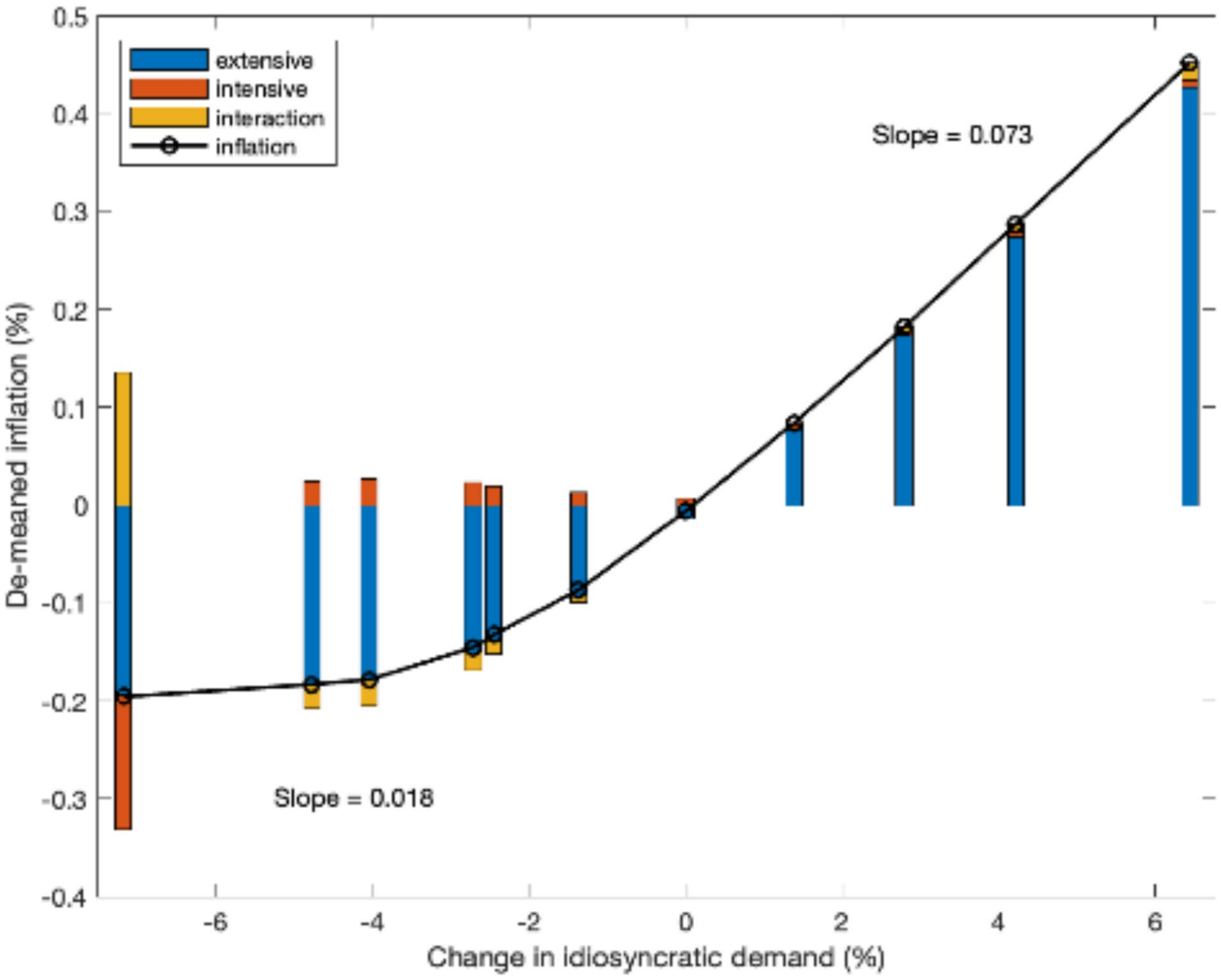
Notes: This figure shows the distribution of demand shocks and unit cost shocks in pre-pandemic years and in 2022. To estimate 'demand shocks' (Panel A), we calculate the average real sales growth forecast errors in 2018 versus 2022. To estimate unit cost shocks (Panel B) in the pre-pandemic period, we use unit cost growth forecast errors in 2018 (comparing realized unit cost growth in 2018 to expectations from 2017). Meanwhile, for 2022, we calculate the difference between realized cost growth in 2022 relative to expected unit cost growth in 2018 (or 2017 if missing) for the same firms and use this as a proxy for the cost shock. The question on unit cost growth was not asked in 2021.

Figure A9: How firms typically set prices



Notes: This figure is based on responses to the question: "Which of the following best describes how your business usually sets prices? 'Mostly change prices in response to specific events (eg changes in costs or demand)' or 'Mostly change prices at fixed intervals (eg once a year or once a quarter, etc)'". These results are based on data from UK firms in the Decision Maker Panel.

Figure A10: Intensive and extensive margin contributions to inflation



Notes: This figure shows the decomposition of the inflation response to a firm-level demand shock. The x-axis is the one-month change in idiosyncratic demand and the y-axis is the one-month de-meaned inflation rate. The extensive margin contribution measures how inflation would change if only the frequency of price changes varies across bins. The intensive margin contribution measures how inflation would change if only the size of price changes varies. The interaction term measures the joint contribution of frequency and size of price changes when they move together.

Table A1: Sample of countries in macro dataset

Country	Number of observations	Country	Number of observations	Country	Number of observations
Australia	35	Greece	30	New Zealand	35
Austria	35	Hungary	26	Norway	35
Belgium	35	Iceland	32	Poland	28
Bulgaria	24	Ireland	30	Portugal	35
Canada	35	Israel	30	Romania	21
Chile	32	Italy	35	Slovak Republic	31
Croatia	30	Japan	35	Slovenia	29
Czech Republic	29	Korea, Rep.	35	Spain	35
Denmark	35	Latvia	26	Sweden	35
Estonia	27	Lithuania	22	Switzerland	35
Finland	35	Luxembourg	32	United Kingdom	35
France	35	Mexico	27	United States	35
Germany	34	Netherlands	25		

Table A2: Response of price growth to Covid demand shock (UK Firms)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable: Realized price inflation Sample period: 2017Q1 to 2022Q2 (quarterly data)							
Covid impact on sales$_{it}$#sales impact positive$_{it}$	0.2614***	0.2440***	0.1247***	0.0832***		0.1038***	0.0900***
	(0.0322)	(0.0311)	(0.0256)	(0.0163)		(0.0251)	(0.0245)
Covid impact on sales$_{it}$#sales impact negative$_{it}$	0.0131***	0.0055	0.0165***	0.0153***		0.0186***	0.0172***
	(0.0026)	(0.0035)	(0.0034)	(0.0034)		(0.0034)	(0.0034)
Dummy for Covid impact on sales positive$_{it}$	-0.2439	-0.7020***	-0.4119**			-0.3979**	-0.3966**
	(0.2172)	(0.2123)	(0.1776)			(0.1723)	(0.1678)
Covid impact on sales$_{it}$					0.0382***		
					(0.0060)		
(Covid impact on sales$_{it}$)^2					0.0004***		
					(0.0001)		
Covid impact on unit costs$_i$#2020Q2-2022Q2						0.0415**	0.0276*
						(0.0173)	(0.0158)
% of non-labour inputs disrupted$_i$#2021Q2-2022Q2						0.0402***	0.0305***
						(0.0062)	(0.0060)
Recruitment much harder than normal$_i$#2021Q2-2022Q2						0.6126***	0.5329**
						(0.2281)	(0.2174)
Import intensity$_i$#2021Q2-2022Q2						0.0082**	0.0068**
						(0.0035)	(0.0033)
Brexit impact on unit costs (2021 vs 2020)$_i$#2021Q2-2022Q2						0.1573***	0.1318***
						(0.0359)	(0.0336)
Percentage of costs that are petrol/coal (2 digit industry data)$_i$#2021Q2-2022Q2						0.1617***	0.1332***
						(0.0502)	(0.0478)
Percentage of costs that are electricity/gas (2 digit industry data)$_i$#2021Q2-2022Q2						0.5734***	0.4938***
						(0.1078)	(0.1050)
Realized price inflation a year ago$_{it}$ (firm level)							0.0818***
							(0.0157)
Expected price inflation a year ahead$_{it}$ (firm level)							0.3132***
							(0.0166)
Firm fixed effects	No	No	Yes	Yes	Yes	Yes	Yes
Time fixed effects	No	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.019	0.138	0.546	0.546	0.546	0.560	0.582
Number of observations	34,076	34,076	34,076	34,076	34,076	34,076	34,076
Test coefficients equal (p-value)	0.000	0.000	0.000	0.000		0.001	0.004

Notes: Standard errors are clustered at the firm level and are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. All variables except the Covid effects on demand are time invariant for each firm and the coefficients on those variables are allowed to vary over time. Impact of Covid on sales is an average of the current and previous quarter. Impact of Covid on unit costs is an average from 2020 Q2 to 2022 Q2. The percentage of non-labour costs disrupted and whether a firm reports recruitment is much harder than normal (a dummy variable) are both averages between 2021 Q4 and 2022 Q2. Import intensity is the percentage of costs that were imports in 2016 H1. The impact of Brexit on unit costs is the percentage point change between 2021 and 2020. Industry energy cost data are for 2019 and are from the ONS Supply and Use tables. All other data used are from the DMP survey. Data is not available for all variables for all firms. Where data are missing for a particular variable, a dummy variable is included to account for that (results not reported), except for the impact of Covid on sales where all observations included in the regressions have data. All columns are based on data from UK firms in the Decision Maker Panel.

Table A3: Price growth and demand shocks: High vs. low inflation sectors (UK Firms)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	Average Price Response (%)		Price growth forecast error (pp)		Price Growth (%)	
Inflation Sectors	High	Low	High	Low	High	Low
Sales volume shock X Shock>0	0.0603***	0.0603***				
	(0.0067)	(0.0071)				
Sales volume shock X Shock<0	-0.0208**	0.0417***				
	(0.0096)	(0.0104)				
Sales growth forecast error X Error ≥0			0.0876***	0.0469***		
			(0.0094)	(0.0072)		
Sales growth forecast error X Error <0			0.0380***	0.0353***		
			(0.0075)	(0.0066)		
Covid impact on sales X sales impact ≥0					0.1595***	0.0560
					(0.0351)	(0.0342)
Covid impact on sales X sales impact <0					0.0126**	0.0194***
					(0.0050)	(0.0047)
Firm fixed effects	No	No	Yes	Yes	Yes	Yes
Time fixed effects	No	No	Yes	Yes	Yes	Yes
R2	0.023	0.032	0.422	0.408	0.607	0.570
Number of observations	3,516	2,864	11,560	11,224	15,689	17,352
Test coefficients equal (p-value)	0.000	0.085	0.000	0.303	0.000	0.291
Difference coefficients positive/negative	0.081	0.019	0.050	0.012	0.147	0.037
Average firm price growth in sample (%)	6.435	4.961	5.224	3.054	3.720	2.156

Notes: High-inflation sectors are sectors for which the average SIC3 price growth (excluding firm i) in a given year exceeds the average price growth in the same year for all firms. All columns are based on data from UK firms in the Decision Maker Panel. Standard errors are clustered at the firm level and are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A4: Relationship between sales and price forecast errors: Longer-run responses (UK Firms)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	Cumulative Price Growth (%)					
Horizon (Years):	1	2	3	4	4	4
Sales growth$_{t,t-1}$ X Sales growth ≥ 0	0.0599***					
	(0.0024)					
Sales growth$_{t,t-1}$ X Sales growth < 0	0.0312***					
	(0.0037)					
Sales growth$_{t+1,t-1}$ X Sales growth ≥ 0		0.0738***				
		(0.0044)				
Sales growth$_{t+1,t-1}$ X Sales growth < 0		0.0535***				
		(0.0080)				
Sales growth$_{t+2,t-1}$ X Sales growth ≥ 0			0.0772***			
			(0.0068)			
Sales growth$_{t+2,t-1}$ X Sales growth < 0			0.0694***			
			(0.0150)			
Sales growth$_{t+3,t-1}$ X Sales growth ≥ 0				0.0731***	0.0435***	0.0349***
				(0.0092)	(0.0065)	(0.0056)
Sales growth$_{t+3,t-1}$ X Sales growth < 0				0.0845***	0.0526***	0.0227
				(0.0283)	(0.0179)	(0.0163)
Firm fixed effects	No	No	No	No	Yes	Yes
Time fixed effects	No	No	No	No	No	Yes
R2	0.036	0.048	0.049	0.045	0.717	0.768
Number of observations	59,295	26,302	13,632	7,346	6,919	6,919
Test coefficients equal (p-value)	0.000	0.046	0.672	0.728	0.649	0.500

Notes: This figure presents the coefficients on regressions of cumulative own-price growth on cumulative nominal sales growth over horizons from one to four years. All columns are based on data from UK firms in the Decision Maker Panel. Standard errors are clustered at the firm level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. This analysis is not shown for US firms, because price growth data over a long enough time period is not available.

Table A5: Price response to hypothetical unit cost shocks

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	Average price response (%)			Average price response (%)		
Sample:	UK Firms (DMP)			US Firms (SBU)		
Sample Period:	August-2024 to October-2024			January 2026		
Unit cost shock	0.4122***	0.4122***		0.4055***	0.4052***	
	(0.0096)	(0.0096)		(0.0147)	(0.0147)	
Unit cost shock^2		0.0106***			0.0097***	
		(0.0004)			(0.0006)	
Unit cost shock X Shock > 0			0.6080***			0.5812***
			(0.0132)			(0.0190)
Unit cost shock X Shock < 0			0.2165***			0.2292***
			(0.0105)			(0.0163)
R^2	0.416	0.497	0.510	0.432	0.506	0.513
Number of observations	3,728	3,728	3,728	1787	1787	1787
Test coefficients equal (p-value)			0.000			0.000

Notes: This table reports results from the question "Suppose that your business's unit costs over the next 12 months are X per cent higher/lower than you currently expect. How would that affect the average price you charge, relative to what you currently expect?" Firms are randomised into one of four scenarios for unit costs: ±5%, ±10%, ±15%, ±20%. Firms are presented with both the positive and negative values for a given scenario. Columns 1-3 are based on data from UK firms in the Decision Maker Panel. Columns 4-6 are based on data from US firms in the Survey of Business Uncertainty. All results are unweighted. Standard errors are clustered at the firm level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Across Columns 3 and 6 , we cannot reject the equality of the slopes on positive unit cost shocks (t-stat = 1.16) or the equality of the slopes on negative unit cost shocks (t-stat=0.66).

Figure B1: Expected inflation questions

Panel A: Scenarios

Decision Maker Panel

BANK OF ENGLAND

Looking ahead, from now to 12 months from now, what approximate % change in your AVERAGE PRICE would you expect in each of the following scenarios?

Note:

Price growth scenarios should be ordered from the lowest to the highest.

The LOWEST % change in my prices would be about:	2	%
A LOW % change in my prices would be about:	3	%
A MIDDLE % change in my prices would be about:	4	%
A HIGH % change in my prices would be about:	5	%
The HIGHEST % change in my prices would be about:	8	%

Panel B: Probabilities

Decision Maker Panel

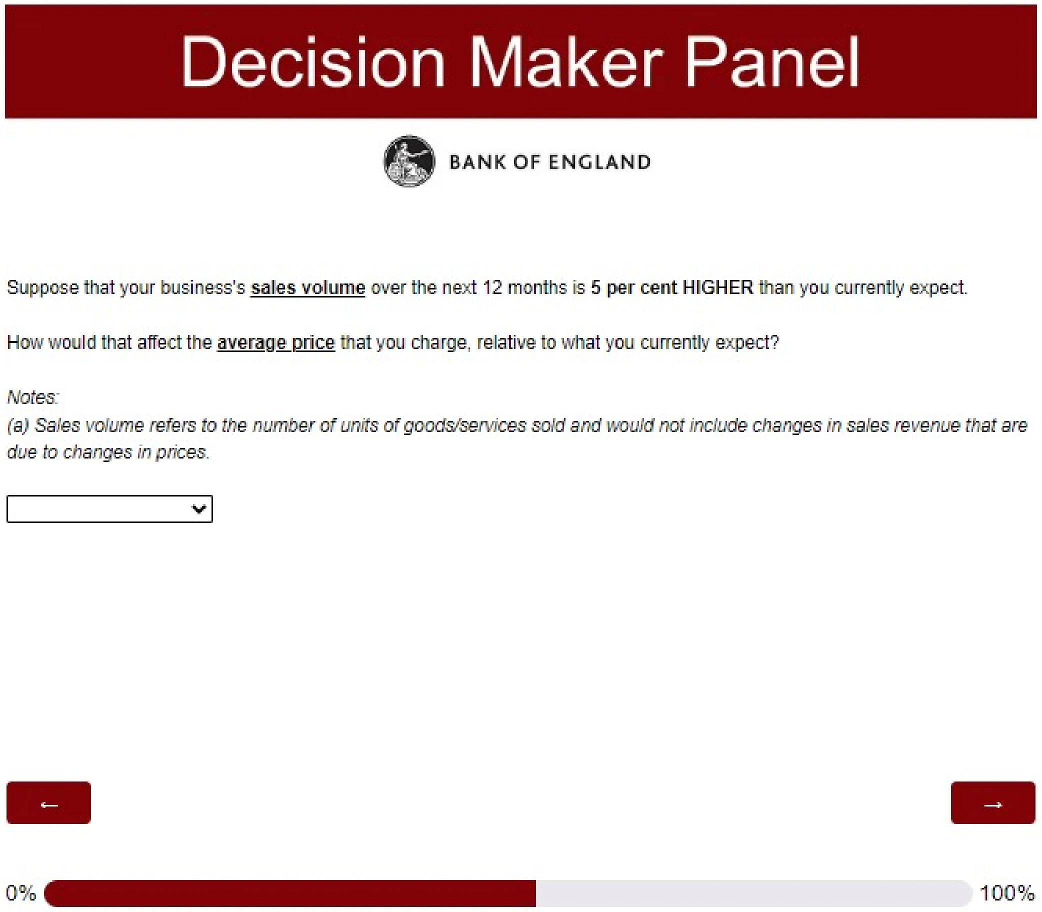
BANK OF ENGLAND

Please assign a percentage likelihood (probability) to the % changes in your AVERAGE PRICES you entered (values should sum to 100%).

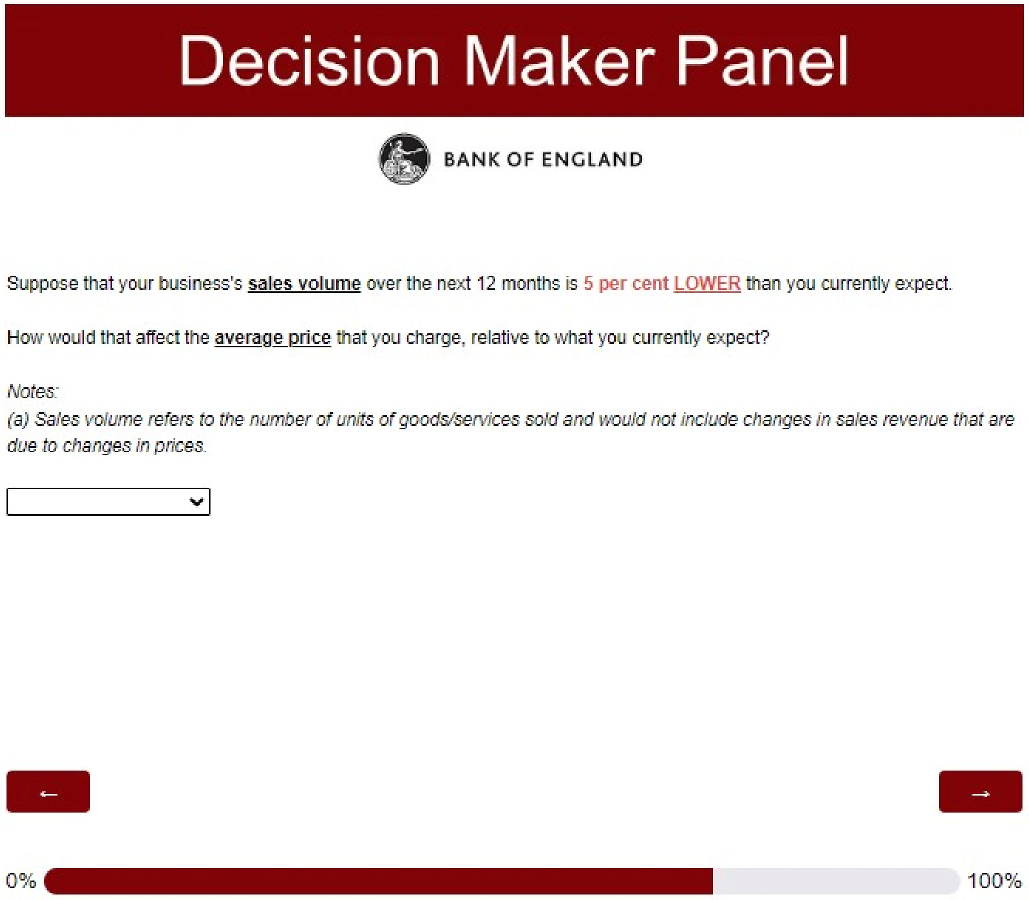
LOWEST: The likelihood of realising about **2%** would be:	5	%
LOW: The likelihood of realising about **3%** would be:	15	%
MIDDLE: The likelihood of realising about **4%** would be:	25	%
HIGH: The likelihood of realising about **5%** would be:	20	%
HIGHEST: The likelihood of realising about **8%** would be:	35	%
Total	100	%

Figure B2: Hypothetical sales volume shock questions

Panel A: Main scenario



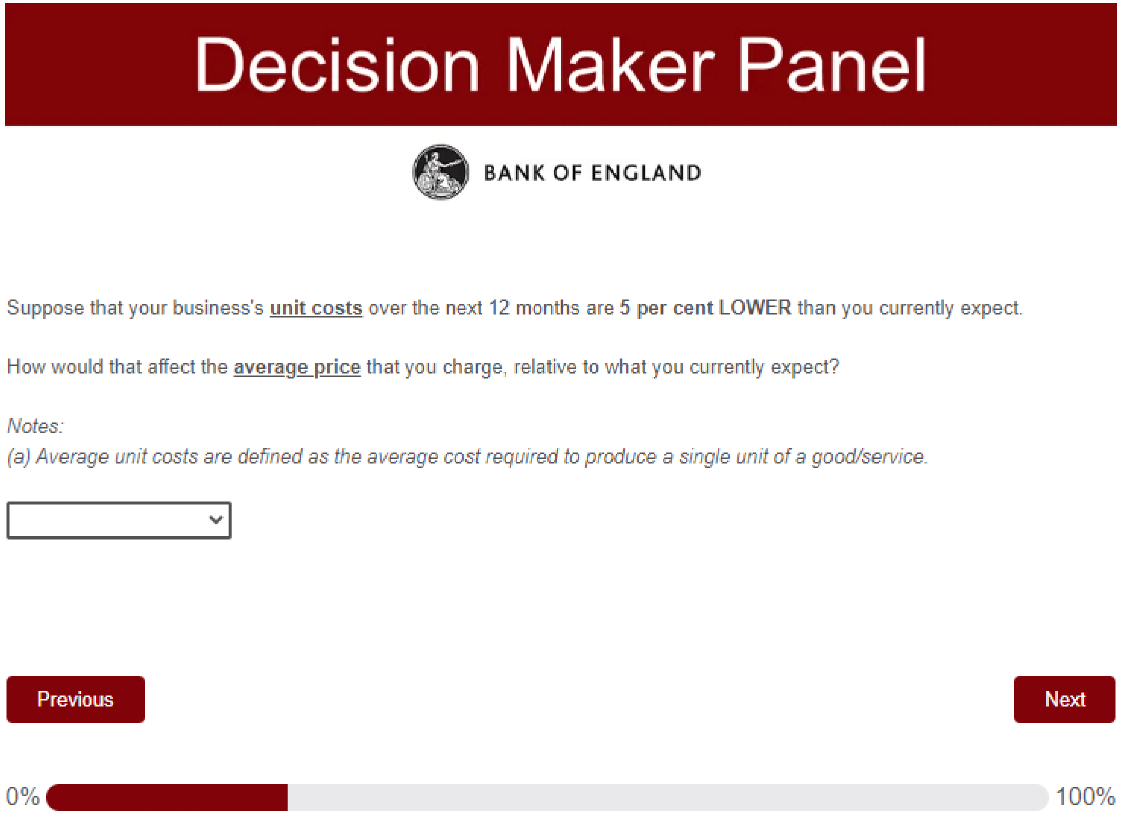
Panel B: Flipped scenario



Notes: Firms are randomised into one of four scenarios for sales volume: ±5%, ±10%, ±15%, ±20%. Firms are presented with both the positive and negative values for a given scenario. These questions were asked in December 2023 to January 2024, and in August 2024 to October 2024.

Figure B3: Hypothetical unit cost shock questions

Panel A: Main scenario



Decision Maker Panel

BANK OF ENGLAND

Suppose that your business's **unit costs** over the next 12 months are **5 per cent LOWER** than you currently expect.

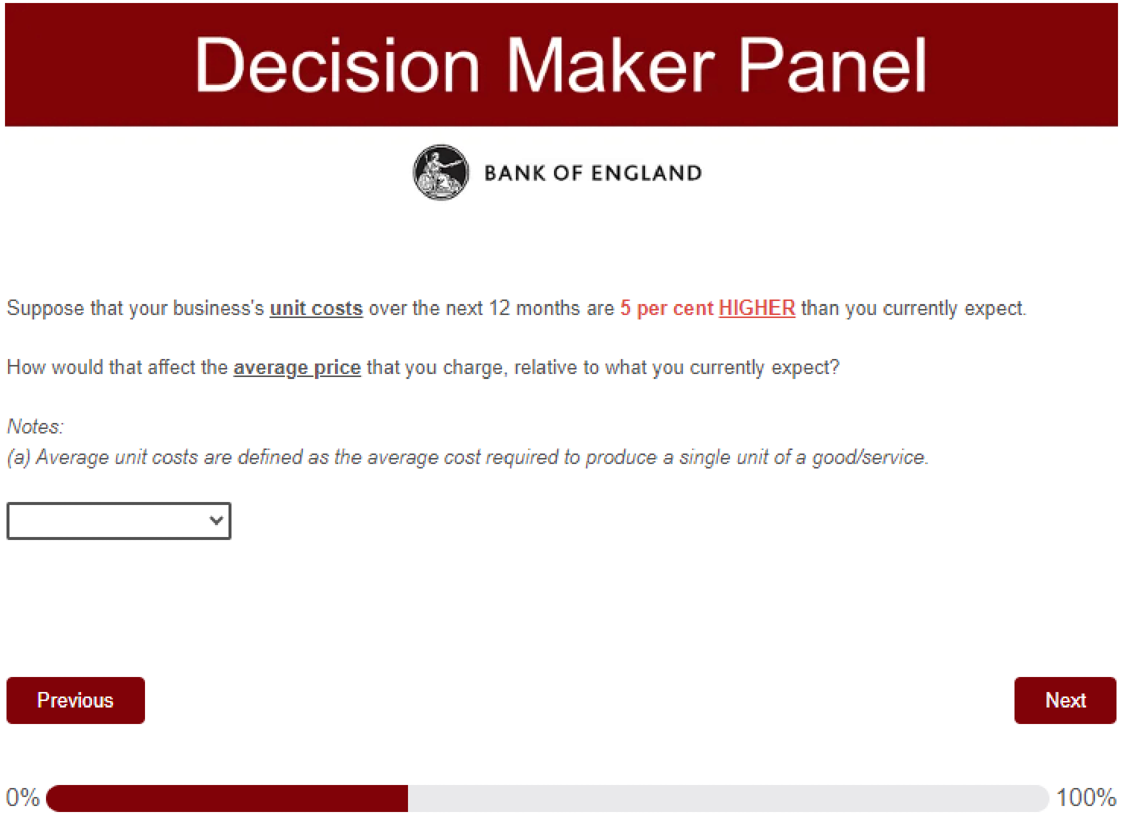
How would that affect the **average price** that you charge, relative to what you currently expect?

Notes:
(a) Average unit costs are defined as the average cost required to produce a single unit of a good/service.

Previous Next

0% 100%

Panel B: Flipped scenario



Decision Maker Panel

BANK OF ENGLAND

Suppose that your business's **unit costs** over the next 12 months are **5 per cent HIGHER** than you currently expect.

How would that affect the **average price** that you charge, relative to what you currently expect?

Notes:
(a) Average unit costs are defined as the average cost required to produce a single unit of a good/service.

Previous Next

0% 100%

Notes: Firms are randomised into one of four scenarios for unit costs: ±5%, ±10%, ±15%, ±20%. Firms are presented with both the positive and negative values for a given scenario. These questions were asked in August to October 2024.

Figure B4: Unit cost growth questions (US: BIE)

Panel A: Realizations

Business Inflation Panel

FEDERAL RESERVE BANK *of* ATLANTA

Looking back, how do your UNIT COSTS compare with this time last year?

- Unit costs down (less than -1%)
- Unit costs about unchanged (-1% to 1%)
- Unit costs up somewhat (1.1% to 3%)
- Unit costs up significantly (3.1% to 5%)
- Unit costs up very significantly (more than 5%)

Panel B: Expectations

Business Inflation Panel

FEDERAL RESERVE BANK *of* ATLANTA

Projecting ahead, to the best of your ability, please assign a percent likelihood to the following changes to UNIT COSTS over the next twelve months. (Values should sum to 100%)

For example, if you think each of these is equally likely, you might answer 20% for each:

Unit costs down (less than -1%)	20
Unit costs about unchanged (-1% to 1%)	20
Unit costs up somewhat (1.1% to 3%)	20
Unit costs up significantly (3.1% to 5%)	20
Unit costs up very significantly (more than 5%)	20
Total	100

Unit costs down (less than -1%)	0	%
Unit costs about unchanged (-1% to 1%)	0	%
Unit costs up somewhat (1.1% to 3%)	0	%
Unit costs up significantly (3.1% to 5%)	0	%
Unit costs up very significantly (more than 5%)	0	%
Total	0	%

Figure B5: Price growth questions (US: BIE)

Panel A: Scenarios

Business Inflation Panel

FEDERAL RESERVE BANK *of* ATLANTA

We would like to learn more about how firms think about their **prices**.

In the next few questions, we will ask you to focus on your firm's **most important** good(s), service(s), or product line(s), and to think about your firm's price(s) for those good(s) or service(s).

If it makes more sense to you, you can focus instead on your firm's **average** price, across all goods, services, or product lines.

When thinking about your firm's **prices**, which measure do you prefer?

- Prices associated with our **most important** good(s) or service(s)
- **Average** prices

Panel B: Expectations & Realizations

Business Inflation Panel

FEDERAL RESERVE BANK *of* ATLANTA

Looking back <u>over the last 12 months</u>, by about what percent did your firm change the price(s) of your **most important** good(s) or service(s)?

- *Please use a negative sign to indicate a decline*

%

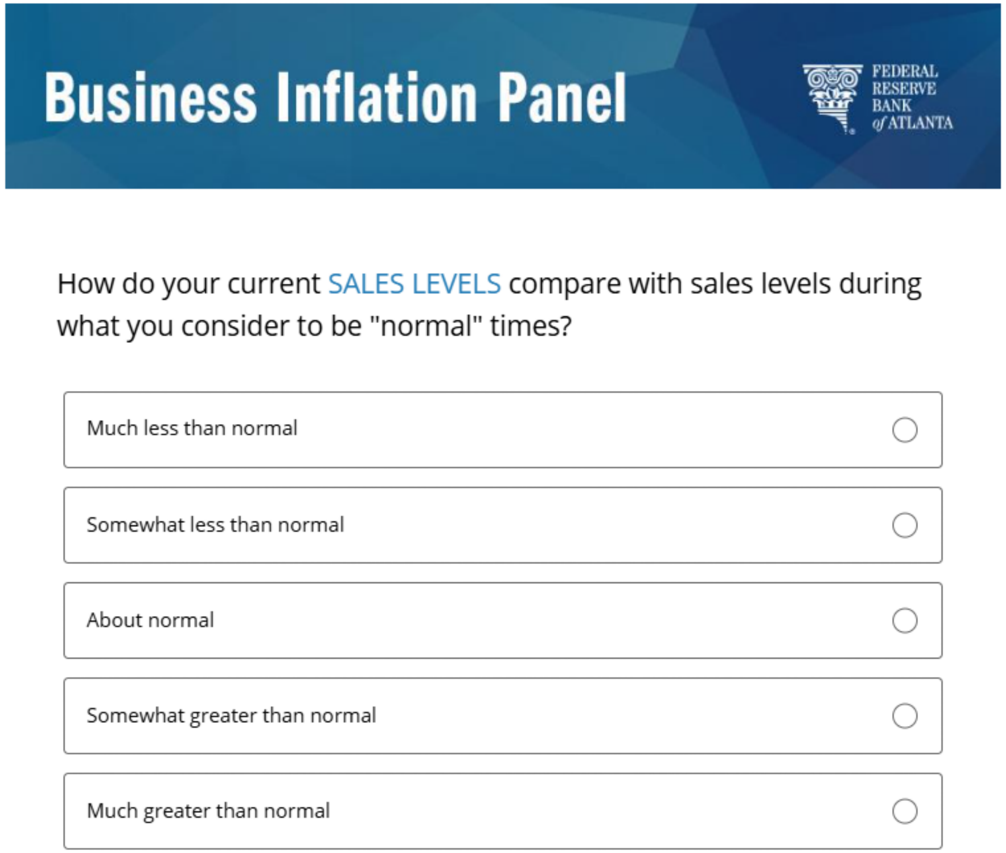
Looking ahead <u>over the next 12 months</u>, by about what percent does your firm expect to change the price(s) of your **most important** good(s) or service(s)?

- *Please use a negative sign to indicate a decline*

%

Figure B6: Sales growth compared to normal questions (US: BIE)

Panel A: Scenarios



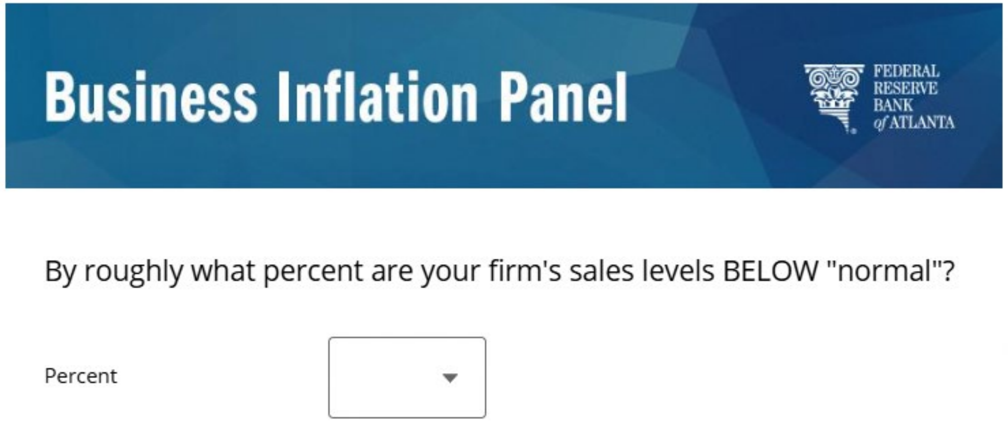
Business Inflation Panel

FEDERAL RESERVE BANK of ATLANTA

How do your current SALES LEVELS compare with sales levels during what you consider to be "normal" times?

- Much less than normal
- Somewhat less than normal
- About normal
- Somewhat greater than normal
- Much greater than normal

Panel B: Percentage above/below



Business Inflation Panel

FEDERAL RESERVE BANK of ATLANTA

By roughly what percent are your firm's sales levels BELOW "normal"?

Percent

Figure B7: Hypothetical sales volume shock questions (US: SBU)

Panel A: Main scenario

SBU Survey of Business Uncertainty

Suppose that your firm's sales volume over the next 12 months is **20 percent lower** than you currently expect.

How would that affect the average price you charge, relative to what you currently expect?

- *Sales volume refers to the number of units of goods or services sold and would not include changes in sales revenue that are due to changes in prices.*

- ○ Average price would be higher
- ○ Little to no impact
- ○ Average price would be lower

Panel B: Percent change

SBU Survey of Business Uncertainty

Continue to suppose that your firm's sales volume over the next 12 months is **20 percent lower** than you currently expect.

Please provide an estimate in percentage terms of how much **lower** your average price would be, relative to what you currently expect.

[ ] %

Panel C: Flipped scenario

SBU Survey of Business Uncertainty

We will now ask you about a hypothetical scenario for your sales volume over the next 12 months with the opposite sign.

Suppose that your firm's sales volume over the next 12 months is **20 percent higher** than you currently expect.

How would that affect the average price you charge, relative to what you currently expect?

- *Sales volume refers to the number of units of goods or services sold and would not include changes in sales revenue that are due to changes in prices.*

- ○ Average price would be higher
- ○ Little to no impact
- ○ Average price would be lower

Notes: Firms are randomised into one of four scenarios for sales volume: ±5%, ±10%, ±15%, ±20%. Firms are presented with both the positive and negative values for a given scenario. The initial questions (Panels A and C) determine the sign, while the second question (Panel B) measures the effect. These questions were asked in June 2024.

Figure B8: Hypothetical unit cost shock questions (US: SBU)

Panel A: Main scenario

Survey of Business Uncertainty

Suppose that your firm's *unit costs* over the next 12 months are **20 percent higher** than you currently expect.

How would that affect the average price you charge, relative to what you currently expect?

- *Average unit cost are defined as the average cost required to produce a single unit of good or service.*

- ○ Average price would be lower
- ○ Little to no impact
- ○ Average price would be higher
- ○ Not applicable - this firm does not charge regular prices

Panel B: Percent change

Survey of Business Uncertainty

Continue to suppose that your firm's unit costs over the next 12 months are **20 percent higher** than you currently expect.

Please provide an estimate in percentage terms of how much lower your average price would be, relative to what you currently expect.

[ ] % lower

Panel C: Flipped scenario

Survey of Business Uncertainty

We will now ask you about a hypothetical scenario for your *unit costs* over the next 12 months with the **opposite sign**.

Now, suppose that your firm's *unit costs* over the next 12 months are **20 percent lower** than you currently expect.

How would that affect the average price you charge, relative to what you currently expect?

- *Average unit costs are defined as the average cost required to produce a single unit of good or service.*

- ○ Average price would be lower
- ○ Little to no impact
- ○ Average price would be higher

Notes: Firms are randomised into one of four scenarios for sales volume: ±5%, ±10%, ±15%, ±20%. Firms are presented with both the positive and negative values for a given scenario. The initial questions (Panels A and C) determine the sign, while the second question (Panel B) measures the effect. These questions were asked in January 2026.