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HOW CURVY IS THE PHILLIPS CURVE?

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ABSTRACT

Macro data suggest a convex relationship between inflation and economic slack, but identifying causality is challenging. Using micro data from large panel surveys of UK and US firms, we show that the response of prices to demand shocks is also convex at the firm level. We obtain similar results using three different empirical exercises examining: the impact of COVID demand shocks, the response to sales shocks, and hypothetical shocks from a survey experiment. This convexity is strongest in firms and industries with higher inflation, disappears at horizons beyond two years, and is also present in response to cost shocks. We rationalize these findings in a menu cost model with positive trend inflation and decreasing returns at the firm level, which replicates firm and aggregate Phillips curve convexity. The non-linearity emerges from trend inflation pushing firms closer to their price increase thresholds.

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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 (Figure 1). The extent of this increase in inflation was greater than most forecasters had expected, even given the rises in energy prices after the Russian invasion of Ukraine and shortages of labor and intermediate goods. Since then, inflation rates have fallen, and by mid-2025 were again close to target levels in most advanced countries. Understanding the dynamics of this inflation episode is crucial for monetary policymakers setting interest rates in response to large shocks. But analyzing the current period 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 proper identification with aggregate data is econometrically challenging. In this paper, we use data from large and representative surveys of UK and US firms to causally 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) 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 and receives close to 2,500 responses each month. Firms are asked how the average price that they charge has changed over the last year, and how they expect prices to

[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 et al. (2025), Gitti et al. (2025), Harding et al. (2023), and IMF (2024), among others.
[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).

change over the next year. The US SBU is organized in a similar manner, run by the Federal Reserve Bank of Atlanta collecting monthly data from around 1,000 firms.[6]

These 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, 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 unexpected developments in firms' actual sales. We calculate firm-level sales growth forecast errors, 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. The results again suggest significant asymmetry, with positive sales growth forecast errors associated with more than two times larger price growth forecast errors. Importantly, we show that this relationship is present in the years before the Covid pandemic and in the period since 2020.

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 sales. 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 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

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

demand curves, or wage rigidities. So, we provide three extensions to help distinguish between these different 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 4% full sample average. Firms with average price growth above 4% (mean of 6.8%) exhibit a strongly non-linear response to positive versus negative shocks across all three empirical exercises described above. In contrast, firms with average price growth below 4% (mean of 1.6%) 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 responses. 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. First, 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. Firms report a 60% cost pass-through to positive shocks in the first year after a shock, but only a 20% pass-through to negative shocks. We also consider the relationship between unit cost growth forecast errors and price growth forecast errors. We find that the response to positive errors is around twice as strong as that to negative errors.

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 closer to the price-increase point (the upper S bound) than firms close to their price reduction point (the lower s bound). So, price increases are more likely to be triggered by positive demand shocks than reductions triggered by negative demand 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 and it wanes over the longer run.

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 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.

Related Literature Our work relates to four different strands of literature: (i) the asymmetric response of inflation to shocks; (ii) how firms set prices and the reasons behind their pricing decisions; (iii) micro data on price non-linearities and (iv) using firm surveys to evaluate the impact of major shocks.

The rise in inflation across the world in 2021-2022 prompted a renewed interest in studying price-setting behavior and the potential for non-linearities. Several recent papers are particularly relevant to the present study. Benigno and Eggertsson (2023, 2024) find evidence that the aggregate wage Phillips curve is non-linear in labor market tightness and they propose a model with a frictional labor market with downwardly rigid wages and a discontinuity in wage setting behavior when labor market tightness exceeds a certain threshold. Harding et al. (2023) posit a quasi-kinked demand schedule for goods which generates a non-linear aggregate Phillips curve and they use this to explain both the missing deflation during the Great Recession and the acceleration in aggregate inflation during 2022. In Boehm and Pandalai-Nayar (2022), capacity constraints at the industry level can generate a convex Phillips curve and increase the

[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 with studies the implications on nonlinear Phillips curves for optimal monetary policy includes Ascari et al. (2025) and Karadi et al. (2024).

welfare costs of business cycles. Juul and Jørgensen (2025) present a model with low substitutability between labor and non-labor inputs, in which supply shocks generate a convex Phillips curve. Similarly, IMF (2024) build a model with sectoral supply constraints (modeled through the labor market) which generates a non-linear Phillips curve relationship. Karadi et al. (2024) use a model similar to ours to study optimal monetary policy with a non-linear Phillips curve. Ball et al. (2022) estimate a price Phillips curve based on weighted median inflation and find significant coefficients on squared and cubed activity terms. Forbes et al. (2021) find empirical evidence of a non-linear Phillips curve using cross-country panel data.

In contrast to these papers, our study relates primarily to individual firms, taking the state of the aggregate economy as given, and does not assume any discontinuity in wage setting or demand beyond a s*ymmetric* menu cost. The kinked price Phillips curve at the firm level in our model arises endogenously from the interaction of menu costs, positive trend inflation, and decreasing returns to scale. Its analog at the aggregate level arises in a similar manner.

Our paper also relates to a long literature on how firms set prices reaching back to the 1970s. The more recent New-Keynesian literature typically uses a time-dependent approach to modeling how prices change, as in the model of Calvo (1983) where a subset of firms chosen randomly change prices at fixed intervals. The alternative state-dependent approach assumes that the decision to change prices depends on the state of the economy and the market faced by the firm; here, costs of changing prices (as in the menu cost models of Mankiw, 1985; Ball and Mankiw, 1994, 1995) create sticky prices or the cost of acquiring information about prices (as in Mankiw and Reis, 2002) prevents prices changing continuously. Several studies have sought to test these models using micro data, including Bils and Klenow (2004), Klenow and Kryvtsov (2008), and Nakamura and Steinsson (2008). Trying to better fit the empirical facts has led to these models being adapted, e.g. Golosov and Lucas (2007) and Midrigan (2011). More recently Auclert et al. (2023) have argued that in low inflation environments (less than 5%) these models all give similar results, while Blanco et al. (2024) highlight important non-linearities in models that match both price change levels and frequencies.

A third literature uses micro data to study the response of prices to demand shocks, typically highlighting larger responses to positive than negative shocks. Peltzman (2000) studies item-level price changes in Dominick's supermarkets, showing prices rise faster in response to positive demand shocks than they fall in response to negative demand shocks. Buckle and Carlson (2000) examine survey data for New Zealand firms, again finding greater responsiveness to positive than negative demand shocks. Benzarti et al. (2020) show Finnish firms had twice the price response to value added tax rises than falls. More recently, Ahlander et al. (2024) use data from Swedish manufacturing firms to estimate firm-level supply curves and find that the slope is steeper during periods of high inflation. Likewise, Hoeck and Renkin (2025) use Danish firm-level data to estimate firm-level supply curves and show how these link to the slope of the aggregate Phillips curve.

Finally, we also contribute to the growing literature on business surveys to evaluate the impact of major shocks. We build on Altig et al. (2022), Bhandari et al. (2020) and Candia et al. (2023). The use of these large, high-frequency forward-looking firm surveys is valuable in this context because of the timely nature of the survey data, and in our case also because the survey has both forward and backward-looking aspects.

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 and the Survey of Business Uncertainty 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 Cross-country evidence on the price Phillips curve

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. To perform this analysis, we collect data from three separate sources. First, we use data on headline consumer price index (CPI) inflation from the World Bank Global Database of Inflation (Ha et al. 2023).[8] Second, we collect data on CPI inflation forecasts 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, $E_t[\pi_{it+5}]$, 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. More precisely, this is estimated as the difference between actual GDP and potential GDP, as a percentage of potential GDP. Table A1 presents the list of

[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

countries and number of observations per country in our combined dataset. In summary, we have data for 38 countries over the period 1990-2024.[10]

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

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

$$\lambda_1 OutputGap_{it} \times OG \geq 0 + \lambda_2 OutputGap_{it} \times OG < 0 + \varepsilon_{it}$$

The coefficients of interest are λ_1 and λ_2, which capture the relationship between the output gap and inflation, separately when the output gap is positive and negative. 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 2 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 in this figure: the coefficient on the positive output gap side is around three times as large as the coefficient on negative output gap out-turns. 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. Columns 1-3 show the linear relationship between inflation and the output gap. This is positive and significant after controlling for country and time fixed effects (Column 2) as well as controls for lagged inflation and long-term inflation expectations (Column 3). Still, we note that the magnitude of the coefficient decreases with the inclusion of these controls. In Column 4, we add a quadratic term on the output gap. This is positive and significant, consistent with the convex relationship from Figure 2. In Column 5 we test this explicitly by separating the slope coefficients depending on

[10] We exclude country-year observations with annual CPI inflation greater than 15% from the sample.

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) 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.[11]

To what extent are these results driven by the pandemic and high-inflation episode since 2020? In Columns 6 and 7, 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.

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 about estimating the Phillips curve using aggregate data, which are well-known in the literature.[12] 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 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

[11] 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.

[12] 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.

model which matches the micro data, using this to study the implications for the aggregate Phillips curve. But our macro analysis nevertheless 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

We use data from two 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. 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.[13] Firms are selected randomly from this sampling frame and are 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.[14] 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 other reasons for not completing the survey. When the DMP recruitment team first contact 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, 79% of respondents are in these two positions (66% are CFOs and 13% 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

[13]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 1 million businesses. FAME itself is part of the global AMADEUS database.

[14] Figure A3 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.

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 reason that the DMP targets the CFOs (or CEOs) at these firms is because they are likely to be sufficiently numerate to respond to somewhat complex quantitative questions.

Since its inception, the DMP has asked firms about how the average price that they charge has changed over the last year. 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 tracks the UK aggregate Consumer Prices Index and Producer Price Index inflation rates (Figure A4).

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 A5 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 more 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.[15]

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. However, questions on prices have not yet featured regularly in the SBU (they were introduced in April 2025). Therefore, the remainder of the empirical analysis in this paper after the hypothetical question is based on data from the DMP survey.

4 Firm price responses to demand shocks

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 A4). 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 (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.

[15] For example, Bloom et al. (2023) study the effects of Covid-19 on productivity using DMP data.

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 experiment within the survey. 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 firms how their prices would respond to hypothetical sales *volume* shocks of different magnitudes.

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. Figure A6 provides screenshots of the exact format of the questions in the survey platform. Over the five months, 3,197 survey responses were received, which means 6,394 observations overall (two scenarios per firm).

In Figure 3 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 (in other words, we estimate the lines of best fit without a constant). 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.

It may be that the convex response to sales volume shocks reflects something specific to UK firm price setting or the DMP survey. To address this, in June 2024, the identical question was implemented in the US by the Federal Reserve Bank of Atlanta in the Survey of Business Uncertainty. In total, 787 US firms responded to this question. Figure 3 Panel B presents the US result. There is again clear evidence of a convex relationship, with positive hypothetical sales volume shocks leading to stronger positive price responses. The responses across US and UK firms are also quantitatively very similar. 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 1-4 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 3, 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 3-4, we explicitly test the difference in responses for negative versus positive shocks. Column 3 shows 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. Finally, 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. In Column 4 we estimate a similar regression, but weighting observations by industry and employment shares, and find that it does not affect our conclusions.[16]

Columns 5 to 8 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 7 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.[17] Overall, the results from Figure 3 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. Due to current data availability, the remaining empirical results are based only on UK firms in the Decision Maker Panel.

4.2 Evidence from sales and price growth forecast errors

To build on our findings using hypothetical shocks, in this section we consider the relationship between sales growth forecast errors and price growth forecast errors. This approach exploits the strong panel dimension of the DMP data. We calculate price growth

[16] 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.

[17] The US figure 3b actually shows firms report slight price rises in response to negative sales shocks on average. This is consistent with a model of income targeting, where firms raise prices if sales fall to maintain a given revenue stream to cover fixed costs (e.g. Gilchrist et al. 2017).

(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 who have provided survey responses in consecutive surveys 12 months apart. 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 should not account for any non-linearities in the data.

Firm expectations are highly correlated with subsequent realizations, highlighting the quality of the forecast data (Figure A7). 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 4 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 (based on a regression without any fixed effects) 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. Overall, this figure provides further 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 growth and price growth forecast errors. Column 1 confirms that there is a strong positive relationship between the two measures, which is highly significant at 1%. However, as suggested in Figure 4, there is likely a non-linearity in this relationship across positive versus negative errors.

Columns 2-5 test for the presence of a convexity in this relationship. 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. Finally, in Column 5 we add an additional control for firm own-price expectations, to more closely match a firm-level Phillips curve specification. The non-linearity remains robust.

In addition to the main finding, which supports the non-linearity presented in Figure 4, we present several additional robustness checks. First, we check whether this is a COVID era phenomenon. To address this, in Columns 6-7 of Table 3 we split the sample into the periods 2018-2019 and 2020-2025. Although the sample size in the earlier period is only around one-fifth that of the latter period (due to the shorter time period and growing survey size), we still find evidence of non-linearities in both time periods. In the period 2018-2019, we again find that the coefficient on positive sales growth forecast errors is more than twice as large as that on negative errors, although the difference is only statistically significant at 20%, likely due to the smaller sample.[18]

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.[19] 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 (see Figure A8 for details).[20] 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

[18] One hypothesis in the literature used to motivate a non-linear Phillips curve is labor market tightness (e.g. Benigno and Eggertsson 2023, 2024). We can test whether labor market tightness explains the non-linear relationship we observe in Figure 4 using a direct survey question on recruitment difficulties which has been asked since 2021. Splitting firms by whether they report current recruitment is 'much harder' or not, in Figure A10 we show that the non-linearity is present in both sample splits. This suggests labor market tightness might not be sufficient to explain the non-linearity in the firm-level Phillips curve.

[19] 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.

[20] 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 have typically been 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.

substantial variation to estimate the effects of changes in demand on inflation.

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 inflation. But for the minority of firms that experienced a positive demand shock, the relationship between demand and inflation was significantly stronger. Figure 5 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.[21]

Including supply-side factors in Column 6 of Table 4 slightly reduces the coefficient on positive demand shocks, but a clear and statistically significant asymmetry in the response of inflation to positive and negative demand shocks remains. 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 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.[22]

Summary of results Overall, this section analyzes how firm prices respond to demand shocks. The three empirical tests we use differ in the sample periods considered, and in the precise measurement of the shock and response components. In the first exercise (Section 4.1), we test the response of prices to hypothetical *sales volume* shocks using data from UK and US firms. This is arguably the cleanest setting in terms of identifying a causal impact. However, it may be that these responses do not correspond to pricing behavior in practice. To address this, in the second exercise (Section 4.2), we analyze price growth and nominal sales growth forecast

[21] 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 A8 shows the data on Covid-related 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).

[22] 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.

errors. This uses the longest sample period available and reflects real-world price expectations and realizations. However, it may still be that forecast errors are influenced by mismeasurement or omitted variables beyond what we capture using controls and fixed effects, and it relies on sales values rather than the ideal measure of sales volumes.[23] For further robustness, in the final exercise (Section 4.3), we test how firm price growth responds to the impact of Covid-19 on firm (nominal) sales, which was a large unexpected demand shock, but also a unique period. Despite the limitations of each individual exercise, 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 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 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. 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 then split firms by whether their average price growth is above or below the

[23] The use of sales values rather than volume should not be able to explain why firm prices respond more to positive demand shocks than negative ones.

full sample average of 4% for all firms. High-inflation firms (those above 4%) have had an average price growth of 6.8%, whereas the average for low-inflation firms (those below 4%) is 1.6%.

In Figure 6, we present the results on the three empirical exercises from Section 4, separately for high-inflation and low-inflation firms. 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.

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, therefore creating some endogeneity. As an alternative, we measure the average price growth at the sector-year level in our 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 also compute the average yearly price growth across all firms in the sample, and 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 (Table A3).

Overall, we conclude from this sub-section that the inflation rate is an important 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 the short-term. 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, 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.[24] 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.

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 4 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.

Table A4 presents the results from Figure 7 in a regression form. Columns 1-4 show the results for each of the four horizons. The last row of the table tests for the equivalence of the coefficients on positive and negative sales growth. As suggested by the figure, we can reject the equivalence over the first and second year. However, by the third and fourth year, the difference is no longer statistically significant, and in Column 4, the coefficient estimates are almost identical. Columns 5-6 show that these results do not change when adding firm (Column 5) or firm and time (Column 6) fixed effects to the specification from Column 4.

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 response to

[24] 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.

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, in this estimation. Second, the inflation episode over 2022-2025 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 two separate empirical exercises.[25]

Hypothetical unit cost shocks

We first analyze how firms respond to cost shocks using a randomized survey experiment conducted over August to October 2024. 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 (Figure A9 shows the precise question). Over the three months, 1,864 firms responded to the hypothetical scenarios, which gives 3,728 observations in total (two scenarios per firm).

Figure 8, Panel A plots the average (unweighted) response to these unit cost shock scenarios. We estimate the lines of best fit using a regression with no constant, such 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% pass-through.

In Table A5, we provide further evidence for the robustness of the responses to hypothetical cost shocks. The convexity is present using a quadratic term in Column 2, and

[25] 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.

furthermore we can reject with a high level of confidence the equality of the coefficients on positive vs. negative unit cost shocks (Columns 3-4). Overall, this exercise 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.[26]

Price growth and unit cost growth forecast errors

A second approach to measure the pass-through of cost shocks to firm prices is to use forecast errors. Questions on realized annual unit cost growth and expected year-ahead unit cost growth have been asked in the DMP survey, although less frequently compared to the questions on sales growth. Nevertheless, there are enough observations to construct unit cost growth forecast errors for part of the sample.[27] These errors are fairly evenly distributed in the sample, with an average error of 0.13 percentage points.

In Figure 8, Panel B, we present a binned scatterplot of the relationship between unit cost growth forecast errors and price growth forecast errors. Consistent with the evidence from the hypothetical unit cost shocks, we find evidence of non-linearity in the effects of positive vs. negative cost errors. On the positive side, a one percentage point cost error is associated with a 0.35 percentage point price growth error (i.e. 35% pass-through). The coefficient on the negative cost errors is around one-half in magnitude, suggesting only 18% pass-through.

In Table A6, we show the main results on unit cost and price growth forecast errors in regression form. Column 3 replicates the results from Panel B of Figure 8 without fixed effects. In Columns 4-5 we add firm and time fixed effects to the specification. This decreases the sample to less than 1,500 observations, because the data on unit cost growth forecast errors are available only for a short sample.[28] It also means we are unable to reject the null that the

[26] 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.

[27] Specifically, we can construct unit cost growth forecast errors for February-April 2018, May-July 2023, May-July 2024, and May-July 2025.

[28] The available firm observations for this exercise is also reduced because the questions on own-price growth and unit cost growth are asked in separate panels. Therefore, although we have 2,941 cost growth forecast error observations, we have matching price growth forecast errors for only 1,621 observations.

coefficients on positive and negative errors are significantly different. However, we note that the magnitude of the coefficients does not change much when including these fixed effects, and indeed only the effect of positive cost growth errors is statistically different from zero. Despite these data limitations, the evidence on forecast errors is also consistent with a non-linear pass-through of cost shocks to prices, with the response to positive shocks around twice as strong as the response to negative shocks.

Summary of results Overall, this section provides several extensions to our main results from Section 4. We show that: (i) the convex response to demand shocks is driven by firms with high own-price inflation; (ii) this convexity is pronounced at the one-year horizon, but over time the responsiveness to positive and negative shocks is more equal; and (iii) there is a similar non-linearity of firm prices in response to unit cost shocks, with pass-through around three times as strong when costs increase. 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 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 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).[29] 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).

6.1 Model structure

Our model is based closely on Nakamura and Steinsson (2010).[30] We make two

[29] In related work, Gödl and Gödl-Hanisch (2024) study the state-dependence of wage setting using firm-level and union-level data.
[30] 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.

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:

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

$\tilde{A}_t(z)$ 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 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:

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

'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 A11.

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 preference shock 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:

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

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:

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

The monetary authority targets aggregate demand, $S_t = P_t C_t$, and S_t 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:

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

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

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 6 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 $E_t[P_{t+1}] = \Gamma\left[\frac{S_t}{P_t}\right]$.

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 annualized 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 double 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. It is noteworthy that the slope of both sides of the Phillips curve is much higher in the simulation than in the empirical data. This is in part because the aggregate output is measured with error in real data, attenuating the slope coefficient. Moreover, the money supply (nominal aggregate demand) process in our model is highly persistent, which generates a stronger price reaction than if a shock was expected to more quickly reverse, or be offset by an activist central bank.

The intuition for this result is that menu cost models generate an endogenous inaction Ss 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(Pit/Pt) 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.

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 center panel this displays a straight line. This is an echo of our empirical finding that the firm-level Phillips curve is approximately linear among low-inflation firms (Figure 6). 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 right panel is the standard model with positive trend inflation displaying a convex Phillips curve. This highlights how our Ss model can deliver simulation results matching the empirical data showing greater convexity at higher trend inflation rates.

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 and, as before, 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 both negative and positive demand shocks fully pass into prices, aligning the model with the empirical results from Figure 7.

Finally, the model can also generate a convex response of prices to cost shocks in a similar manner to demand shocks because firms focus on their markups. 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 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 and of convergent (and rising) responses of prices to positive and negative 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. This 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 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 growth and price growth forecast errors, leveraging the strong panel dimension of the survey. 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 pass-through around twice as strong 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 and linearity over long-run horizons.

Taken together, our results can help explain the dynamics of 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 rationalize the sharp rise in inflation during 2022, following large positive cost shocks. 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.

Appendix – model details

Household Behavior

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

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

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:

$$C_t = \left[\int_0^1 c_t(z)^{\frac{\theta-1}{\theta}} dz \right]^{\frac{\theta}{\theta-1}}, \tag{2}$$

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:

$$c_t(z) = C_t \left(\frac{p_t(z)}{P_t} \right)^{-\theta} d_t(z), \tag{3}$$

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:

$$P_t = \left[\int_0^1 p_t(z)^{1-\theta} dz \right]^{\frac{1}{1-\theta}}. \tag{4}$$

The price level P_t has the property that $P_t C_t$ is the minimum cost for which the household can purchase the amount C_t of the composite consumption good.

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

$$P_t C_t + E_t\left[D_{t,t+1} B_{t+1}\right] \leq B_t + W_t L_t + \int_0^1 \pi_t(z) dz, \tag{5}$$

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:

$$D_{t,T} = \beta^{T-t}\left(\frac{C_T}{C_t}\right)^{-\gamma}\frac{P_t}{P_T}, \tag{6}$$

$$\frac{W_t}{P_t} = \omega L_t^{\psi} C_t^{\gamma}, \tag{7}$$

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:

$$y_t(z) = \widetilde{A_t}(z)[L_t(z)^{1-s_m}M_t(z)^{s_m}]^{\lambda}, \tag{8}$$

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:

$$M_t(z) = \left[\int_0^1 m_t\,(z,z')^{\frac{\theta-1}{\theta}}dz'\right]^{\frac{\theta}{\theta-1}}, \tag{9}$$

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:

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

Firms maximize the discounted value of expected profits:

$$E_t \sum_{\tau=0}^{\infty} D_{t,t+\tau}\, \pi_{t+\tau}(z), \tag{10}$$

where profits in period t are:

$$\pi_t(z) = p_t(z)y_t(z) - \mathrm{W_t}[L_t(z) + \kappa I_t(z)] - P_t M_t(z) \tag{11}$$

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:

$$\log A_t(z) \quad = \rho_A \log A_{t-1}(z) + \varepsilon_t^A(z), \tag{12}$$

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

$$d_t(z) = \rho_d d_{t-1}(z) + \varepsilon_t^d(z) \tag{13}$$

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

The monetary authority targets nominal output, $S_t = P_t C_t$, and aggregate S_t follows a random walk with drift:

$$S_t = \mu + S_{t-1} + \eta_t \tag{14}$$

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

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

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.

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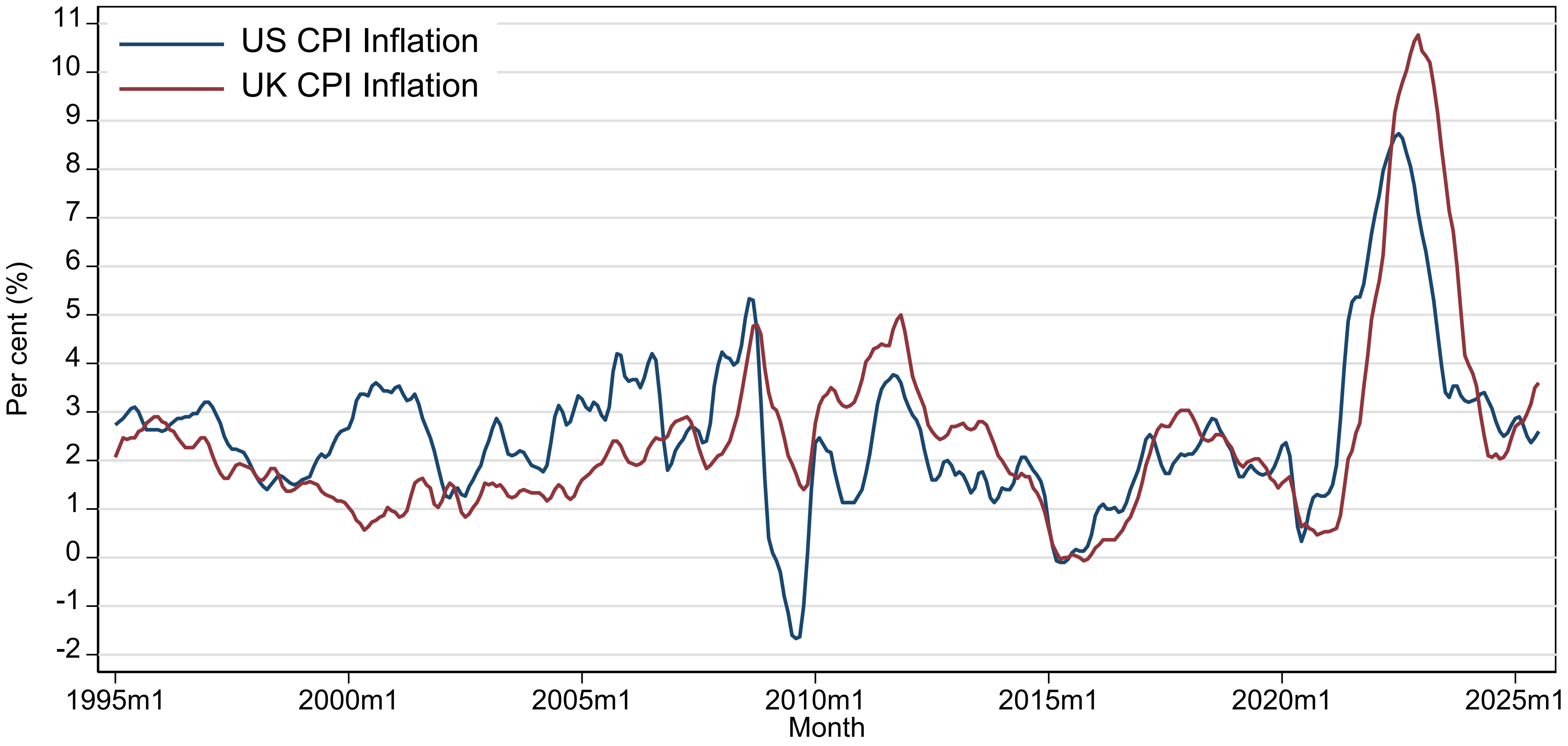
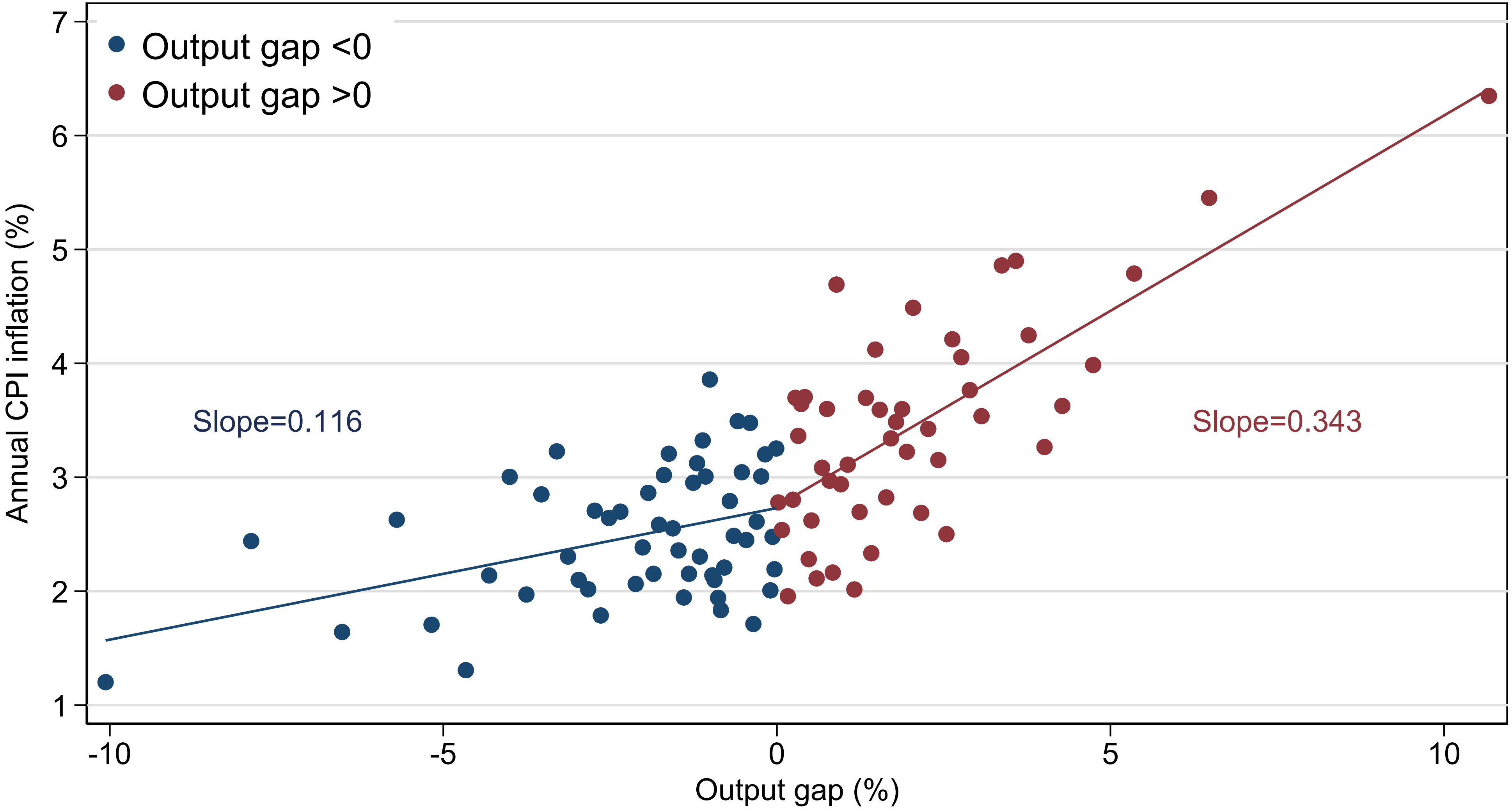
Figure 1: UK and US annual CPI inflation rates



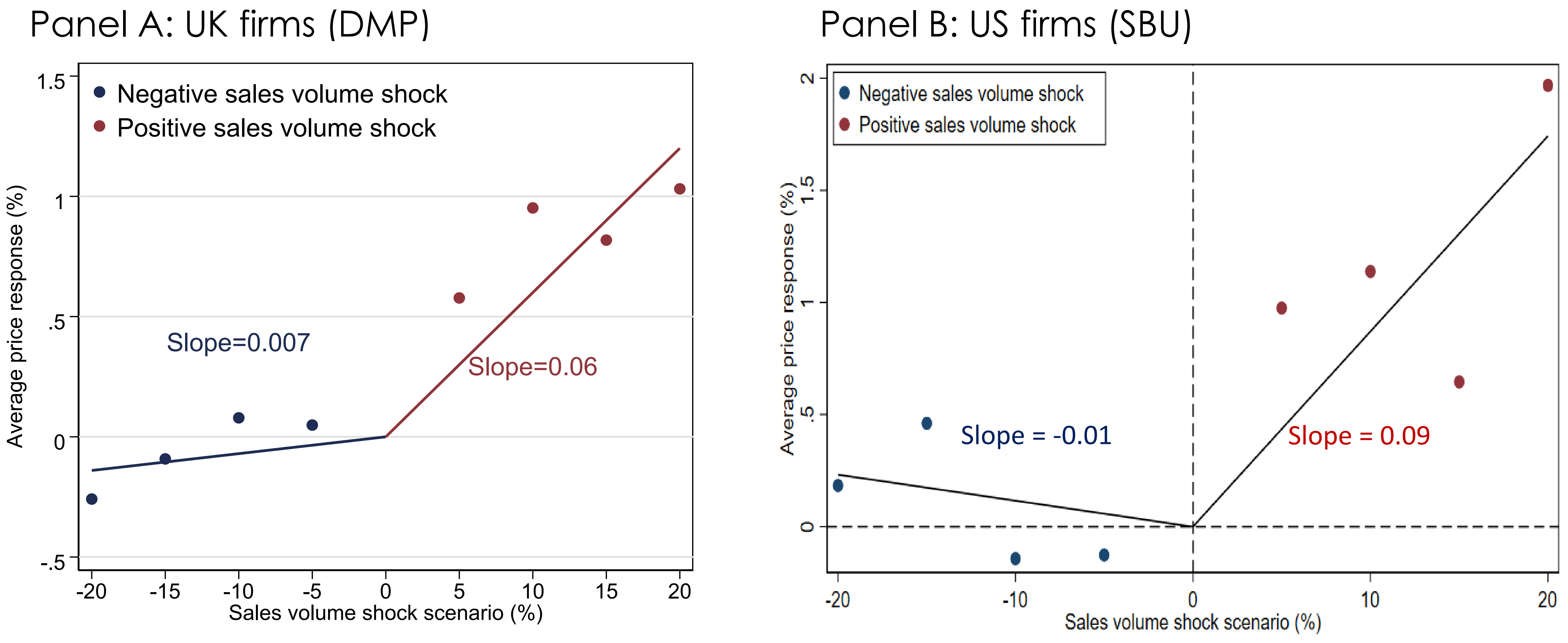
Notes: Data are three-month moving averages. Sources: UK Office for National Statistics and US Bureau of Labor Statistics.

Figure 2: Macro evidence on inflation and output gap



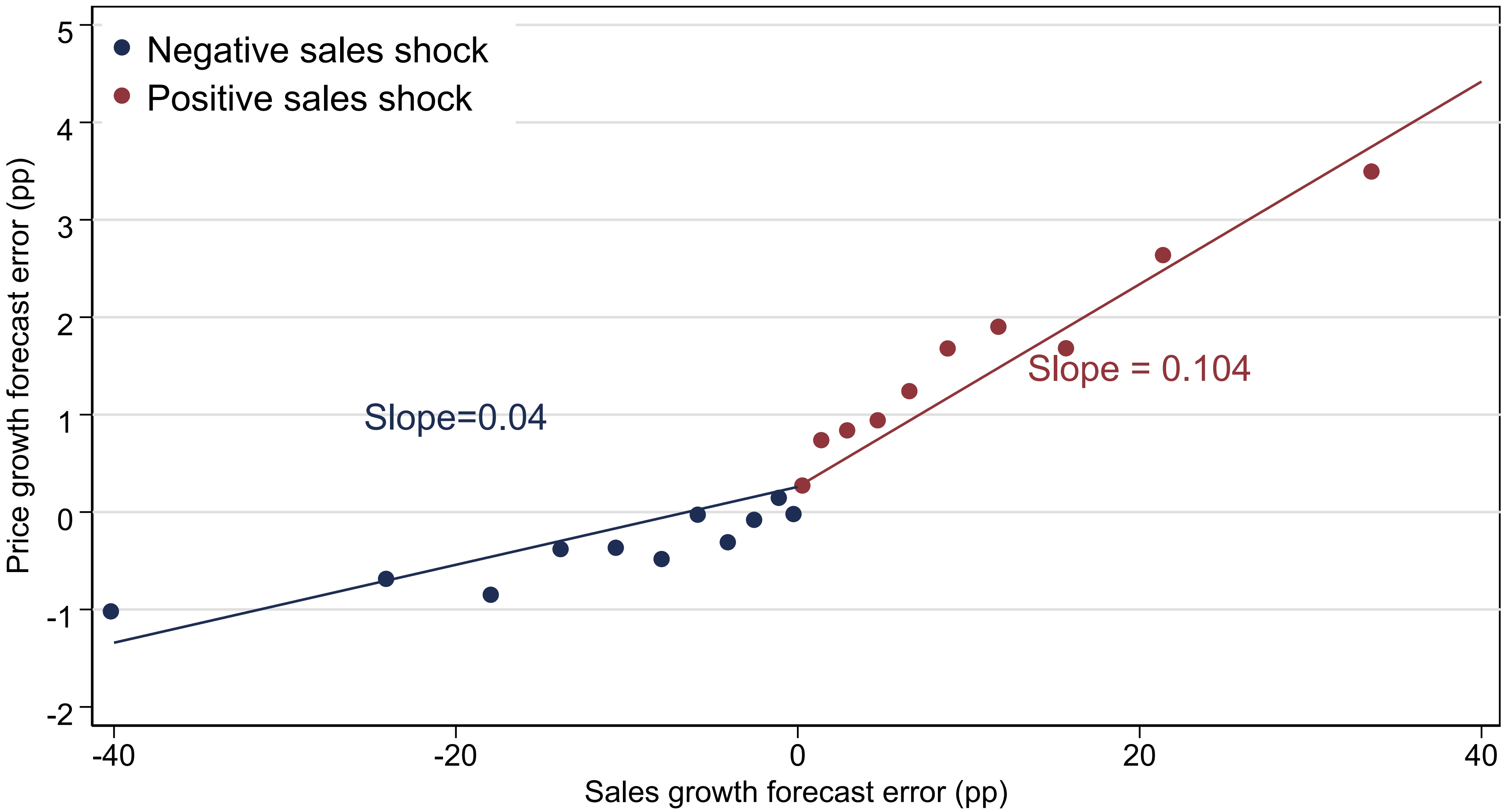
Notes: This figure is a binned scatterplot of annual CPI inflation rates on output gap estimates for 38 countries over the period 1990-2024. Data on annual inflation rates is taken from the World Bank cross-country database of inflation (Ha et al. 2023). Data on output gap estimates is obtained from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

Figure 3: Price response to hypothetical sales volume shocks



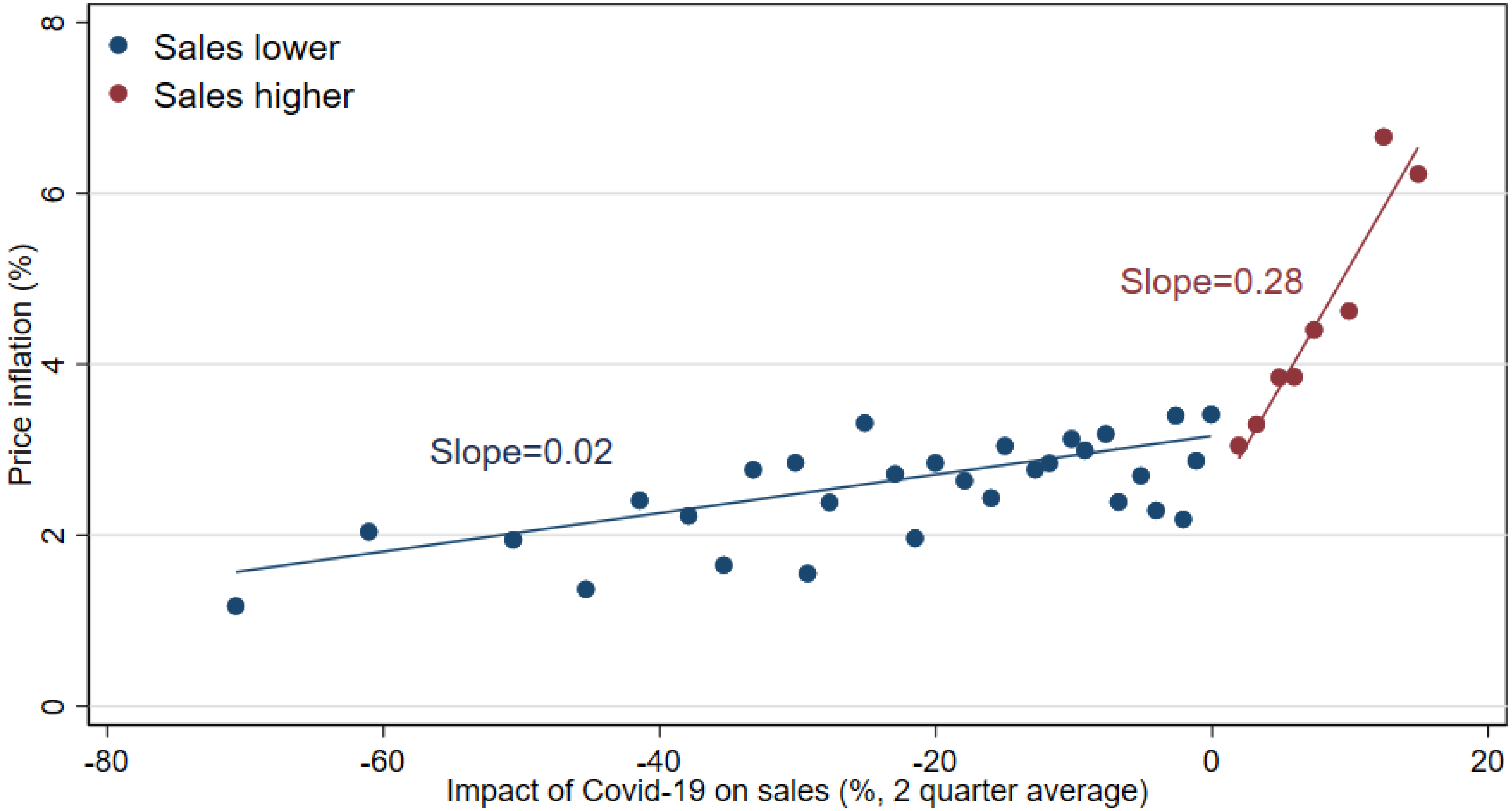
Notes: This figure reports responses to the question "Suppose that your business's sales volume over the next 12 months is X per cent higher/lower than you currently expect. How would that affect the average price you charge, relative to what you currently expect?" Firms are randomised into one of four 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 787 US firms which responded to the June 2024 survey wave of the Survey of Business Uncertainty (see Meyer et al. 2024).

Figure 4: Relationship between sales and price forecast errors



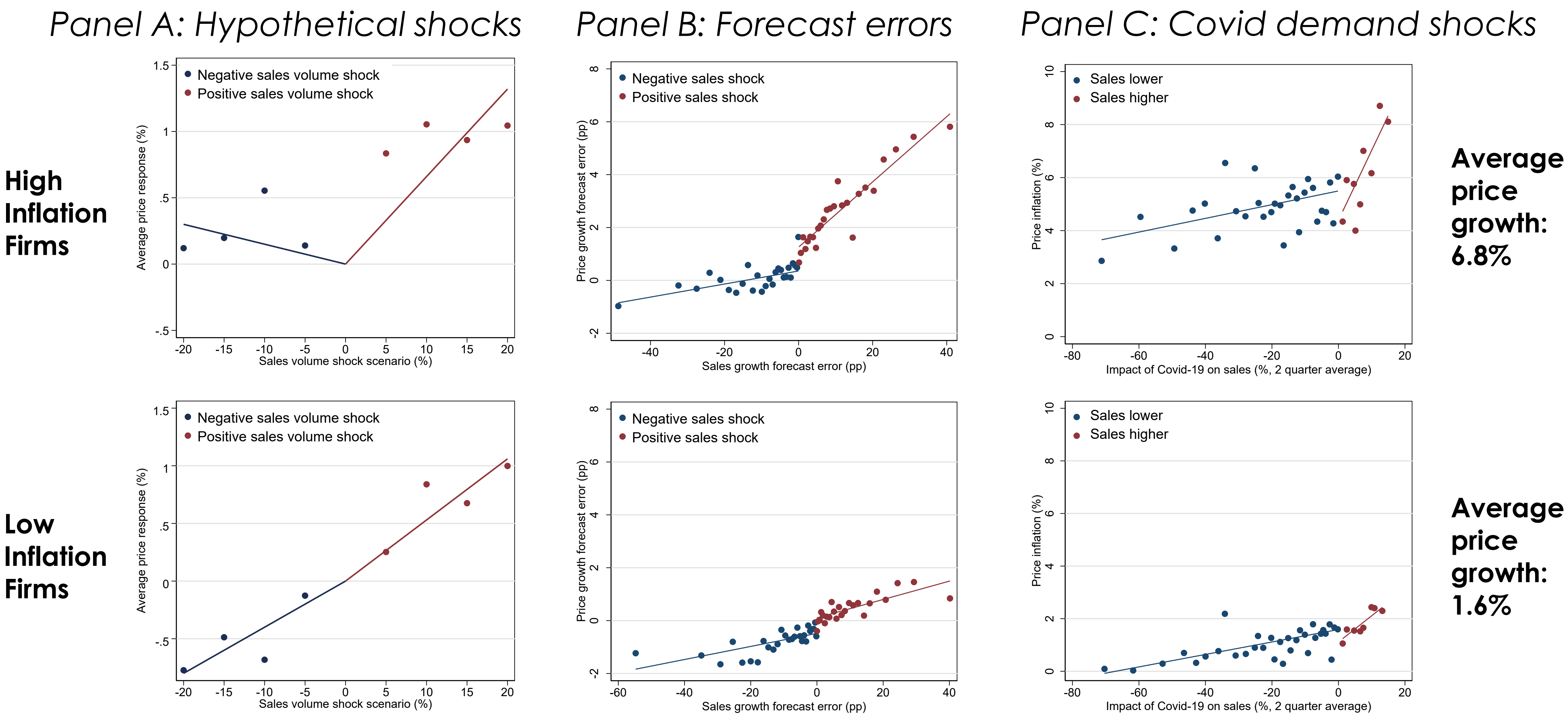
Notes: This figure shows the relationship between nominal sales growth forecast errors and annual price growth forecast errors. Each dot represents 5% of the sample between January 2018 and August 2025. Sales forecast errors are trimmed at the 5th and 95th percentiles by quarter. Price forecast errors are winsorised at the 1st and 99th percentiles. The scatter plot is based on 22,958 observations for 4,410 UK firms in the Decision Maker Panel.

Figure 5: Realized inflation and impact of Covid-19 on sales



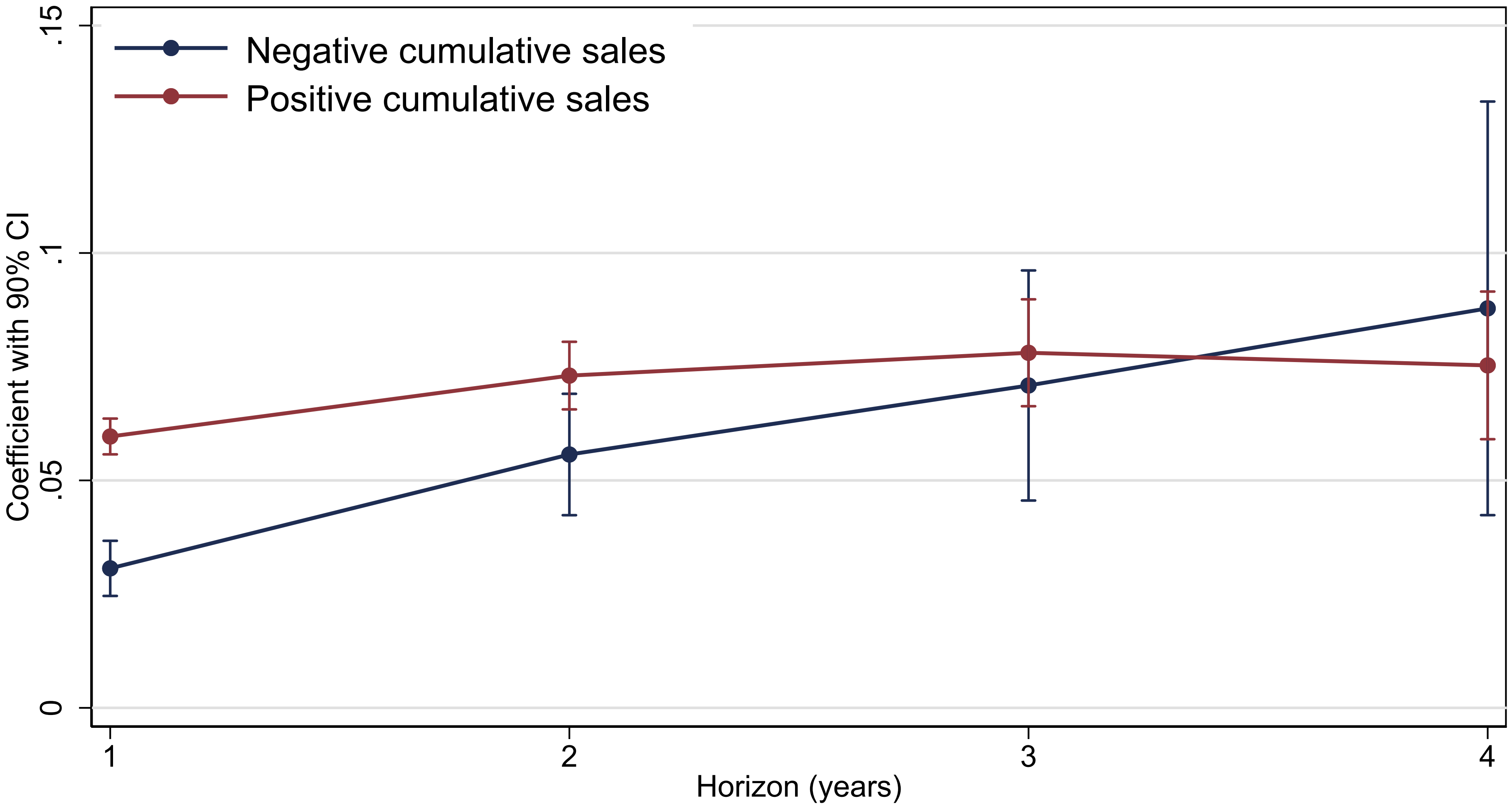
Notes: Each dot represents 2% of observations (during the pandemic, 2020 Q2 to 2022 Q2), grouped by impact of Covid-19 on sales. Zero responses are excluded. The scatterplot is based on 11,343 observations from 3,694 UK firms in the Decision Maker Panel.

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



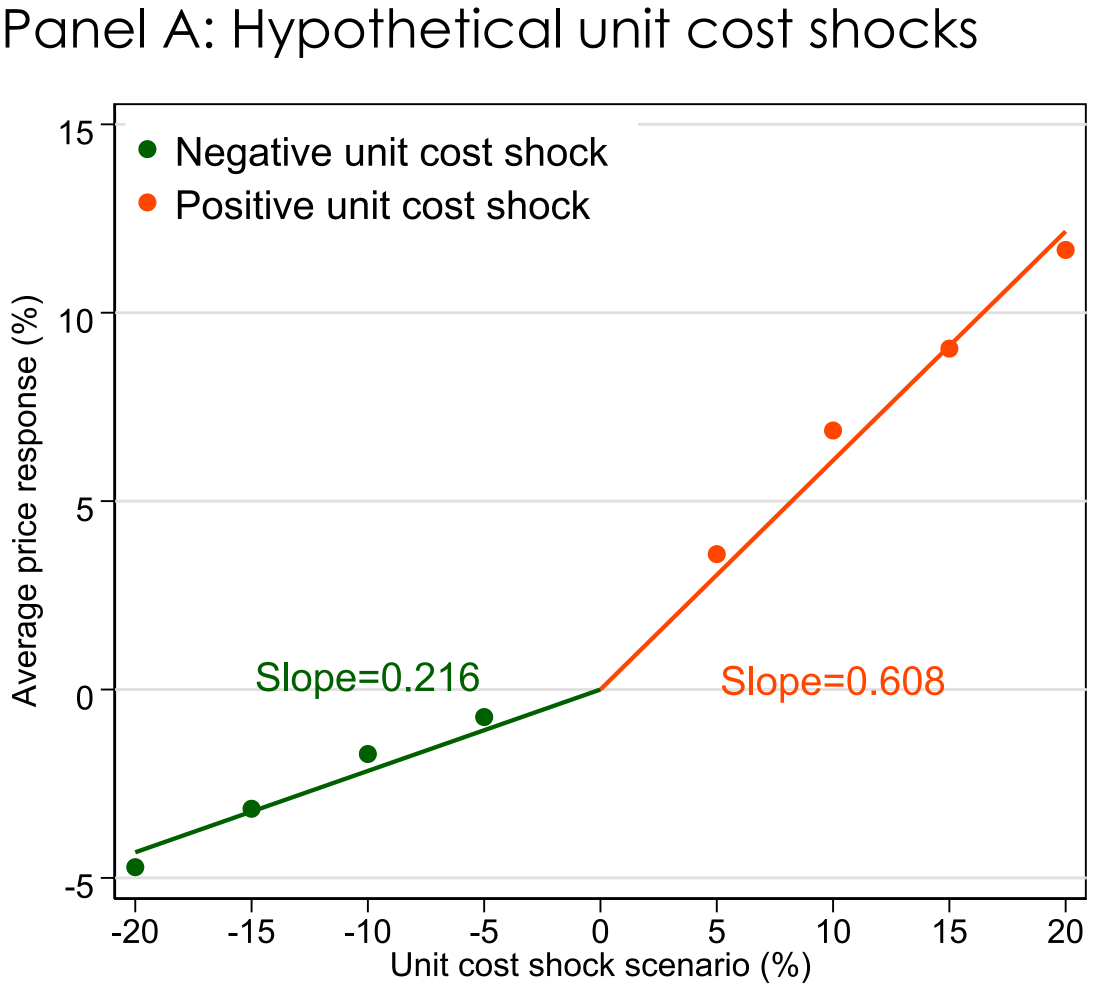
Notes: High-inflation firms are firms with average price growth across the full sample above 4% (sample average). Low-inflation firms are firms with average price growth across full sample below 4%. All figures are based on data from UK firms in the Decision Maker Panel.

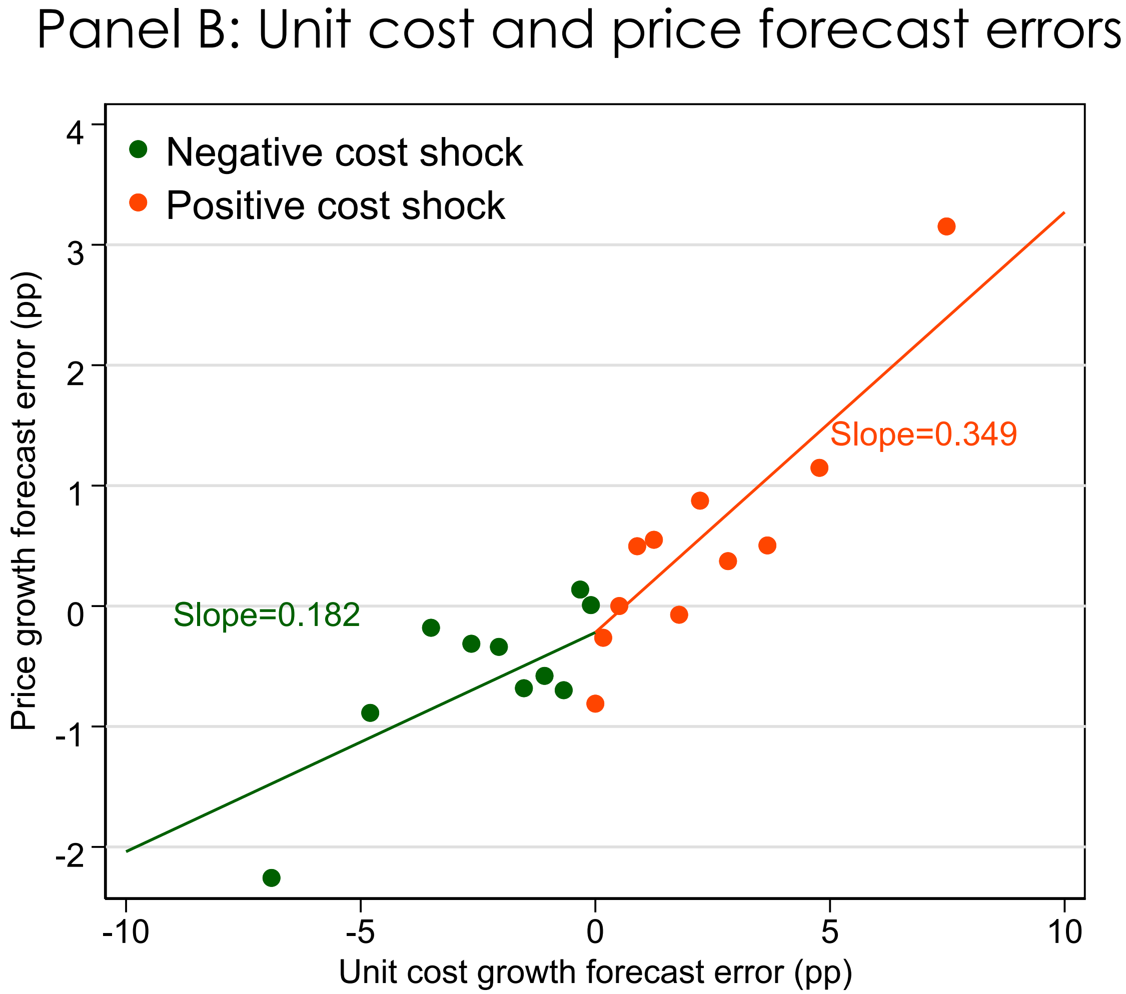
Figure 7: Relationship between sales and price forecast errors: Longer-run responses



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.

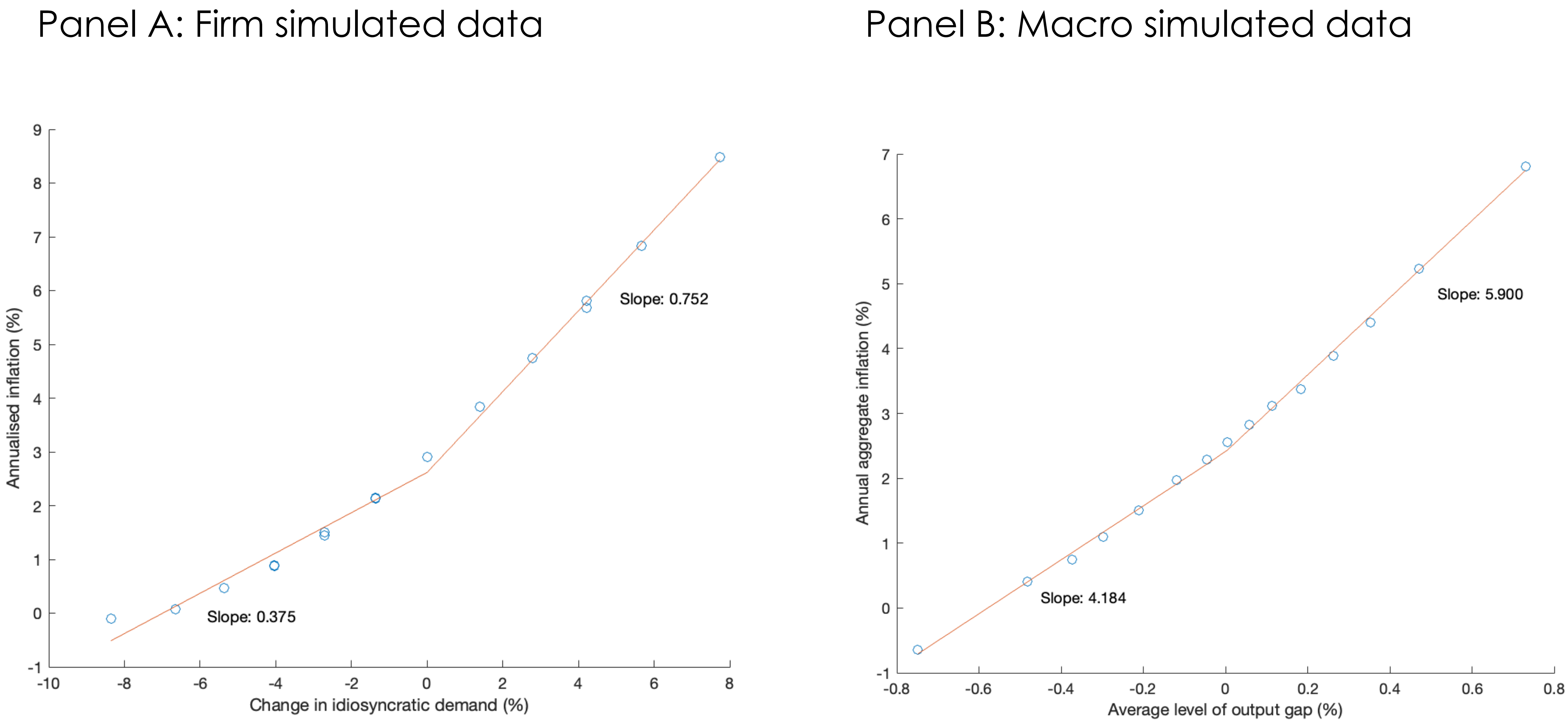
Figure 8: Firm price responses to unit costs





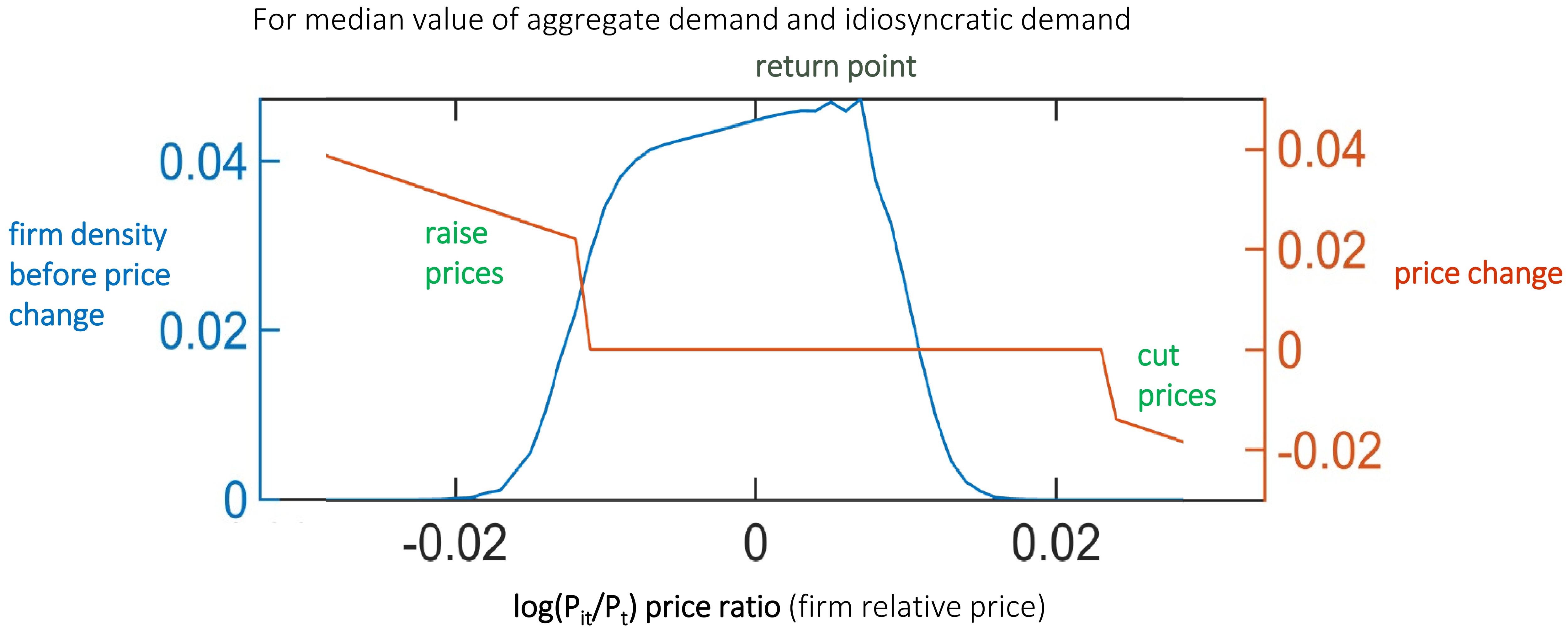
Notes: Panel A reports responses to the question "Suppose that your business's unit costs over the next 12 months are X per cent higher/lower than you currently expect. How would that affect the average price you charge, relative to what you currently expect?" Firms are randomised into one of four scenarios for unit costs: ±5%, ±10%, ±15%, ±20%. Firms are presented with both the positive and negative values for a given scenario. The scatter plot is based on 3,728 observations from 1,864 UK firms in the Decision Maker Panel. The results are unweighted. Panel B shows the relationship between unit cost growth forecast errors and annual price growth forecast errors. Each dot represents 5% of the sample between 2018Q1 and 2025Q3 (with gaps). Unit cost growth 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 2,260 observations for 1,364 UK firms in the Decision Maker Panel.

Figure 9: Simulated Phillips curves from menu cost model



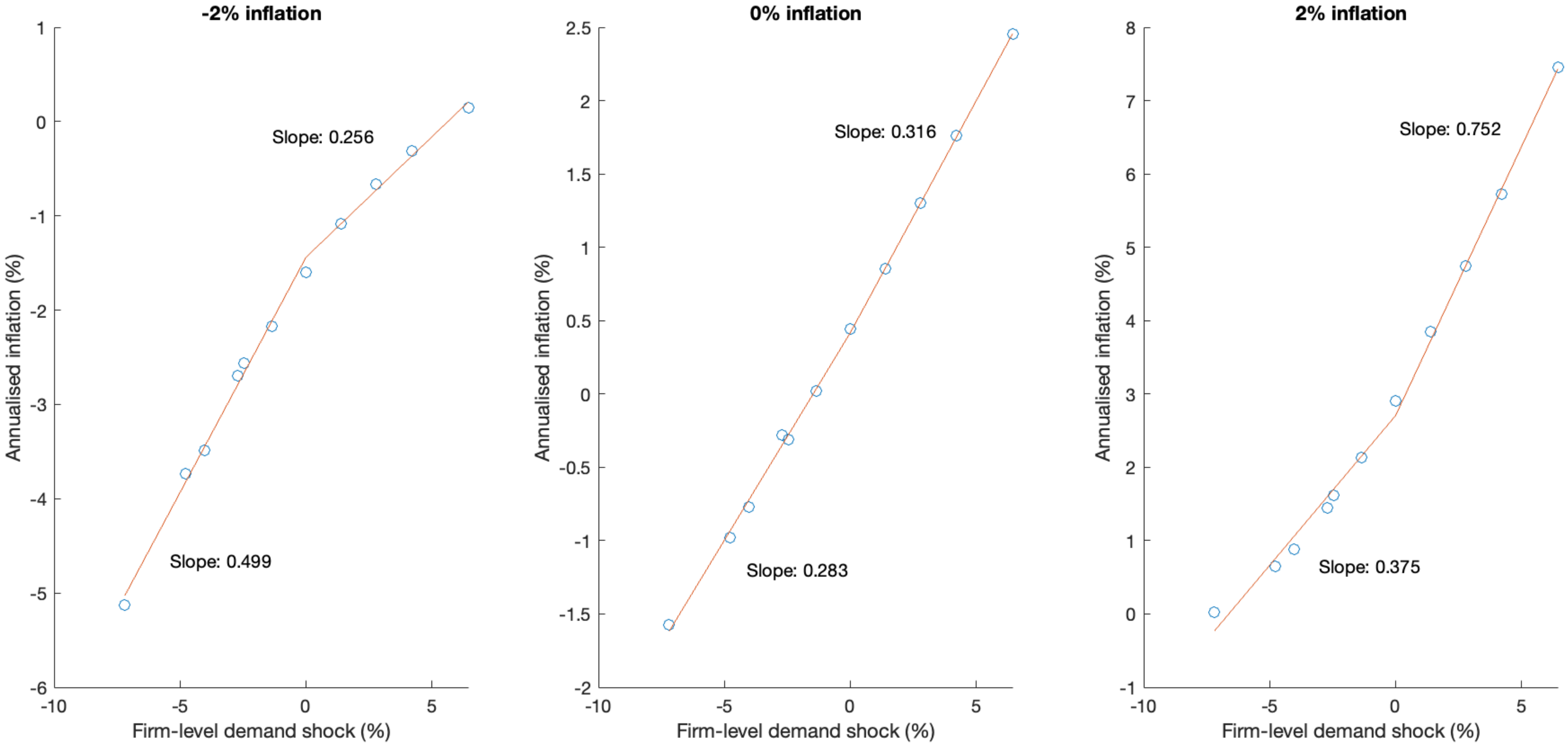
Notes: : The left-hand figure presents simulated firm-level data from the model outlined in Section 6. The x-axis is the one-month change in idiosyncratic demand and the y-axis is the annualised one-month inflation rate. The scatter plot uses 20 quantile bins. The right-hand figure presents simulated 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 annualised twelve-month inflation rate. The scatter plot uses 15 quantile bins.

Figure 10: Distribution of firms in inaction zone



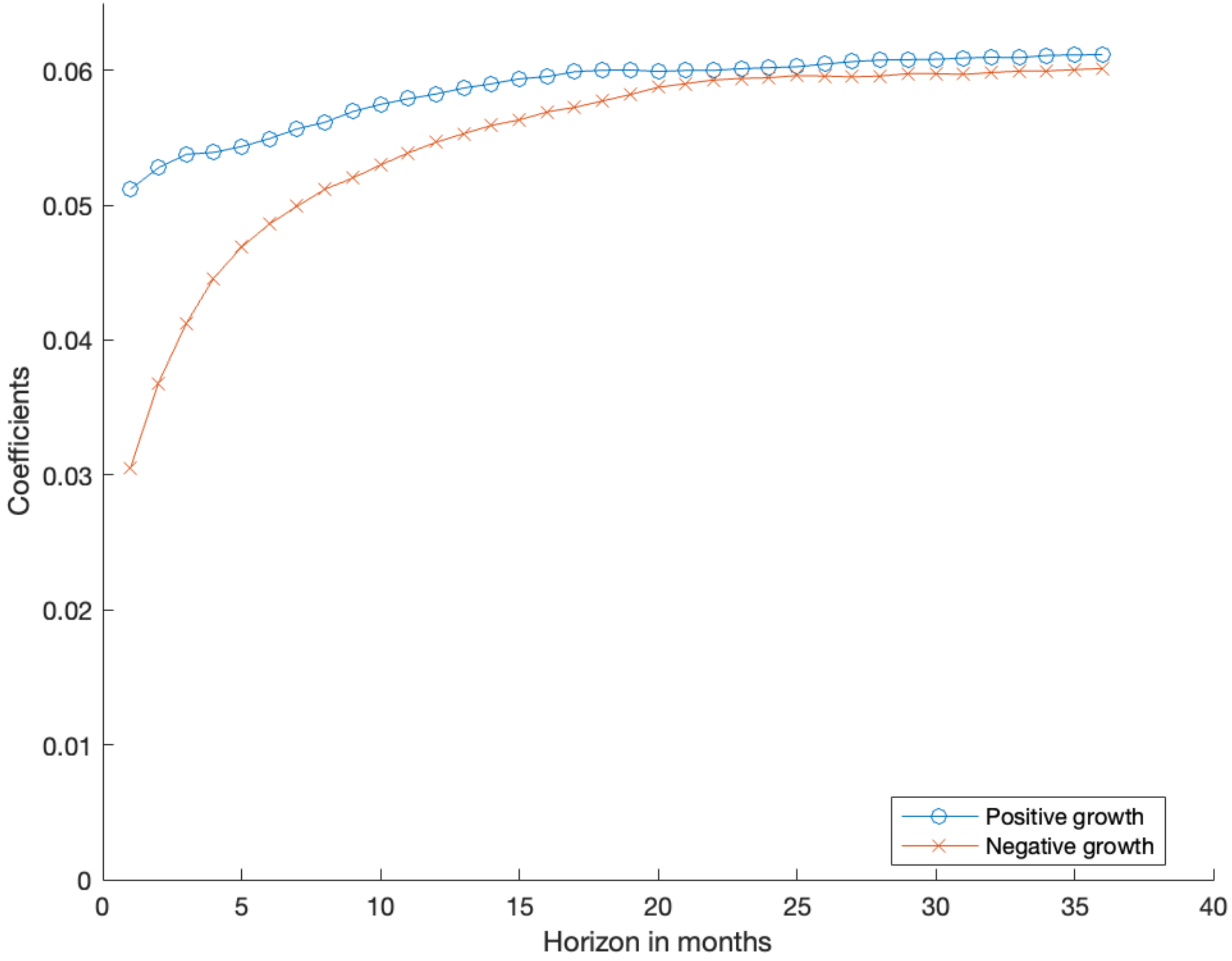
Notes: This figure presents simulated firm-level data from the model outlined in Section 6. It shows the density of firms within the zone of inaction (blue line) and the price changes that firms do conditional on changing prices (red line). It is drawn at the median value of aggregate and idiosyncratic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

Figure 11: Simulated firm-level Phillips curves at low and high inflation rates



Notes: This figure presents simulated firm-level data from the model outlined in Section 6. Panel A shows a simulation with -2% 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% 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 annualised one-month inflation rate. The scatter plots use 20 quantile bins.

Figure 12: Simulated firm-level long differences



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.

$$p^i_{t+h} - p^i_t = \alpha^h_o + \alpha^h_i + \alpha^h_t + \beta^h_+ \left(x^i_{t+h} - x^i_t\right) I\left[x^i_{t+h} - x^i_t > 0\right] + \beta^h_- \left(x^i_{t+h} - x^i_t\right) I\left[x^i_{t+h} - x^i_t < 0\right] + \varepsilon_{it}$$

Table 1: Macro evidence on inflation and output gap

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable:				Annual Headline CPI Inflation (%)			
Sample Period (annual data)			1990-2024			1990-2019	2020-2024
Output Gap_{it}	0.2247^{***}	0.1638^{***}	0.1167^{***}	0.1182^{***}			
	(0.0271)	(0.0388)	(0.0217)	(0.0209)			
Output Gap_{it}^2				0.0067^{***}			
				(0.0022)			
Output Gap_{it} X OG > 0					0.1909^{***}	0.1769^{***}	0.4122^{***}
					(0.0408)	(0.0363)	(0.1482)
Output Gap_{it} X OG < 0					0.0558	0.0640	0.0284
					(0.0350)	(0.0380)	(0.0764)
$Inflation_{it-1}$			0.4863^{***}	0.4816^{***}	0.4831^{***}	0.5232^{***}	-0.0468
			(0.0289)	(0.0311)	(0.0309)	(0.0310)	(0.0697)
$E_t[Inflation_{it+5}]$			0.6538^{***}	0.6673^{***}	0.6716^{***}	0.6006^{***}	0.4608
			(0.0901)	(0.0916)	(0.0940)	(0.0927)	(0.7833)
Country fixed effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	No	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.062	0.597	0.773	0.775	0.775	0.752	0.870
Number of observations	1,205	1,205	1,159	1,159	1,159	981	178
Test coefficients equal (p-value)					0.036	0.078	0.034

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. 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)	(7)	(8)
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***			0.0365***	0.0377***		
	(0.0048)	(0.0048)			(0.0090)	(0.0089)		
Sales volume shock^2		0.0013***				0.0028***		
		(0.0002)				(0.0005)		
Sales volume shock X Shock > 0			0.0601***	0.0592***			0.0871***	0.1039***
			(0.0050)	(0.0095)			(0.0127)	(0.0128)
Sales volume shock X Shock < 0			0.0074	-0.0027			-0.0116	0.0478***
			(0.0072)	(0.0143)			(0.0123)	(0.0120)
R^2	0.013	0.019	0.021	0.018	0.0204	0.0555	0.0578	0.0943
Number of observations	6,394	6,394	6,394	6,392	1,574	1,574	1,574	1,574
Test coefficients equal (p-value)			0.000	0.000			0.0000	0.0014

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 Columns 1-3 and 5-7 and are unweighted. The results in Columns 4 and 8 are weighted by industry and employment. 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.

Table 3: Relationship between sales growth and price growth forecast errors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable:			Price Growth Forecast Error (pp)			Price Growth Forecast Error (pp)	
Sample Period:			Nov-2017 to Aug-2025			Nov-2017 to Dec-2019	Jan-2020 to Aug-2025
Sales growth forecast error	0.0533***	0.0563***					
	(0.0036)	(0.0038)					
Sales growth forecast error^2		0.0004***					
		(0.0001)					
Sales growth forecast error X Error≥0			0.1042***	0.0738***	0.0707***	0.0517***	0.0748***
			(0.0066)	(0.0065)	(0.0066)	(0.0126)	(0.0069)
Sales growth forecast error X Error<0			0.0390***	0.0358***	0.0342***	0.0240*	0.0387***
			(0.0044)	(0.0053)	(0.0052)	(0.0127)	(0.0057)
Expected year-ahead own-price growth					0.2069***		
					(0.0343)		
Firm fixed effects	Yes	Yes	No	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	No	Yes	Yes	Yes	Yes
R2	0.351	0.352	0.046	0.352	0.370	0.453	0.370
Number of observations	21,710	21,710	22,958	21,710	21,129	3,340	17,720
Test coefficients equal (p-value)			0.000	0.000	0.000	0.174	0.000

Notes: This table shows the relationship between nominal sales growth forecast errors and annual price growth forecast errors. 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 constant of the regressions are also estimated but not reported. 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 4: Response of price growth to Covid demand shock

	(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 $\text{sales}_{it})^2$					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

	(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	0.0661***	0.0526***				
	(0.0068)	(0.0073)				
Sales volume shock X Shock<0	-0.0154	0.0399***				
	(0.0098)	(0.0108)				
Sales growth forecast error X Error ≥0			0.0969***	0.0428***		
			(0.0102)	(0.0071)		
Sales growth forecast error X Error <0			0.0458***	0.0269***		
			(0.0094)	(0.0054)		
Covid impact on sales X sales impact ≥0					0.1410***	0.0662**
					(0.0360)	(0.0288)
Covid impact on sales X sales impact <0					0.0129**	0.0184***
					(0.0061)	(0.0037)
Firm fixed effects	No	No	Yes	Yes	Yes	Yes
Time fixed effects	No	No	Yes	Yes	Yes	Yes
R2	0.024	0.031	0.367	0.317	0.487	0.382
Number of observations	3,696	2,478	10,710	11,000	12,925	21,135
Test coefficients equal (p-value)	0.000	0.248	0.001	0.105	0.001	0.101
Difference coefficients positive/negative	0.081	0.013	0.051	0.016	0.128	0.048
Average firm price growth in sample (%)	7.394	2.583	6.480	1.983	5.256	1.466

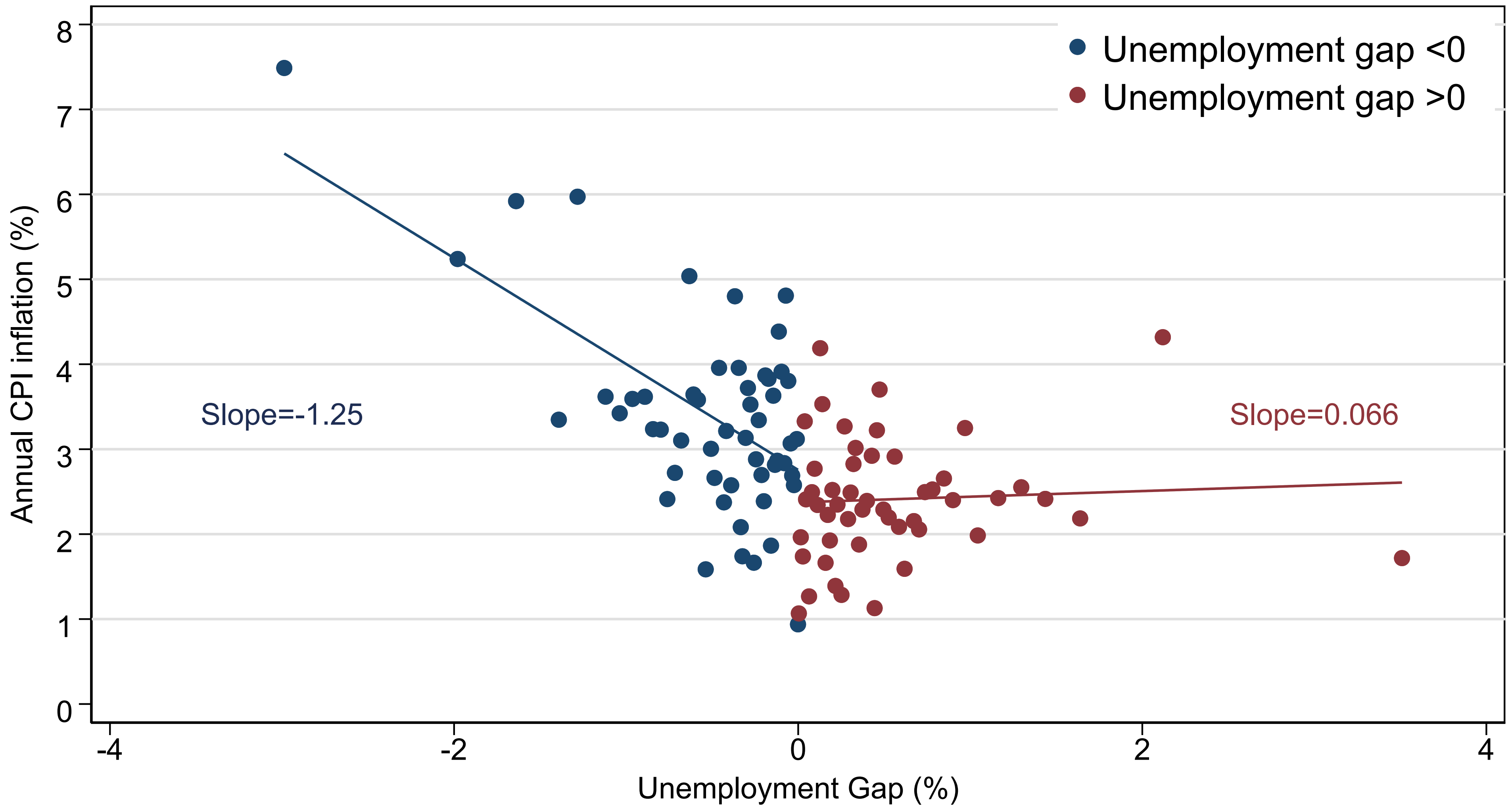
Notes: High-inflation firms are firms with average price growth across the full sample above 4% (sample average). Low-inflation firms are firms with average price growth across full sample below 4%. All columns are based on data from UK firms in the Decision Maker Panel. Standard errors are clustered at the firm level and reported in parentheses, with *** p<0.01, ** p<0.05, * p<0.1.

Table 6: 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 to 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)

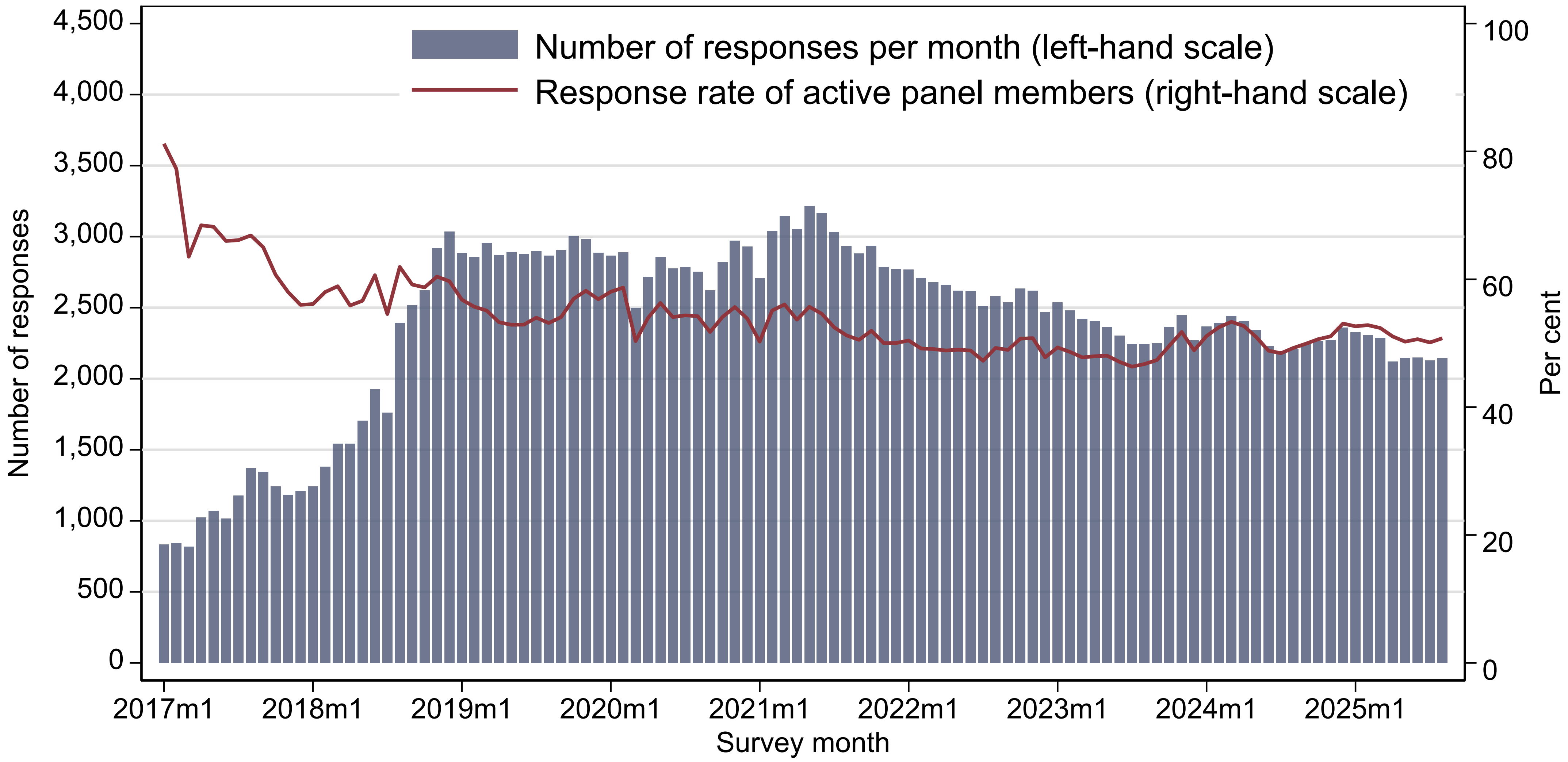
Appendix Figures and Tables

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.

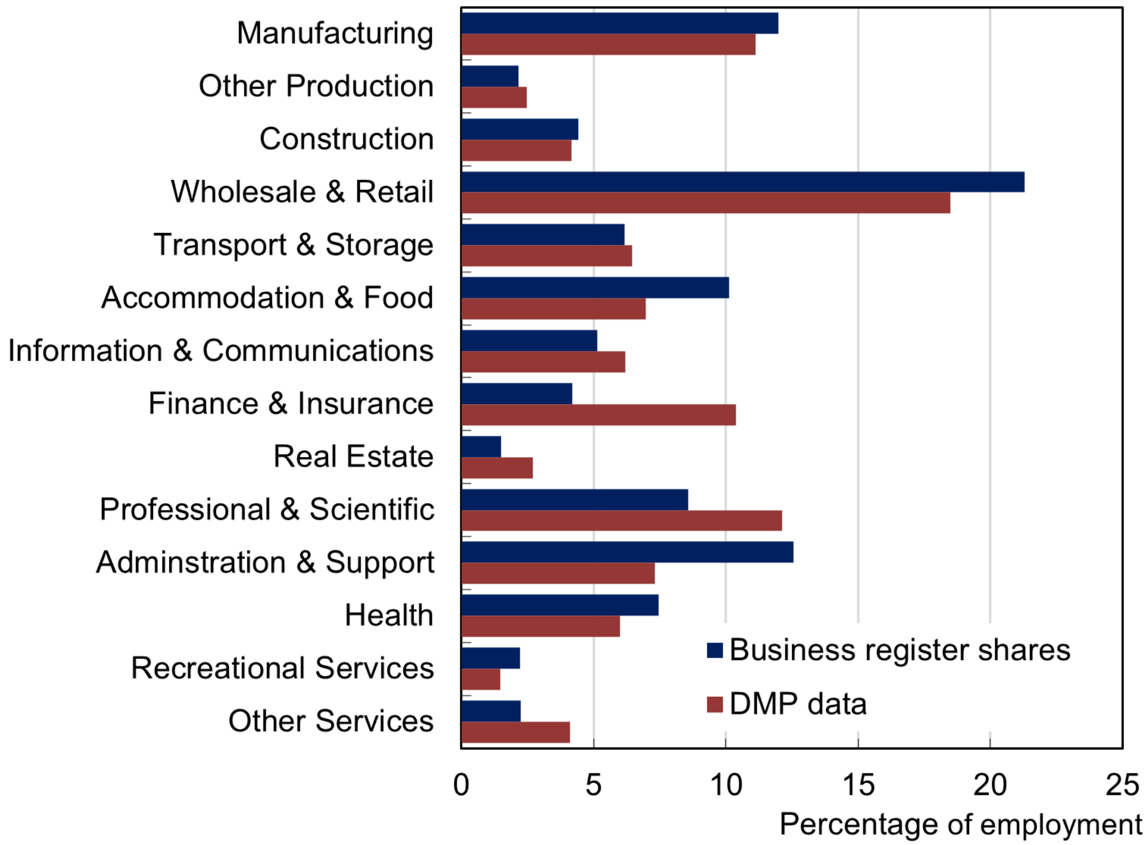
Figure A2: DMP Response rate



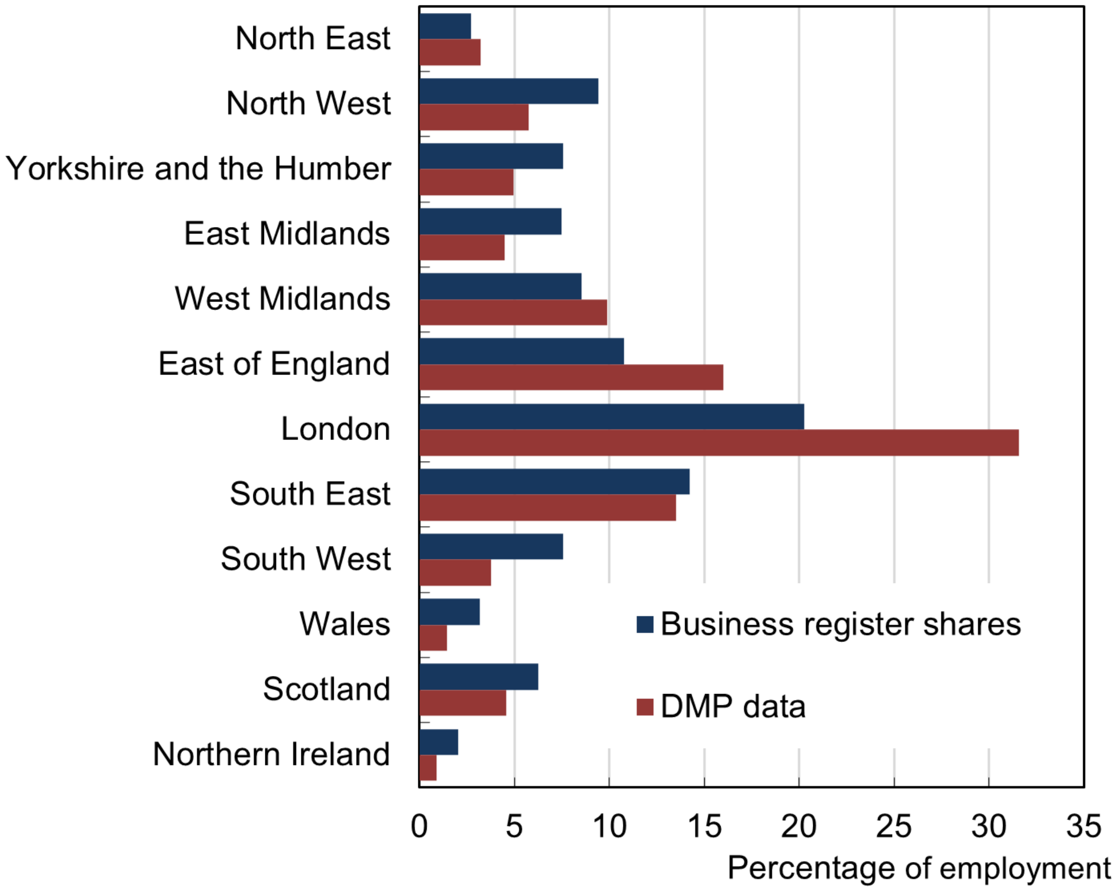
Notes: The response rate of active panel members in the Decision Maker Panel is calculated as the percentage of panel members who had completed at least one survey over the last twelve months who responded to the survey in a given month.

Figure A3: DMP vs. UK industrial and regional distribution

Panel A: By Industry

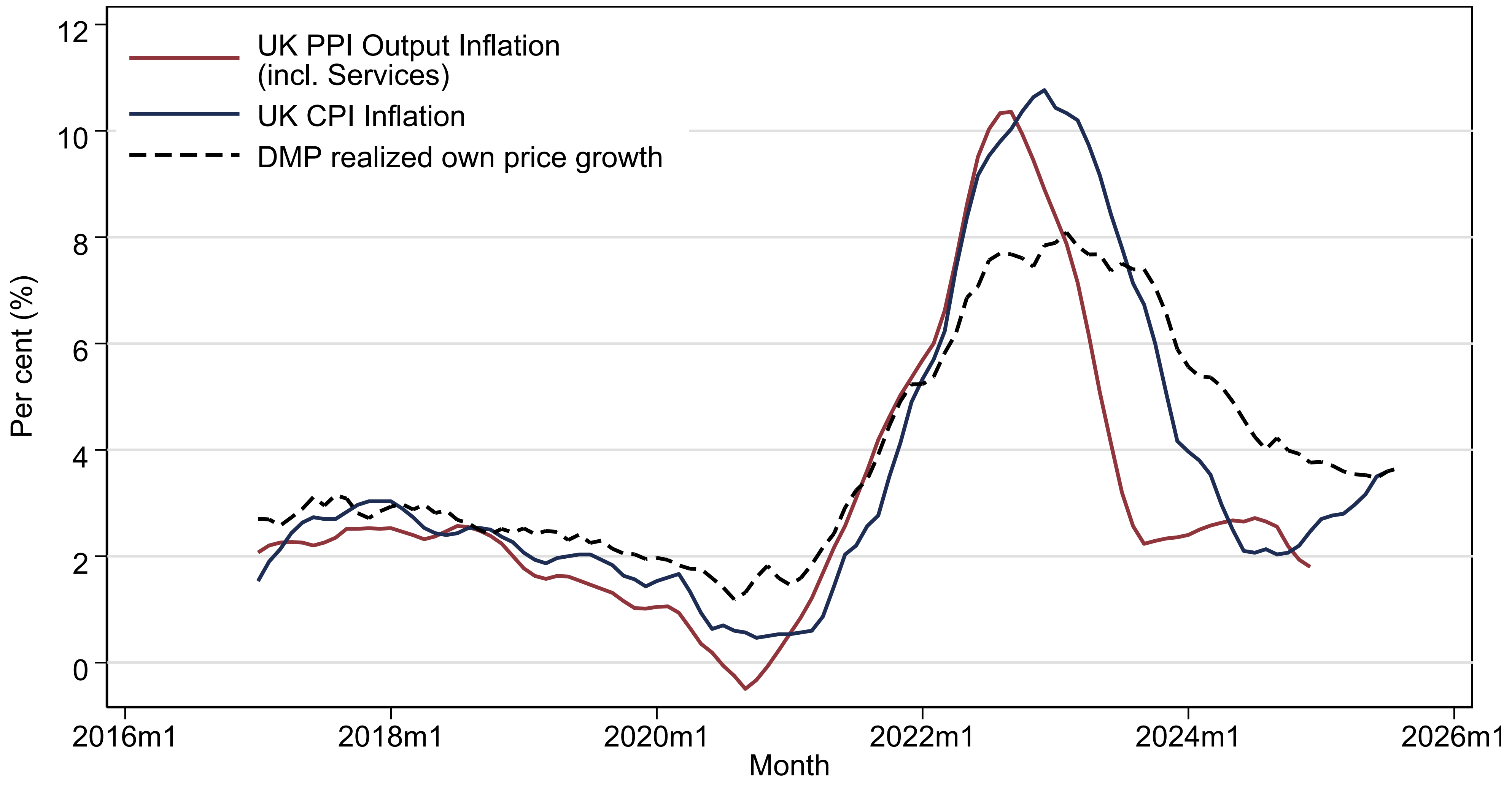


Panel B: By Region



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 2023.

Figure A4: UK CPI inflation, UK PPI inflation, and DMP price growth



Notes: Data are three-month moving averages. Sources: DMP, UK Office for National Statistics. The PPI series combined data on output PPI inflation with quarterly data on Services PPI, with weights 0.33 and 0.67 respectively. The publication of PPI series by the ONS was temporarily paused at the beginning of 2025.

Figure A5: 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

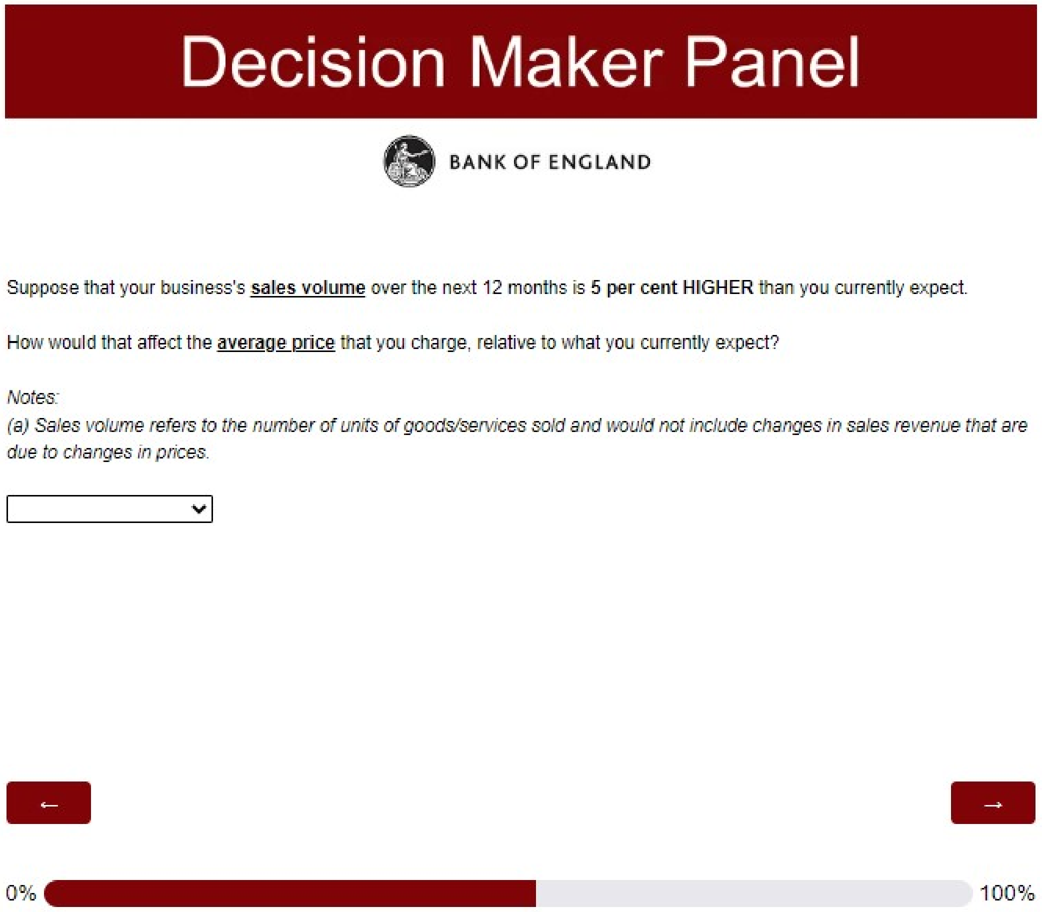
BANK OF ENGLAND

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

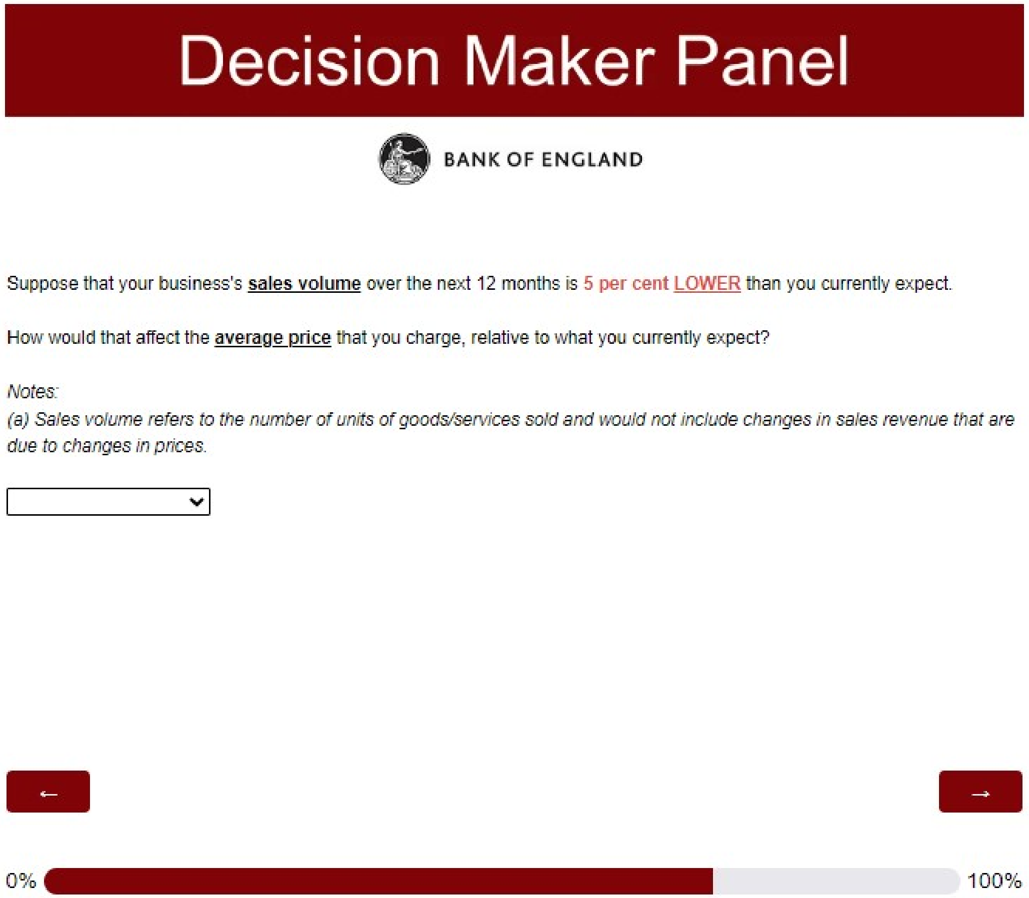
LOWEST: The likelihood of realising about **2%** would be:	5	%
LOW: The likelihood of realising about **3%** would be:	15	%
MIDDLE: The likelihood of realising about **4%** would be:	25	%
HIGH: The likelihood of realising about **5%** would be:	20	%
HIGHEST: The likelihood of realising about **8%** would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

Figure A6: Hypothetical sales volume shock questions

Panel A: Main scenario

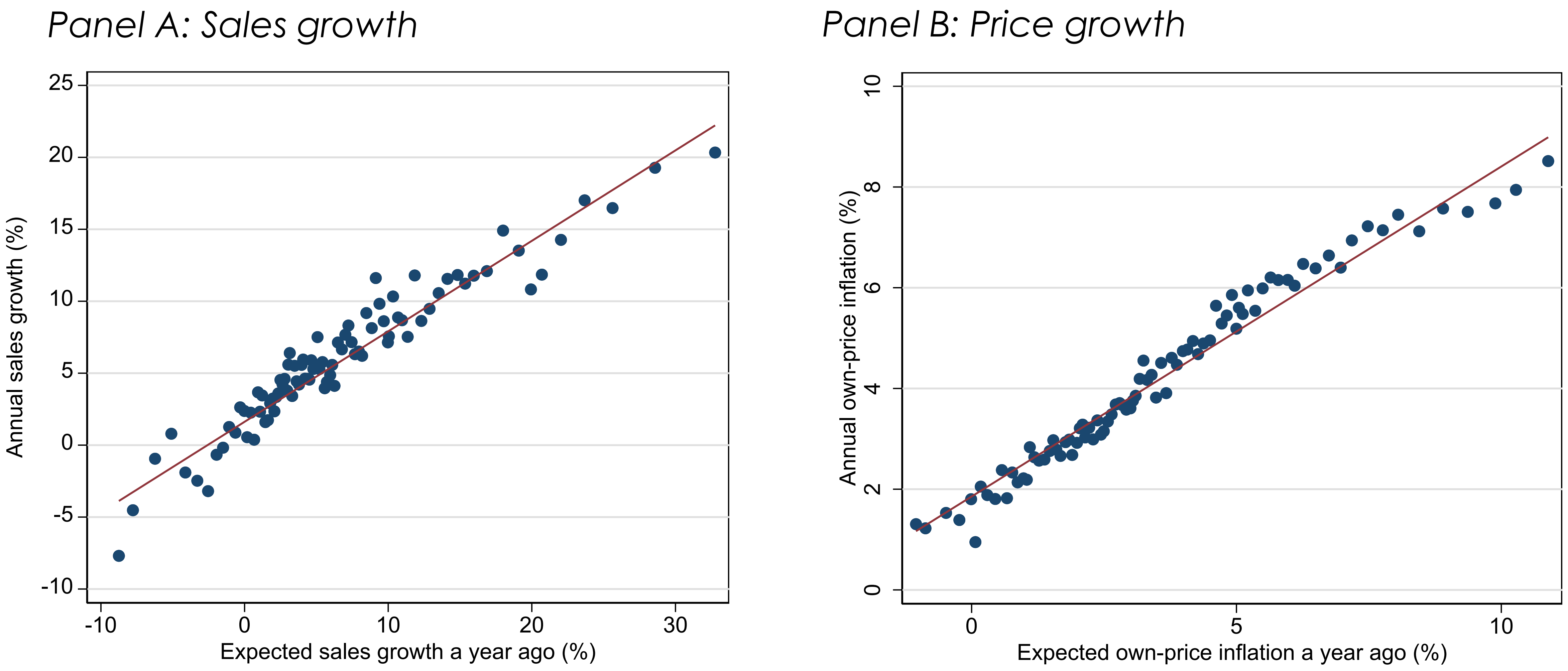


Panel B: Flipped scenario



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.

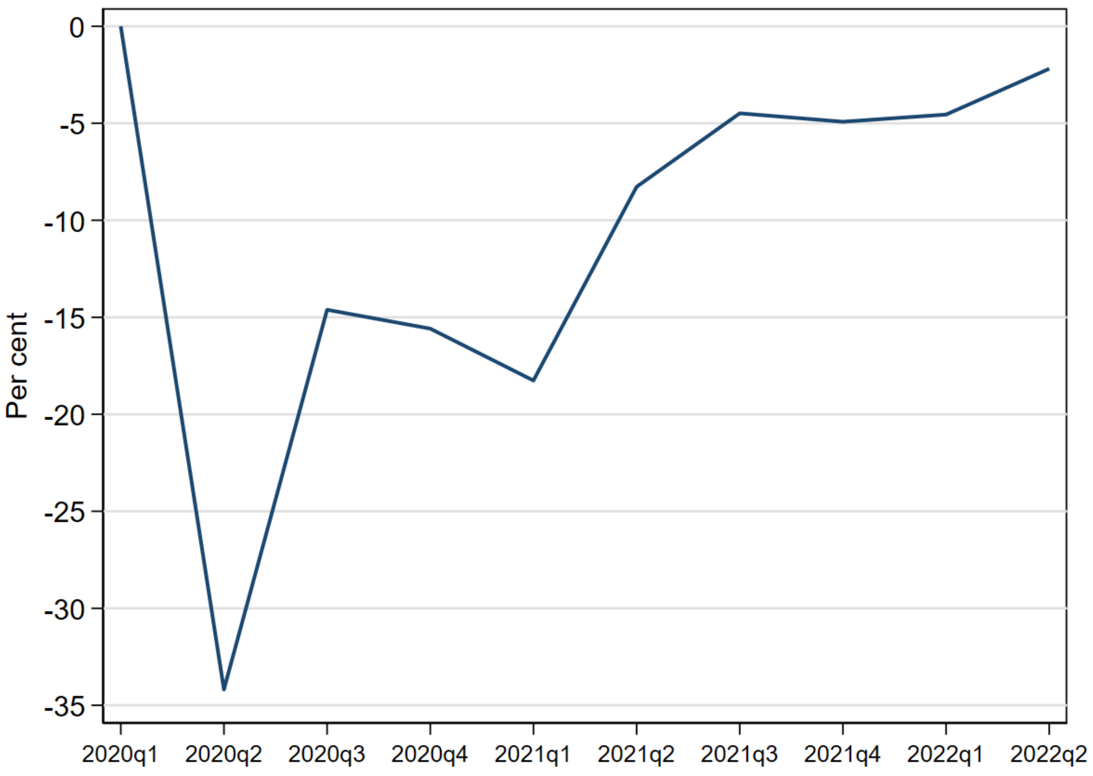
Figure A7: Comparison of firm year-ahead expectations with realizations



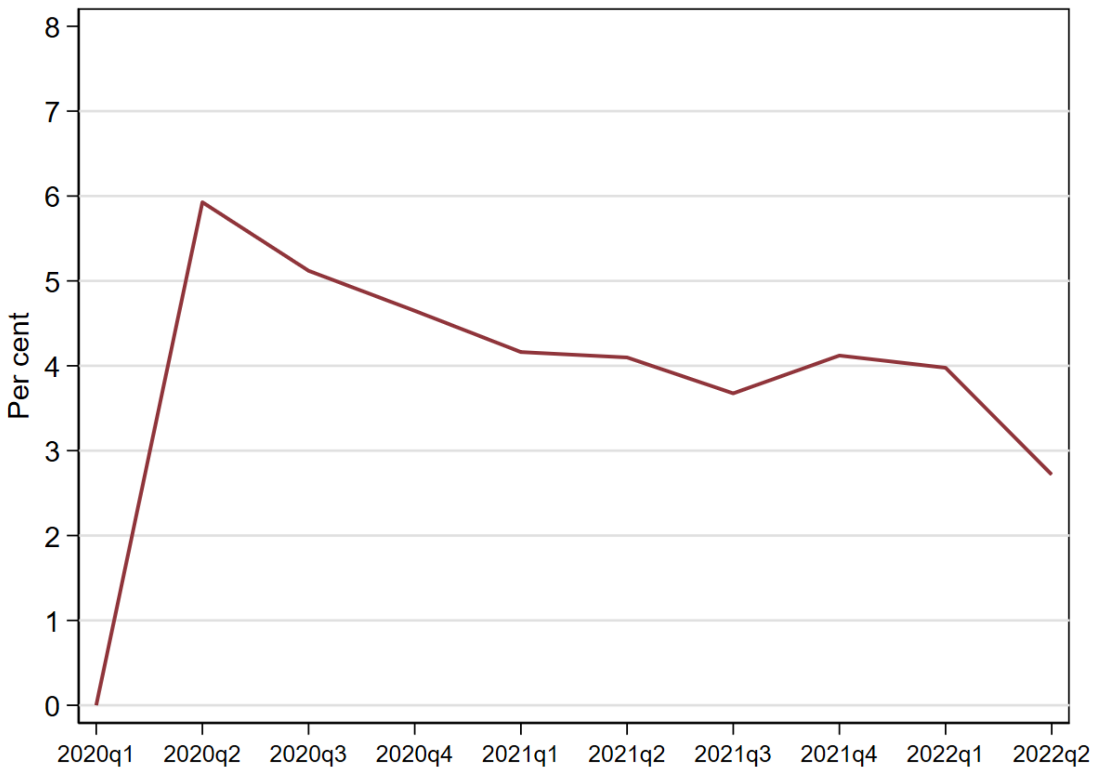
Notes: This figure presents binned scatter plots comparing year-ahead expectations for sales growth (Panel A) and price growth (Panel B) with realisations for the respective variables a year later. Each dot represents 1% of the sample. The figures are based on data from UK firms in the Decision Maker Panel over the period January 2019 to August 2025.

Figure A8: Impact of Covid-19 on sales and unit costs

Panel A: Sales



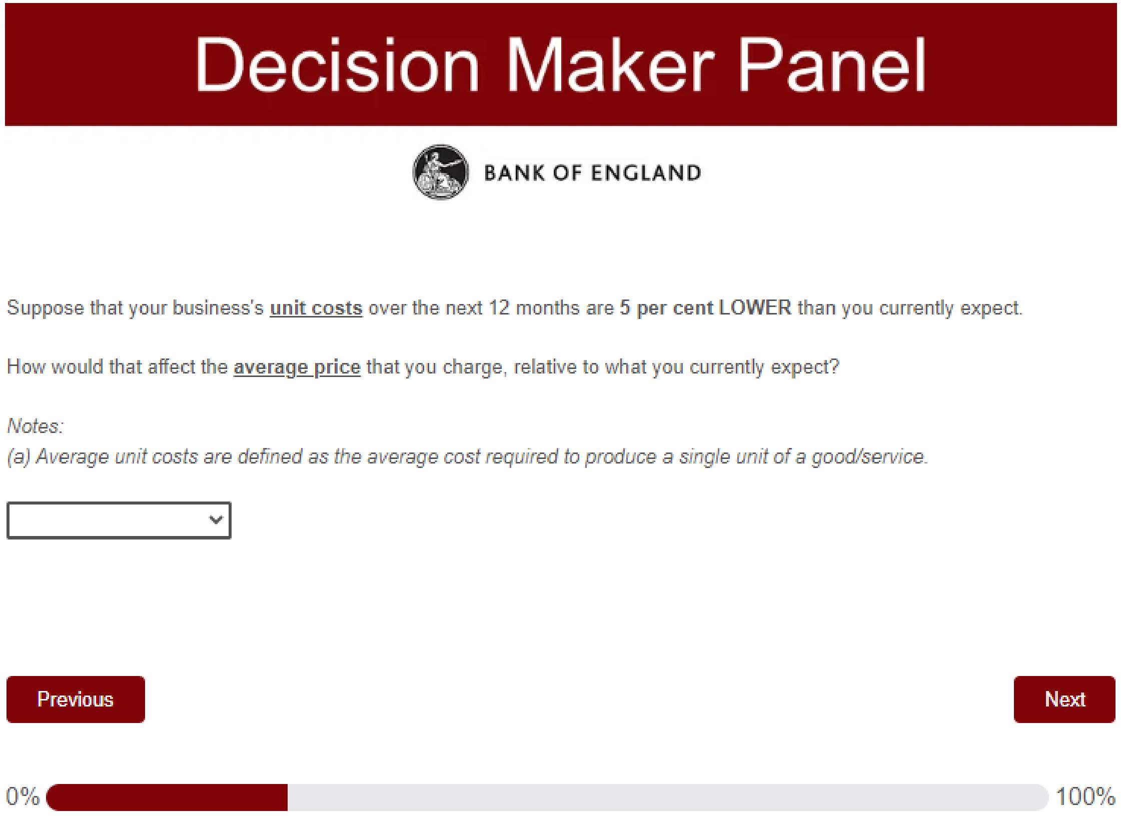
Panel B: Unit costs



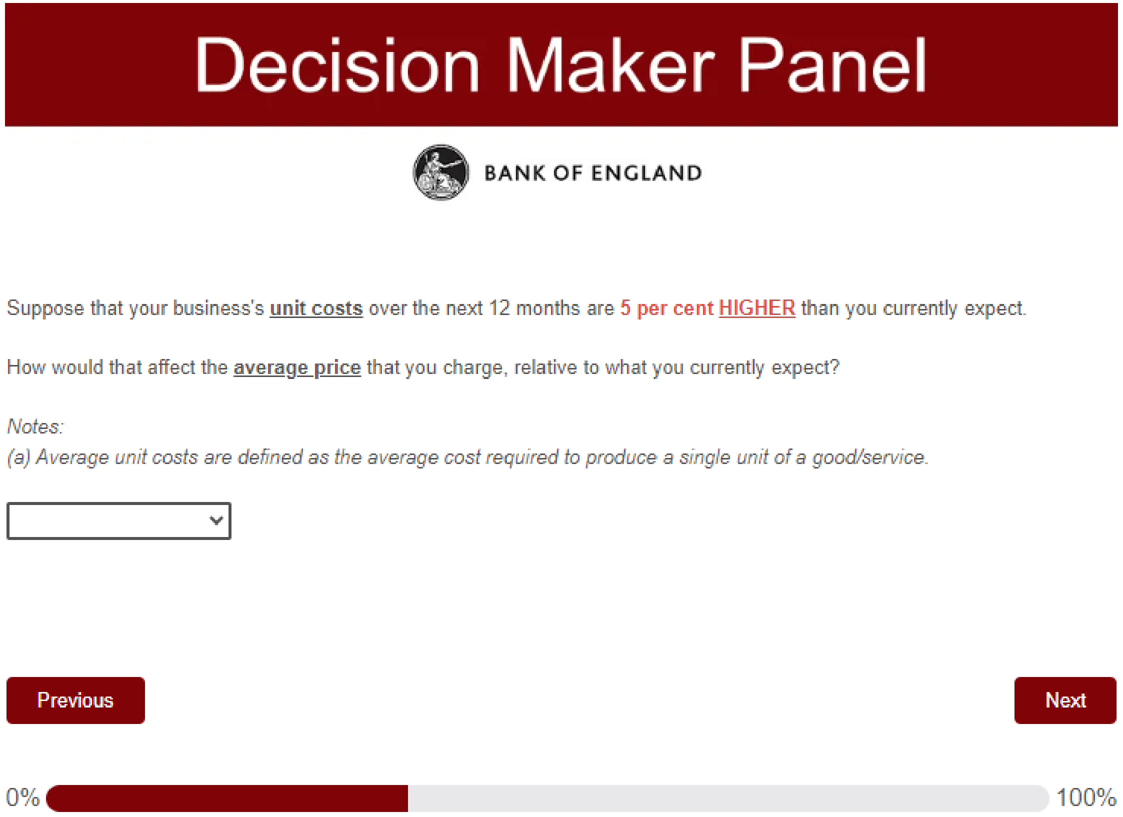
Notes: The results are based on the questions: 'Relative to what would otherwise have happened, what is your best estimate for the impact of the spread of Covid-19 on the sales of your business in each of the following periods?'; 'Relative to what would otherwise have happened, what is your best estimate 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 A9: Hypothetical unit cost shock questions

Panel A: Main scenario

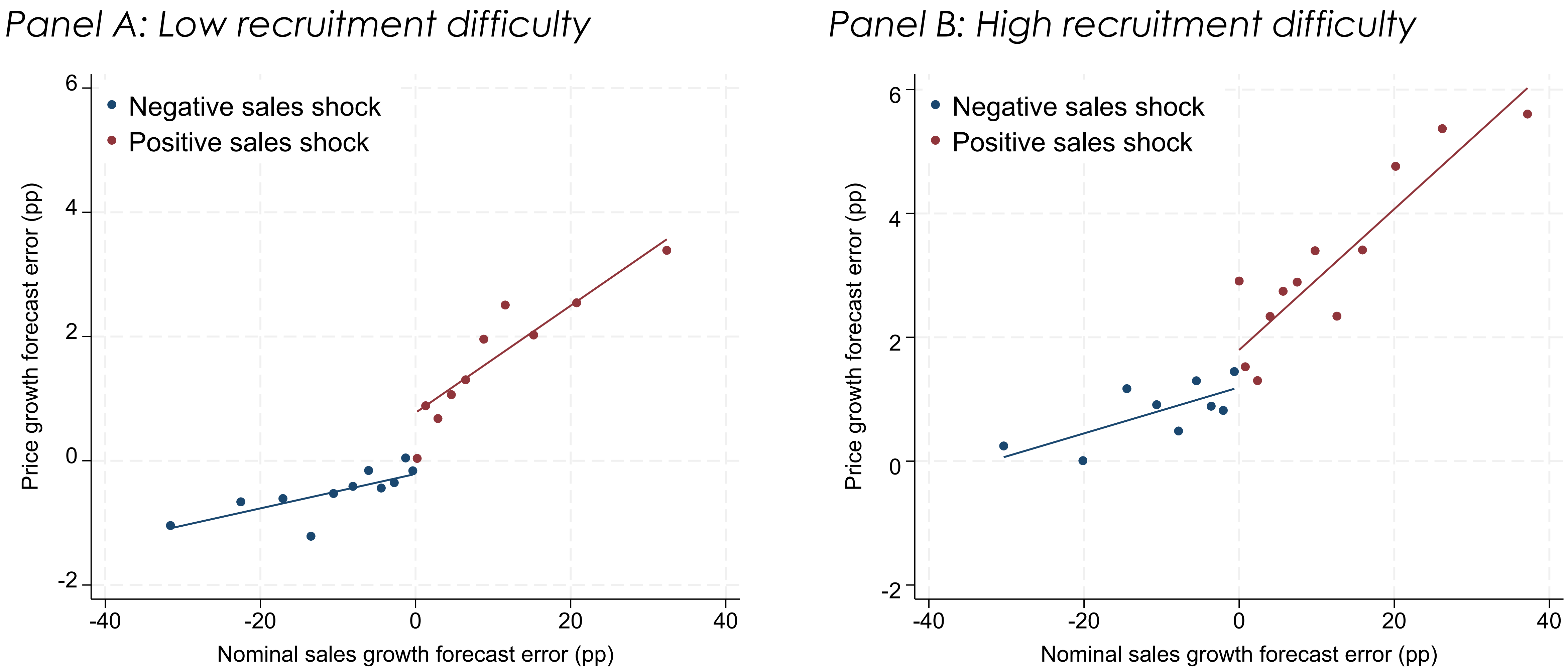


Panel B: Flipped scenario



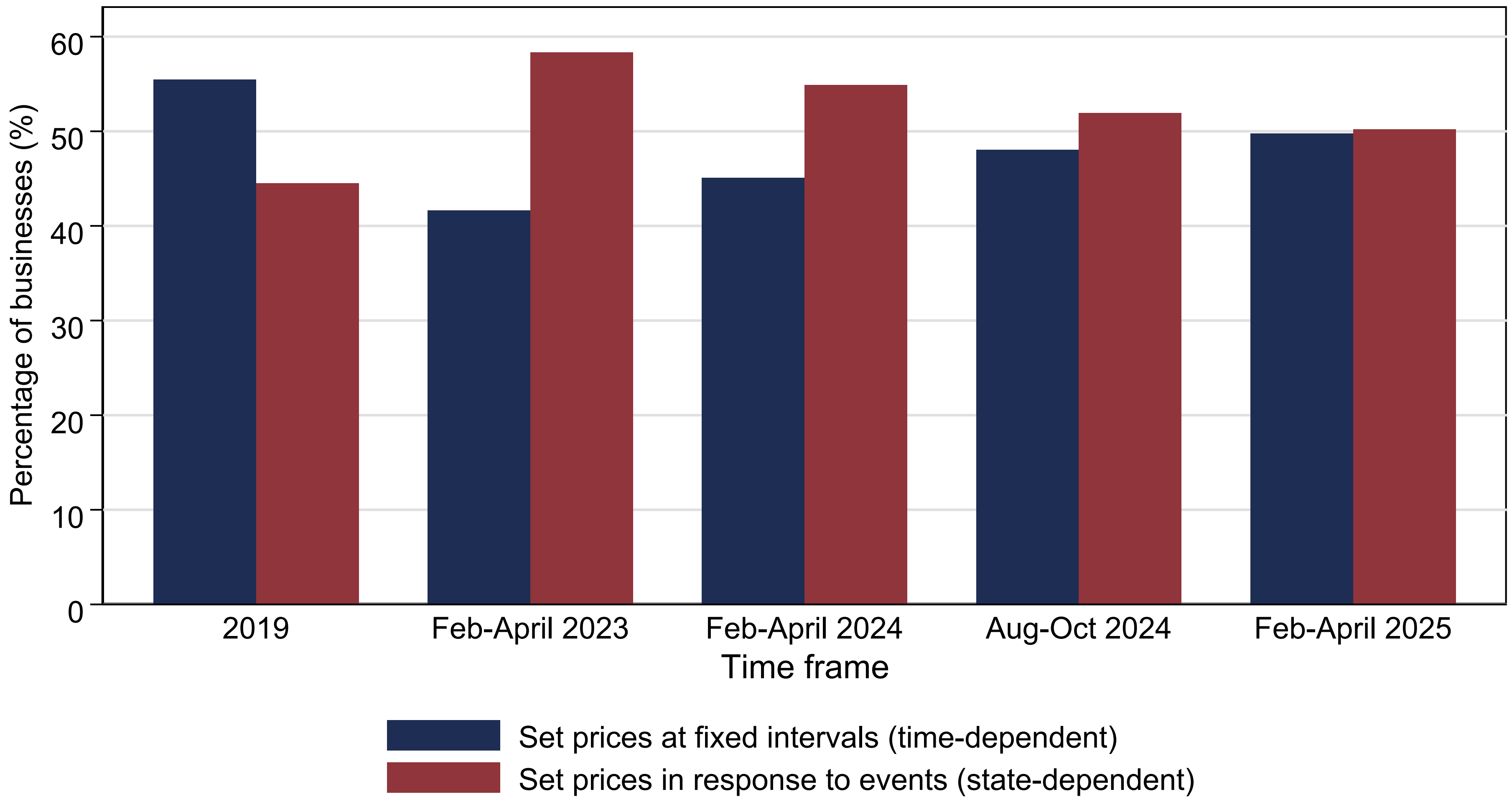
Notes: Firms are randomised into one of four scenarios for unit costs: ±5%, ±10%, ±15%, ±20%. Firms are presented with both the positive and negative values for a given scenario. These questions were asked in August to October 2024.

Figure A10: Relationship between sales and price forecast errors: Heterogeneity by 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 A11: 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.

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

	(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

	(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	0.0595***	0.0612***				
	(0.0066)	(0.0073)				
Sales volume shock X Shock<0	-0.0194**	0.0426***				
	(0.0093)	(0.0108)				
Sales growth forecast error X Error ≥0			0.0884***	0.0463***		
			(0.0097)	(0.0073)		
Sales growth forecast error X Error <0			0.0387***	0.0348***		
			(0.0078)	(0.0067)		
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**	0.0196***
					(0.0050)	(0.0047)
Firm fixed effects	No	No	Yes	Yes	Yes	Yes
Time fixed effects	No	No	Yes	Yes	Yes	Yes
R2	0.022	0.033	0.432	0.425	0.607	0.570
Number of observations	3,634	2,746	10,622	10,311	15,705	17,339
Test coefficients equal (p-value)	0.000	0.092	0.000	0.320	0.000	0.293
Difference coefficients positive/negative	0.079	0.019	0.050	0.011	0.147	0.036
Average firm price growth in sample (%)	6.418	4.960	5.315	3.066	3.718	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

	(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	0.0597***					
	(0.0024)					
Sales growth$_{t,t-1}$ X Sales growth < 0	0.0307***					
	(0.0037)					
Sales growth$_{t+1,t-1}$ X Sales growth ≥ 0		0.0730***				
		(0.0045)				
Sales growth$_{t+1,t-1}$ X Sales growth < 0		0.0557***				
		(0.0081)				
Sales growth$_{t+2,t-1}$ X Sales growth ≥ 0			0.0781***			
			(0.0071)			
Sales growth$_{t+2,t-1}$ X Sales growth < 0			0.0709***			
			(0.0154)			
Sales growth$_{t+3,t-1}$ X Sales growth ≥ 0				0.0753***	0.0441***	0.0333***
				(0.0099)	(0.0072)	(0.0062)
Sales growth$_{t+3,t-1}$ X Sales growth < 0				0.0878***	0.0626***	0.0256
				(0.0276)	(0.0185)	(0.0159)
Firm fixed effects	No	No	No	No	Yes	Yes
Time fixed effects	No	No	No	No	No	Yes
R2	0.036	0.048	0.050	0.049	0.728	0.784
Number of observations	56,061	24,310	12,272	6,425	6,026	6,026
Test coefficients equal (p-value)	0.000	0.096	0.704	0.699	0.384	0.672

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.

Table A5: Price response to hypothetical unit cost shocks

	(1)	(2)	(3)	(4)
Dependent Variable:	Average price response (%)			
Sample Period:	August-2024 to October-2024			
Unit cost shock	0.4122***	0.4122***		
	(0.0096)	(0.0096)		
Unit cost shock^2		0.0106***		
		(0.0004)		
Unit cost shock X Shock > 0			0.6080***	0.6179***
			(0.0132)	(0.0198)
Unit cost shock X Shock < 0			0.2165***	0.2470***
			(0.0105)	(0.0168)
R^2	0.416	0.497	0.510	0.542
Number of observations	3,728	3,728	3,728	3,728
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. 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 A6: Relationship between unit cost growth and price growth forecast errors

	(1)	(2)	(3)	(4)	(5)
Dependent Variable:	Price Growth Forecast Error (pp)				
Sample Period:	2018Q1 – 2025Q3 (with gaps)				
Unit cost growth forecast error	0.2691***	0.2633***			
	(0.0626)	(0.0629)			
Unit cost growth forecast error^2		0.0104			
		(0.0129)			
Unit cost growth forecast error X Error≥0			0.3491***	0.3859***	0.3807***
			(0.0662)	(0.1133)	(0.1122)
Unit cost growth forecast error X Error<0			0.1820***	0.1443	0.0968
			(0.0692)	(0.1150)	(0.1129)
Expected year-ahead own-price growth					0.4496***
					(0.1062)
Firm fixed effects	Yes	Yes	No	Yes	Yes
Time fixed effects	Yes	Yes	No	Yes	Yes
R2	0.473	0.474	0.037	0.475	0.505
Number of observations	1,472	1,472	2,260	1,472	1,459
Test coefficients equal (p-value)			0.134	0.206	0.130

Notes: This table shows the relationship between unit cost growth forecast errors and annual price growth forecast errors. Unit cost forecast errors are trimmed at the 5th and 95th percentiles by quarter. Price forecast errors are winsorised at the 1st and 99th percentiles. The constant of the regressions are also estimated but not reported. 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.