Sectoral Phillips Curves: The Role of Expectations and Production Networks in Price Setting in the UK

Cristina Griffa*

September 22, 2023

Preliminary and Incomplete

Please do not cite or circulate

LINK TO THE LATEST VERSION

Abstract

The recent inflation surge has spurred renewed interest about understanding its main drivers. This has prompted a search for enhanced empirical methods and more sophisticated data to estimate the Phillips Curve. In this paper, I examine price-setting behaviour across 52 sectors in the UK and identify the main determinants of the heterogeneity in this process uncovered. I first estimate the Phillips Curve at the sector level using heterogeneous panel methods that account for unobserved time-varying heterogeneity. This approach enables me to identify the Phillips Curve parameters with significant and positive slopes when using labour costs. My analysis also reveals that the introduction of production networks through intermediate goods costs also yields a significant and positive slope, suggesting relevant dynamics across sectors which are usually not accounted for in the traditional estimation of the Phillips Curve. My analysis also reveals substantial heterogeneity across industries in the degree of forward- and backward-lookingness, and in the responsiveness to costs. After uncovering this asymmetry, I further investigate its main drivers, focusing on sector-specific cost and market structure. These results reveal that the level of concentration is positively associated with the relevance of expectations in firms' price-setting decisions. This finding suggests that expectations play a larger role in the price-setting decisions of sectors facing less competition.

JEL: C21, C23, E31, E70

*School of Economics, University of Nottingham. Website: cristinagriffa.com. Email: Cristina.Griffa@nottingham.ac.uk I am very grateful to Kevin Lee, Paul Mizen and Rahul Mukherjee for their invaluable support and guidance throughout this research project. I thank Galina Potjagailo for her comments and helpful conversations. I thank Omar Licandro, Nacho Vizcaino, Markus Eberhardt, colleagues from the University of Nottingham, colleagues from the Bank of England and participants in the Edinburgh-Nottingham Joint Macro PhD Workshop, ESCoE Conference on Economic Measurement, Money Macro and Finance PhD Conference, Warwick Economics PhD Conference, IAAE conference and CEF conference for insightful discussions. I thank the IAAE for awarding me the Student Travel Grant to present at the 2023 IAAE conference. I am also grateful to the CBI for help and advice on accessing the CBI Suite of Business Surveys.

1 Introduction

The recent surge in inflation has triggered renewed interest in the main drivers of inflation. The Phillips Curve is a fundamental element in models employed by central banks to study the inflation process. It helps explain how expected future inflation and firms' costs collectively shape the current inflation rate. The slope of the Phillips curve, i.e. the sensitivity of inflation to real activity suggests that when the economy is above its potential, higher demand pushes up labour costs, which are, to some extent, transferred to prices. The strength of this relationship has been broadly documented, with many studies showing a disconnect between inflation and the forcing variable. A weak relationship complicates the central bank's task of maintaining stable prices. To achieve the inflation target, larger shifts in economic activity and interest rates would be required. This has called into question the ongoing usefulness of the Phillips curve and prompted a search for enhanced ways of estimating it.

The first goal of my paper is to provide an enhanced identification of the Phillips Curve parameters by using sectoral and survey-based data. The second goal is to uncover the heterogeneity across sectors in the role of costs, expectations and the production network. Lastly, I further investigate the potential sources of the heterogeneity, focusing on some industry characteristics that are not included in the traditional microfoundation of the Phillips Curve.

The weak identification and instability in the estimation of the Phillips Curve could be related to various sources[1], being some of them related to the misspecification of the structural parameters while others to the use of weak proxies due to lack of data availability. Some common assumptions behind the derivation of the aggregate Phillips Curve are: one-sector economy, price stickiness, optimal price setting by monopolistically competitive firms, labour-based production function, constant frictionless markup, perfect competition in labour markets and rational expectations. A more realistic understanding of the inflation process is obtained through studying a multi-sector economy, affected by sectoral shocks, with asymmetric price rigidities, heterogeneity in markups and sector-level production costs. By modelling an economy with these assumptions, a Sectoral Phillips Curve is obtained. Another potential layer of misspecification may arise from the assumptions behind the production function. For instance, Imbs, Jondeau, and Pelgrin, 2011 derived a Sectoral Phillips Curve with firms exposed to only labour costs, while more recently, Rubbo, 2023 proposed a new derivation by incorporating the intermediate goods as an extra source of costs variation.

[1] See Mavroeidis, Plagborg-Møller, and Stock, 2014, Abbas, Bhattacharya, and Sgro, 2016 and DelNegro et al., 2020 for more details.

I estimate the Sectoral Phillips Curves based on the two frameworks and show that their structural parameters are very similar in the case of the role of expectations and lagged inflaton. However, the responsiveness to costs is significantly smaller when labour costs are considered alone compared to when intermediate goods costs are also taken into account. When intermediate goods costs are included in firms' expenses, it introduces sectoral linkages and additional nominal rigidities within the supply chain. This becomes particularly relevant during the recent inflation spike, as production networks and sectoral linkages introduce a crucial layer to understanding the inflation process. Both frameworks suggest that the slope has not disappeared and prices respond positively and significantly to marginal costs. Also, through the estimation of sector-specific Phillips Curves, I will also show evidence of the heterogeneity across sectors in the strength of the slope and in the role of expectations.

Having unmasked the asymmetric price setting behaviour across sectors, the second goal is to investigate its main sources. I do so by focusing on the sector-specific slopes. I study the extent to which the role of expectations is associated with some industry-characteristics. Among other findings, I observe a positive relationship between the degree of market concentration and the forward-looking parameters of the Phillips Curve. This suggests that in sectors with higher concentration, expectations play a larger role in firms' price-setting behaviour[2].

Regarding the use of weak proxies, a flat or negative slope might result from employing aggregate data. This is because monetary policy aims to offset demand shocks by raising interest rates, which leads to lower inflation. This does not hold when using more disaggregate data as the central bank cannot directly offset regional or sectoral shocks[3]. Another potential reason for weak identification could stem from using output gap as proxy for marginal costs. A negative slope might suggest a low elasticity of marginal cost to the output gap and not necessarily a low response of prices to costs[4]. Finally, potential measurement errors may arise from using indirect measures of expectations, such as forecasts from professionals or households expectations[5], actual inflation as an instrument, or assuming rational expectations.

This paper aims to address some of the identification challenges by estimating Sectoral Phillips Curves based on labour and intermediate goods costs, using survey data from UK firms and accounting for sectoral linkages through the input-output table. The specific

[2]This result is in line with Leith and Malley, 2007.

[3]McLeay and Tenreyro, 2019 and Hazell et al., 2022 have shown evidence of statistically and economically significant slopes by employing regional data.

[4]Gagliardone et al., 2023, Rubbo, 2023 have highlighted the advantage of using costs as forcing variable instead of output.

[5]Coibion, Gorodnichenko, and Kamdar, 2018

research questions addressed by this paper are as follows: Can the identification of the Phillips Curve be enhanced by using sectoral and survey-based data? Can the Sectoral Phillips Curve reveal underlying heterogeneity? If so, which sectors exhibit a more prominent role for expectations? What are the primary drivers behind these sectoral asymmetries? By tackling these questions, this study not only contributes to the academic literature but also carries implications for policymaking. This is because monetary policy can influence inflation by managing inflation expectations and can be further refined by utilising more sophisticated slope estimations.

I leverage the panel dimension of the dataset to enhance the identification approach. By estimating heterogeneous dynamic panel data models I aim to mitigate the potential cross-sectional dependence while retrieving sector-specific coefficients. The Phillips Curve has typically been estimated at the economy-wide level[6], assuming homogeneity across firms and sectors. More recent works[7] have shown evidence against that assumption. When homogeneity is imposed -and discrepant with the data-, estimations show potentially misleading and inconsistent results such as large inflation inertia and low significance of real marginal costs. Imbs, Jondeau, and Pelgrin, 2011 and Byrne, Kontonikas, and Montagnoli, 2013 estimated labour cost-based Sectoral Phillips Curves for manufacturing firms, showing evidence of the relevance of sector-level heterogeneity.

A novel aspect of this work is the use of survey-data on firms' expectations and labour and intermediate goods costs to estimate the Phillips Curve. The most common approach for proxying expectations has been to use future inflation as an instrument or rational-expectations[8], mainly due to the lack of available data on firms' expectations. However, these methods have faced scrutiny and criticism regarding the problem of weak instruments[9]. As for the forcing variable, most papers use a measure of the output gap or labour share since data on firm's labour costs are usually not available. It is important to acknowledge that survey-based expectations are not perfect either, since these are subject to measurement errors. Nevertheless, direct measures make the estimation more realistic and mitigate the statistical problem that might arise from using weak instruments. To the best of my knowledge, this is the first work to estimate Sectoral Phillips Curves with direct measures of firms' inflation expectations, self-reported measures of labour costs and the effects of production networks. Therefore, the results might not be directly comparable to previous evidence.

[6] Among others, Gali and Gertler, 1999, Sbordone, 2002, Rudd and Whelan, 2006

[7] Andrade et al., 2022, Byrne, Kontonikas, and Montagnoli, 2013, Imbs, Jondeau, and Pelgrin, 2011, Maćkowiak, Moench, and Wiederholt, 2009, Leith and Malley, 2007

[8] Some examples: Gali and Gertler, 1999, Leith and Malley, 2007, Maćkowiak, Moench, and Wiederholt, 2009, Imbs, Jondeau, and Pelgrin, 2011, Byrne, Kontonikas, and Montagnoli, 2013

[9] See e.g. Byrne, Kontonikas, and Montagnoli, 2013 and Nason and Smith, 2005)

The results of the paper speak to recent policy debates on the relevance of inflation expectations in the firms' price setting behaviour and the heterogeneity across sectors. More backward-looking inflation expectations may need the monetary policy to lean more heavily and quicker against inflation to minimise the risks of further rising inflation (IMF, 2022). Also, monetary policy effects are larger and more persistent when accounting for the heterogeneity across sectors (Carvalho, 2006).

Related literature. This paper contributes to the broad literatures on inflation dynamics, the estimation of the Phillips Curve, non-rational expectations, and heterogeneity in macroeconomics. Mavroeidis, Plagborg-Møller, and Stock, 2014 provides a comprehensive review of the literature and discusses the weak identification and instability in the estimation of the Phillips Curve. A non-exhaustive list of the related topics and papers includes:

- on the use of more disaggregated data: McLeay and Tenreyro, 2019 and Hazell et al., 2022 use regional data;
- on the relevance of forward-looking expectations: originally highlighted by Friedman, 1968, recently claimed in relevant works by Hazell et al., 2022, Werning, 2022, and in the recent speech by Mann, 2022;
- on the relevance of intermediate goods costs and the production network: Rubbo, 2023
- on the importance of using direct measures of expectations, firstly suggested in Roberts, 1995, and studied more recently in Adam and Padula, 2011;
- on the use of firms' expectations: Coibion and Gorodnichenko, 2015 & Coibion, Gorodnichenko, and Kamdar, 2018; in particular, for the UK: Boneva et al., 2020;
- on the heterogeneity across agents: Leith and Malley, 2007, Imbs, Jondeau, and Pelgrin, 2011 and Byrne, Kontonikas, and Montagnoli, 2013 using sectors and Meeks and Monti, 2022 and Candia, Coibion, and Gorodnichenko, 2021 for households;
- on the use of output gap as proxy for the forcing variable: Gagliardone et al., 2023;
- and on the study of the sources of asymmetries across sectors in the price setting behaviour and in the role of expectations: Andrade et al., 2022 & Klenow and Malin, 2010

Outline. The rest of the paper is structured as follows. Section 2 explains the economics of price-setting behaviour and the microfoundation of the Sectoral Phillips Curve for the case where costs are explained by the labour factor, and when intermediate goods costs are also included. Section **??** delves into some of the estimation and measurement issues found in previous works and proposes solutions to some of them. Section 4 describes the data used for the estimations. Section 5 shows the results from the empirical estimation. Section 6 examines additional industry characteristics associated with the sector-specific Phillips Curve parameters. Section 7 provides the conclusion.

2 The economics of price-setting behaviour and cross-industry heterogeneity

In this section, I will discuss two frameworks for studying sectoral inflation dynamics. First, I will introduce the labour cost-based Sectoral Phillips Curve, based on IJP. This framework extends the traditional microfoundation approach used to derive the aggregate Phillips Curve by incorporating distinct key assumptions that allow it to explain sectoral inflation processes, rather than aggregate inflation dynamics. One notable limitation of this framework is its omission of sectoral interactions within the theoretical setting. IJP acknowledge the presence of production linkages in real-world firms' pricing behaviour and approximate them empirically by allowing potential correlations in sectoral disturbances and incorporating cross-sectoral interdependencies that may exist in the data through econometric techniques. I'll take a step further and estimate the Sectoral Phillips Curves with the production linkages embedded in the production function. The omission or weak approximation of these sectoral interactions is likely to result in mis-specified sector-specific parameters.

Recent literature has increasingly focused on explicitly incorporating the production network into the Phillips Curve microfoundations. To this end, the second framework will be based on the Sectoral Phillips Curve expression obtained by Rubbo, 2023. Using the input-ouput table, I will proxy intermediate goods costs and sectoral linkages, and present novel empirical evidence on how sectoral interconnections affect the inflation process. I will delve deeper into this framework in the second part of this section.

Finally, in the third part of this section I will discuss additional industry-characteristics not accounted for in the studied theoretical frameworks that are also associated with the cross-industry heterogeneity.

2.1 Labour cost-based Sectoral Phillips curve

Combining insights from Gali, Gertler, and David Lopez-Salido, 2001, Sbordone, 2002, and Woodford, 2003, but extending the analysis to encompass multiple sectors, Imbs, Jondeau, and Pelgrin, 2011 (henceforth IJP) derived a sectoral New Keynesian Phillips Curve (NKPC).

Some of the main assumptions in the IJP framework are:

- Optimal price setting by monopolistically competitive firms.
- Price updating follows a $(1-\alpha_k)$ probability distribution, similar to Calvo, 1983[10]. Importantly, here the degree of price stickiness, α_k, is allowed to vary across sectors.
- The production function features labour as the only factor of production and sector-specific technology:

$$Y_{ikt} = Z_{kt}\, L_{ikt}^{1-a_{kt}}$$

where $1-a_{kt}$ represents the share of labour in sector k's value added

- Demand function:

$$Y_{ikt} = Y_{kt}\left(\frac{P_{ikt}}{P_{kt}}\right)^{-\eta}$$

In this equation, P_{ikt} is the price of firm i of good k chosen taking P_{kt} (price index in k) and Y_{kt} (AD) as given. The parameter $\eta > 1$ is the elasticity of substitution across varieties within sector k, and assumed homogeneous across sectors.

- A constant frictionless markup μ.
- Perfect competition in labour markets, i.e. labour is undifferentiated and fully mobile across industries.

Based on the sticky prices mechanism, prices in sector k are comprised by $(1-\alpha_k)$ share of firms that have updated prices at time t and a α_k share of firms that have maintained last period's prices. As they anticipate a delay before the next price change prices, firms form expectations about future cost and demand conditions, in addition to current conditions. They then optimally set their prices as a mark-up over their marginal costs. Therefore, the sectoral price level in period t is calculated as:

$$\hat{p}_{kt} = \alpha_k\, \hat{p}_{k\,t-1} + (1-\alpha_k)\, \hat{p}^*_{kt}$$

Real marginal cost is defined as: $S_{ikt} = \Psi'(Y_{ikt})/P_{ikt}$. Costs in steady state are assumed as follows: $S_{ik\,t,t+j} = S_k = \eta/(\eta-1)$. Nominal variables are expressed as log deviations from the steady state[11]: $\hat{s}_{ikt} = s_{ikt} - \overline{s}_{ik}$, and $\hat{p}_{ikt} = p_{ikt} - \overline{p}_{ik}$.

IJP derive the following linearised hybrid Sectoral Phillips Curve. Detailed derivation is provided in Appendix A. This expression is analogous to the aggregate Phillips Curve [12],

[10] One advantage of Calvo's time-dependent framework (as opposed to state-dependent ones) is its explicit closed-form equation to describe the relationship between aggregate inflation and aggregate output.

[11] When taken to the data, the steady state is approximated through the sample mean.

[12] Microfounded in seminal works by Clarida, Galí, and Gertler, 1999, and Woodford, 2003

but instead of being economy-wide, it yields sector-specific parameters:

$$\hat{\pi}_{kt} = \frac{\omega_k}{\phi_k}\,\hat{\pi}_{k\,t-1} + \frac{\beta\alpha_k}{\phi_k}\,E_t\hat{\pi}_{k\,t+1} + \frac{(1-\omega_k)(1-\alpha_k)(1-\beta\alpha_k)}{\phi_k}\,h_k\,\hat{s}_{kt} \tag{1}$$

This can also be expressed in the reduced-form:

$$\pi_{kt} = \gamma_k^b\,\pi_{k\,t-1} + \gamma_k^f\,E_t\,\pi_{k\,t+1} + \gamma_k^s\,h_{kt}\,\hat{s}_{kt} + \varepsilon_{kt}^{\pi} \tag{2}$$

where

$$\phi_k = \alpha_k + \omega_k\,[1 - \alpha_k(1-\beta)]$$

$$h_{kt} = \frac{1}{\left(1 + \frac{\eta\,a_{kt}}{1-a_{kt}}\right)}$$

The factor h_{kt} depends on the elasticity of substitution across varieties (η) and the labour share $(1-a_{kt})$. For estimation purposes, I will adopt IJP's approach of computing h_{kt} using observed labour shares[13], and a value for η corresponding to a level of markups calibrated at 10% which gives $\eta = 11$. The error term ε_{kt}^{π}, is a cost-push shock.

$$\mu = 1.1$$
$$\eta = \frac{\mu}{\mu-1} = 11$$

The expression in Equation 2 describes inflation dynamics in each sector π_{kt}, as a function of past and expected future inflation and real marginal costs; where γ_k^b, γ_k^f and γ_k^s are functions of the underlying deep parameters: the degree of backward lookingness (ω_k), the degree of price stickiness (α_k), and the discount factor (β).

An important drawback of this framework is its omission of sectoral interactions within the theoretical framework. IJP recognize the presence of production linkages in real-world firms' pricing behaviour and address this empirically by allowing for potential correlations in sectoral disturbances and incorporating cross-sectoral interdependencies that may exist in the data. I will discuss this in more detail in subsection 3.2.

In line with Gali, Gertler, and David Lopez-Salido, 2001, IJP advocates a marginal cost-based Phillips curve. They claim that this setting directly captures the impact of productivity gains on inflation. However, other studies support the use of the output gap as a measure of economic activity. In Subsection 3.3, I will explore the upsides and downsides of each approach in greater detail.

[13]IJP estimate h_k as they may not have data on labour shares for all periods. In my case, I use yearly data from the input output tables; therefore, the 't' in h_{kt} refers to years instead of quarters.

2.2 Labour and intermediate goods cost-based Sectoral Phillips curve

A widespread consensus attributes the recent inflation surge in most advanced economies to a combination of demand and supply shocks, impacting sectors heterogeneously, and followed by deanchoring and a rise in inflation expectations [14]. This complex inflation process demanded a more sophisticated theoretical framework that integrates the production network into the Phillips Curve microfoundation. The following section delves into the second framework rooted in the Sectoral Phillips Curve model introduced by Rubbo, 2023.

Leveraging data from input-output tables, the estimation of this framework allows us to capture intermediate goods costs and sectoral linkages, providing novel empirical insights into how sectoral interconnections influence inflation dynamics. Rubbo claims that price rigidities compound at each step along the production chain, with price rigidity in the intermediate goods sector reducing the pass-through of wages into the final good producer's marginal cost.

Key differing assumptions in Rubbo's framework compared to IJP:

- The Production function has only one factor of production and sector-specific technology that is constant over time. The main difference with IJP is that the firms take also intermediate goods from all industries, X_{kj}, as inputs.

$$Y_k = Z_k \, F_k \left(L_k, [X_{kj}]_{j=1}^{N}\right)$$

- Sectoral linkages are captured by micro level intermediate input shares.
- Nominal rigidities can also result from wage stickiness.
- Firms choose for the input combination that minimises costs, being the industry-level marginal costs as follows:

$$MC_{kt} = \min_{[X_{kjt}],L_{kt}} W_t \, L_{kt} + \sum_j P_{jt} \, X_{kjt}$$

The main expressions[15] I will use from Rubbo's framework are the following[16]:

$$\pi_{kt} = A(mc_{kt} - p_{k\,t-1}) + \beta \, (I - A) E_t \, \pi_{k\,t+1} \tag{3}$$

[14]See Reis, 2023 for a comprehensive analysis of the main factors behind the recent rise in inflation in most western advanced economies.

[15]Some details on the derivation are provided in Appendix B.

[16]These linearised equations correspond to Equations 14 and 15 in Rubbo's paper; the notation has been changed to match this paper's notation.

Equation 3 represents the sectoral inflation rate process, jointly explained by sector-level marginal costs (net of same sector lagged prices) and sector-level inflation expectations. The parameter A corresponds to the diagonal of sector-level price stickiness.

$$mc_{kt} = (1 - a_k)\, w_{kt} + \Lambda\, p_{kt} - logZ_{kt} \tag{4}$$

Equation 4 represents the evolution of marginal costs for any sector. It is explained by the sector-level labour cost w_{kt}, which is weighted by the share of labour; the contemporaneous prices in the other sectors from which sector k buys intermediate inputs, weighted by the shares of expenditures in those sectors; and the logarithm of productivity. The parameter Λ is the matrix of shares of intermediate goods.

By combining Equation 3 and Equation 4 and after working out the algebra, I obtain the expression shown in Equation 5. I show an illustrative derivation for 2 sectors in Appendix B. Despite the expression looking similar to the reduced form from IJP, the underlying structural parameters derived from Rubbo embed the sectoral linkages, and hence, the interpretation is less straightforward.

$$\pi_{kt} = \gamma_k^f\, E_t\, \pi_{k\,t+1} + \gamma_k^s\, s_{kt}^R + \varepsilon_{kt}^{\pi} \tag{5}$$

where γ_k^f and γ_k^s depend on A and α.

I approximate the Rubbo's cost measure, s_{kt}^R[17], by using: the labour share for each sector, $(1 - a_{kt})$, the intermediate goods share bought by sector k from sector j, a_{kjt}, and sector j's intermediate goods' prices, $\hat{p}_{jt}$, being $\hat{p}_{jt}$ the log deviation of price from the sectoral sample mean and $\hat{w}_{kt}$ the log deviation of wage from the sectoral sample mean.

$$s_{kt}^R = \hat{s}_{kt} - \hat{p}_{k\,t-1}$$
$$\hat{s}_{kt} = (1 - a_{kt})\, \hat{w}_{kt} + \sum_j \lambda_{kjt}\, \hat{p}_{jt}$$

2.3 Additional industry-characteristics affecting the price-setting behaviour

2.3.1 Open economy Phillips Curve framework

The Phillips Curve proposed by IJP does not consider the role of foreign factors such as the price of import prices, the price of oil, and the degree of openness. Abbas, Bhattacharya, and Sgro, 2016 show evidence that the open economy NKPC, which incorporates prices of imported goods, performs better in explaining the process of inflation dynamics for Australia, Canada, New Zealand and the UK.

[17] For more details, see Equations 14 and 15 from her paper

Batini, Jackson, and Nickell, 2005 derived an open NKPC framework to capture employment adjustment costs and the openness of the UK economy. They find that their modifications to the baseline NKPC are relevant for UK data and that inflation is explained by changes in the added variables: employment, real import prices and oil prices. Below is the expression they derived, slightly modified to match the notation in this work.

$$\pi_t = \gamma^f\, E_t\{\pi_{t+1}\} + \gamma^b\, \pi_{t-1} + \gamma^s\, s_t + \alpha_1\, z_{p,t} + \alpha_2\, (p_t^W - p_t) + \alpha_3\, s_{L,t} + \alpha \Delta n_t + \varepsilon_t^\pi \qquad (6)$$

where $z_{p,t}$ is product market competition, $(p_t^W - p_t)$ is the weakness or strength of foreign competition, $s_{L,t}$ is the labour share, $p_{m,t}$ is the real price of imports and n is a measure of employment.

To my knowledge, nobody has derived the sectoral NKPC framework for an open economy. Therefore, this paper estimates the structural framework based on Woodford, 2003 and IJP as well as some modified versions, combining elements from Batini, Jackson, and Nickell, 2005. I show in the empirical section that these modifications, such as controlling for oil inflation and real import prices, might improve the results in some cases, i.e. yield parameters more consistent with the theory.

2.3.2 The sectoral Phillips Curve framework allows to unmask asymmetries across sectors

Policymakers have struggled recently to understand why inflation dynamics differ from the predictions of workhorse models. Poor results has sparked a debate about the usefulness of the aggregate Phillips curve framework for policy analysis (DelNegro et al., 2020, Hazell et al., 2022) and suggested to use dissagregate data, either regional or sectoral, as a way of addressing the identification issues.

Also, aggregate dynamics can mask heterogeneous dynamics across sectors which might inform the policymakers for expectations and communication management. Monetary policy (MP) effects are larger and more persistent when accounting for the asymmetries across sectors (Carvalho, 2006). The asymmetries in the frequency of price changes across sectors lead to differences in the speed of reaction to a shock. Furthermore, more backward-looking inflation expectations may need the MP to lean more heavily and quicker against inflation to minimise the risks of further rising inflation (IMF, 2022).
Having unmasked the asymmetric price setting behaviour across sectors, the next question is: what are the main drivers of those asymmetries? The closest work to this type of analysis is Leith and Malley, 2007, which estimated the NKPC structural parameters for US industries and found that market concentration (Herfindahl-Hirschman index) is positively

correlated with the estimated measure of price stickiness. They argue that, the more concentrated an industry (less competition), the more sticky its price-setting behaviour and the more likely it is to set prices in a forward-looking manner. They also show evidence that industries are more backward-looking when output in that industry is more volatile.

Klenow and Malin, 2010 provide a (non-exhaustive) list of factors affecting the frequency of price changes investigated by researchers by the time of the publication of the handbook (2010), which include: inflation variability, the frequency and magnitude of cost and demand shocks, the structure and degree of market competition, and the price collecting methods of statistical agencies. Also, Bils and Klenow, 2004 studies the correlation between frequency of price change in different product categories and measures of market structure: the concentration ratio, wholesale markup, and rate of non-comparable substitutions in those categories and find that the first two measures are not significant after controlling for whether a good is raw/processed. They claim a positive relationship between the frequency of price changes and the degree of competition because firms therein face more elastic demand.

Kato, Okuda, and Tsuruga, 2021 show evidence that sectoral inflation persistence is negatively correlated with market concentration. Their inflation persistence could be captured in the NKPC framework by γ^b. Given that the NKPC framework predicts that γ^b and γ^f move in opposite directions, these authors' findings might be interpreted as $\uparrow$ HHI & $\uparrow \gamma^f$. Using US producer price data, they show that pricing complementarity (the sensitivity of individual prices to their competitor's prices) among monopolistically competitive firms decreases as market concentration increases. Intuitively, when the market is more concentrated, firms' products are more differentiated and less substitutable. As substitution becomes more difficult across products, the price of a firm's product becomes less sensitive to its competitors' prices. Thus, pricing complementarity becomes weaker.

Other relevant and related works examine the factors driving price changes instead of using the NKPC parameters. Vermeulen et al., 2007 shows evidence that firms with a higher labour cost share tend to change prices less frequently, whereas firms with higher energy cost share and non-energy intermediate goods change prices more frequently. Moreover, they find that the higher the degree of competition, the higher is the frequency of producer price changes.

Lastly, Domberger, 1979 finds the opposite results: a positive relationship between the speed of price adjustment and market concentration. He reflects on two plausible hypotheses: the first claims that price coordination in concentrated industries is much easier due to relatively low costs of information gathering and communication among sellers, potentially rising the speed of price adjustment; the second one is associated with "administered prices" and states that sellers in highly concentrated markets tend to adjust prices unilaterally either due to the difficulties of oligopolistic collusion or through the use of mark-up pricing. While Domberger shows evidence supporting the first hypothesis, it is important to mention that the sample studied (1963-1974) is characterised by a rising inflation period and, hence, mostly upward price movements. Also, his sample comprises mainly industrial sectors whereas my sample includes services and distributive sectors as well, showing a wider spectrum of market structures.

2.3.3 Forward-looking parameter is positively related to price stickiness

From the microfoundation of the Phillips Curve we know that γ^f is a combination of β (discount factor), α (price stickiness; the share of firms that do not update prices in t) and ϕ (which ultimately depends on α, β, ω). β is usually assumed close to 1. Intuitively, the larger the price stickiness (larger α) in sector k, the more firms without the chance to update prices every t and will give more weight (larger γ^f) to expected future markups. That is because firms will have to stick to the same price for a longer time. As a result, γ^f is positively related to the rigidity in prices.

This argument is in line with Werning, 2022 who argues that firms set their price initially above their ideal price, but over time their price ends up below their ideal price. Then, the greater the expected inflation, the greater must be the price over the currently ideal price. Hence, firms in sectors that face lower frequency of price changes will overshoot inflation proportionally more to compensate. The larger α (share of firms that do not have the chance to update prices), the higher pass-through from expectations of future inflation to current inflation.

2.3.4 Forward-looking parameter and the Herfindahl-Hirschman Index

Bils and Klenow, 2004 find an inverse relationship between the concentration ratio and the frequency of price changes. These authors claim that the greater frequency of price changes in markets with more competition is because firms face more elastic demand, based on models of price adjustment (e.g., Barro, 1972). With more competition, substitution becomes easier across products, the price of a firm's product becomes more sensitive to its competitors' prices. Thus, pricing complementarity is larger.

To study this relationship I calculate the Herfindahl-Hirschman Index for each sector given that it's not officially calculated in the UK.

2.3.5 Other determinants of the cross-sector heterogeneity in the forward-lookingness

Competition: Besides the indices of degree of concentration already mentioned, Vermeulen et al., 2007 also studies the impact of external competition through an indicator of "import penetration" derived from input–output tables. Alvarez and Hernando, 2007 obtain that the degree of import penetration has a significant positive but weak effect on the frequency of price changes. These authors measure import penetration as total imports over total resources (production plus total imports), using the Input–Output tables.

Inflation variability: Dhyne et al., 2006 show that the overall frequency are significantly higher in sectors in which the variability of inflation is higher. Then we may expect that firms move quicker when they face more volatility in inflation as a way of staying closer to the optimal price.

Cost structure: Vermeulen et al., 2007 and Alvarez and Hernando, 2007 show that firms in labour-intensive sectors adjust prices less frequently ($\uparrow\ \alpha$), potentially because wages adjust less frequently than other input prices. Both mentioned works also show that firms with higher share of energy and intermediate inputs in total costs is positively correlated with the frequency of price changes, because prices of raw materials change very frequently.

I will test the potential drivers of the degree of forward-lookingness in section 6.

3 Sectoral NKPC: an empirical investigation

In the empirical analysis that follows, I adopt a partial equilibrium approach to estimate the sectoral Phillips Curve as in IJP. These authors use French data to estimate the Philips Curve for each sector k, where the magnitude of backward-looking behaviour and price stickiness are sector-specific.

In the first part of this section I briefly describe the main identification issues encountered and discussed in the literature related to the estimation of the Phillips Curves. For a comprehensive review, see Mavroeidis, Plagborg-Møller, and Stock, 2014 and Abbas, Bhattacharya, and Sgro, 2016. In the second part I explain how I address some of the issues using direct measures of expectations, sectoral data, and panel methods, among other aspects. In the third part I discuss the tradeoff between using the marginal cost and the output gap as a proxy for the slack measure.

3.1 Identification and estimation challenges

Over the last decade, the empirical performance of the Phillips Curve has been largely debated. Some of the main identification problems raised in the literature are: the assumption about homogeneity across sectors, the use of aggregate data and/or aggregate expectations, the choice of the slack variable, the use of actual/realised inflation as a proxy for expected future inflation, and the approach used to mitigate the simultaneity problem.

The Phillips Curve has typically been estimated at the aggregate level, assuming homogeneity across firms and sectors. Nonetheless, if there is heterogeneity across sectors in the data and homogeneity is imposed, the results will have an aggregation bias as explained before. Imbs, Jondeau, and Pelgrin, 2011 and Byrne, Kontonikas, and Montagnoli, 2013 estimated the sectoral NKPC and obtained lower persistence of inflation and significantly large coefficients on real marginal costs, as compared to the aggregate level, thereby confirming the empirical importance of sector-level heterogeneity.

As an example against the use of actual inflation as a proxy for inflation expectations, Roberts, 1995 compared the estimation of the economy-wide NKPC by using survey data and actual inflation. He found that only the former yield the correctly signed (positive) and statistically significant slope. These estimates were statistically insignificant when actual future inflation is used as a proxy for inflation expectations.

Simulateneity problem: the estimation of the Phillips Curve also faces the simultaneity problem of distinguishing demand and supply shocks, as argued by Hazell et al., 2022. They explain that supply shocks comove both inflation and unemployment positively. If the variation used to identify the slope of the Phillips Curve is contaminated by such shocks, the estimated slope will be biased.

The flat slope might be driven by the endogenous response of the monetary policy: Another simultaneity problem faced when estimating the aggregate Phillips Curve is the disconnect between inflation and the real activity generated by a forceful response of the monetary policy to inflation. As explained in McLeay and Tenreyro, 2019, the slope of the Phillips Curve is the result of the interaction between the Aggregate Supply (AS) and the Aggregate Demand (AD). The AS captures the positive relationship between inflation and real activity. The AD relationship tells us that the central bank aims to offset demand shocks with the monetary policy. Being successful in its goal, the AD would offset the AS and we would only see a negative slope, reflecting the endogenous response of the monetary policy to inflationary pressures: when inflation is rising, the central bank tightens slowing down the economy. This argument would explain the empirical evidence on flat Phillips Curves when using aggregate data. As a way of addressing this problem, some researchers showed that cross-sectional data (either regional or sectoral) can help overcome this simultaneity issue. See McLeay and Tenreyro, 2019 for an example with regional data.

3.2 Solutions proposed to the described challenges

3.2.1 Using disaggregate data

If there is heterogeneity across sectors in the data and homogeneity is imposed, the results will have an aggregation bias. Estimations show potentially misleading and inconsistent results such as large inflation inertia and low significance of real marginal costs. Imbs, Jondeau, and Pelgrin, 2011 and Byrne, Kontonikas, and Montagnoli, 2013 estimated the sectoral Phillips Curve and obtained lower persistence of inflation and significantly large coefficients on real marginal costs, as compared to the aggregate level, thereby confirming the empirical importance of sector-level heterogeneity.

Using disaggregate data not only captures better inflation dynamics but it has also helped to reveal some interesting policy implications. Sheedy, 2007 shows that inflation persistence is lower with heterogeneity in price stickiness across sectors than without it. Carvalho, 2006 argues that the presence of heterogeneity in the frequency of price changes across sectors leads to differences in the speed of reaction to a shock. Monetary policy shocks are larger and more persistent in heterogeneous economies.

3.2.2 Survey-based expectations

The importance of future prices raises the issue of how to deal with expectations about prices. The most common approach to estimate the forward-looking component of the Phillips Curve has been using system-built expectations, either IVs or rational-expectations (GG, Leith and Malley, 2007, Maćkowiak, Moench, and Wiederholt, 2009, Imbs, Jondeau, and Pelgrin, 2011, Byrne, Kontonikas, and Montagnoli, 2013) mainly due to the lack of available data on firms' expectations.

Byrne, Kontonikas, and Montagnoli, 2013 and Nason and Smith, 2005 claim that those methods have been under scrutiny and criticism regarding the problem of weak instruments, and suggest as a solution to use surveys of disaggregate expectations. Similarly, Coibion, Gorodnichenko, and Kumar, 2018 state: "The survey-based Phillips Curve addresses one of the weaknesses of the RE-based Phillips Curve which is that it does not reflect the evolving structure of an economy where the policymakers objective function is not fully known by private agents".

The use of survey data as a proxy for inflation expectations in the Phillips Curve was introduced by Roberts, 1995. The latter as well as Adam and Padula, 2011 used survey-based expectations from professional forecasters and consumers to estimate the Phillips Curve model and obtained significant and theoretically-consistent results.

In another study, Coibion and Gorodnichenko, 2015 stress the importance of using direct measures of firms' expectations for optimal analysis. Not having firms' expectations available, they provide evidence that even household data serves as a more accurate proxy for firms' expectations than professional forecasters and financial markets.

Importantly, the original microfoundation of the Phillips Curve states that rational expectations are crucial. This condition has been examined by Adam and Padula, 2011, who argue that nonrational expectations can be incorporated into the Phillips Curve framework as long as economic agents satisfy the Law of Iterated Expectations (LIE), which is a weaker assumption than Full Information Rational Expectations (FIRE). This condition entails that agents are unable to predict revisions in their own or other agents' forecasts. Coibion and Gorodnichenko, 2012[18] provide a test for this condition on survey-based expectations and fail to detect deviations from LIE. For a comprehensive review of the role of expectations across various papers and specifications, refer to Mavroeidis, Plagborg-Møller, and Stock, 2014.

One interesting aspect of the survey that I am using is that firms are being asked about inflation in their sector. A priori, one would expect firms to pay more attention and be better informed about prices in their sector compared to aggregate economic conditions. This aligns with the findings of Andrade et al., 2022, who show that French firms respond much more rapidly to industry-specific shocks than aggregate shocks, suggesting their preference for more detailed sector-specific information.

3.2.3 Dynamic panel mean group estimation

The mean group estimation procedure employed in this study primarily follows the approach proposed by Chudik and Pesaran, 2015 using the common correlated effects (CCE) estimator. This methodology takes into account heterogeneous coefficients, endogeneity, and the inclusion of covariates to address the potential effects of unobserved common factors, which reflect cross-sectional linkages or common macroeconomic shocks.

The common correlated effects (CCE) estimator is a panel data technique that can be used to control for omitted variables that are common to all sectors in the panel. It aims to capture unobserved heterogeneous information about the inflation process through time-varying covariates. These are combined with sector-specific "factor loadings" aiming to capture the various sector-specific shocks using a much smaller number of variables. This way, this approach reduces the dimensionality of the data and helps to avoid overfitting by focusing on the most important factors that influence the outcomes of interest, as suggested in Eberhardt, 2022.

[18] See also Coibion, Gorodnichenko, and Kamdar, 2018 for the derivation of the Phillips Curve with survey-based expectations.

I employ various empirical approaches to estimate the Phillips Curve based on equation 3.

$$\pi_{kt} = \alpha_k + \gamma_k^f \, F_{kt}\{\pi_{k\,t+1}\} + \gamma_k^b \, \pi_{k\,t-1} + \gamma_k^s \, \chi_t \, + u_{kt} \tag{7}$$

$$u_{kt} = g_k \, f_t + \varepsilon_{kt}^{\pi} \tag{8}$$

where α_k are the sector fixed-effects, g_k is the heterogeneous factor loading and f_t are the unobserved common factors, which are approximated by z_t (the cross-sectional means).

The common correlated effects (CCEs) are approximated by taking the cross-section averages of the dependent variable and the individual-specific regressors, as initially proposed by Pesaran, 2006. This method was extended by Chudik and Pesaran, 2015[19] to estimate dynamic heterogeneous panel data models with weakly exogenous regressors. By not accounting for the different impact that the shocks might have across sectors, that effect will enter into the residuals, hence losing efficiency. For instance, Byrne, Kontonikas, and Montagnoli, 2013 justify the use of CCEs to adjust for the possibility that shocks to inflation or marginal costs may be cross-sectionally correlated.

Ignoring the heterogeneity across sectors in dynamic panels and estimating a pooled (homogeneous) model can lead to inconsistent and potentially misleading coefficient estimates, as argued by Pesaran and Smith, 1995.

$$\begin{aligned}\pi_{kt} =& \gamma_k^f \, F_{kt}\{\pi_{k\,t+1}\} + \gamma_k^b \, \pi_{k\,t-1} + \gamma_k^s \, \chi_t \, + u_{kt} \\ & \gamma^f \, F_{kt}\{\pi_{k\,t+1}\} + \gamma^b \, \pi_{k\,t-1} + \gamma^s \, \chi_t \, + \varepsilon_{kt}\end{aligned}$$

As long as $\gamma_k^f \neq \gamma^f$, $\gamma_k^b \neq \gamma^b$ or $\gamma_k^s \neq \gamma^s$, then the errors ε_{kt} will be correlated with the explanatory variables.

$$\varepsilon_{kt} = \Big[u_{kt} + (\gamma_k^f - \gamma^f) \, F_{kt}\{\pi_{k\,t+1}\} + (\gamma_k^b - \gamma^b) \, \pi_{k\,t-1} + (\gamma_k^s - \gamma^s) \, \chi_{kt} \Big]$$

3.2.4 Other identification issues

It is standard in the derivation of the Phillips Curve to assume that trend inflation is constant. This implies that shifts in trend inflation may confound the identification of the parameters. Gagliardone et al., 2023 uses time fixed effects to control for shifting trend inflation. I propose using CCEs as an enhanced object compared to time fixed effects to control for potential shifting trend inflation. While the CCEs are also time-components,

[19] They develop a mean group estimator of the mean coefficients, and show that CCE types estimators once augmented with a sufficient number of lags and cross-sectional averages perform well even in the case of models with lagged dependent variable and weakly exogenous regressors

proxies through a common factor across sectors, the panel technology which implements them have the advantage of allowing for heterogeneous loadings associated to each sector.

Despite the use of dissaggregate data and enhanced measures of expectations and marginal costs, there are still some potential sources of endogeneity in the estimation. One concern is related to the overlapping periods of the variables, as the perceived and expected inflation measures refer to annual changes while the frequency is quarterly. To address the potential correlation over time or the potential nonstationarity of the inflation measures, I employ lagged variables[20] to instrument out the regressors. Also, it is plausible that inflation expectations are simultaneously determined along with the current inflation rates. By conducting a first-stage regression, the resulting fitted value mitigates the endogenous effect. I show in Table 6 the potential endogenous variables regressed on their lags. In the case of expectations, all coefficients have the expected sign and are highly significant, reflecting the time overlapping effect. The labour cost series has been converted from a yearly to a quarterly measure. This is reflected in the short-dated corrrelation, as only one lag is statistically significant. It is also noteworthy that the lags of expectations have practically no predictive power on labour costs, and viceversa.

Lastly, the addition of sector fixed effects also help mitigate any measurement error in the proxies used for the marginal cost or any error coming from the survey-based data.

3.3 Slack measure: output gap or marginal cost

The slack measure of the Phillips Curve varies in response to real disturbances of any of several types (productivity shocks, taste shocks of various sorts, among others), according to the theory. These disturbances affect supply and demand conditions for all goods in the same way in the case of the aggregate Phillips Curve whereas in different ways in the sectoral-Phillips Curve.

For the empirical analysis, Sbordone, 2002 and Gali and Gertler, 1999 argue that the most direct measure of time variation in the output gap that is relevant to the aggregate Phillips Curve would not be one based on output data at all, but rather on variation in production costs. In fact, Woodford, 2003 argues that the output that is relevant as a measure of inflationary pressure should be monotonically related to variations in the level of real marginal cost.

$$s_t = \zeta(\hat{Y} - \hat{Y}^n)$$

Sbordone, 2002 uses data on the average level of unit labour cost in the US economy as a measure of nominal marginal cost and proves that no other measure of marginal cost is

[20] As emphasised in Mavroeidis, Plagborg-Møller, and Stock, 2014, lags can be used as instruments for robust inference in the presence of unit roots.

better than unit labour cost. Regarding marginal costs vs. average costs, she illustrates two different classes of factors that might cause average and marginal cost to vary differently: 1) in the presence of a 'real wage bias': the marginal cost of hours is not equal to the wage, or 2) in the presence of a 'productivity bias': the growth rate of the effective variable input is larger than the growth rate of total labour hours, which is used to compute unit labour costs. In her paper, she proposes some ways to account for these potential biases.

Moreover, the expression with real marginal cost more directly generalises to models such as the multisector one studied here. The expression obtained for the sector-level Phillips Curve by Woodford, 2003 contains both relative prices and aggregate output gap[21] whereas the sectoral inflation equation which uses the real marginal cost (instead of the output gap) does not require relative prices. Sector-level nominal marginal costs are calculated as the average of the costs across firms of sector k, as shown in Equation **??**.

I will employ various measures of output gap, real activity and labour costs for empirical comparison.

4 Data and descriptives

4.1 Survey of firms' expectations

The Confederation of British Industry (CBI) suite of business surveys comprises four surveys[22] completed by firms operating in the UK. It gathers information from thousands of firms on inflation expectations at the sector level, both retrospectively and in expectation, along with other firm-level outcomes such as output, investment, capacity, and inventories. The same firms are being targeted on a quarterly basis but their completion is voluntary.

Although the CBI survey began in 1958, the quantitative question on past and expected future price movements started being collected in 2008[23]. The CBI collects this information through supplementary questions managed jointly with the Bank of England (BoE). The CBI-BoE dataset is an excellent source of data regarding firms' inflation expectations, given its panel structure which allows to track firms over a significant period of time. It provides quarterly reports about perceptions since 2009, 1-year ahead expectations since 2009 and 2-year ahead expectations reports since 2014. Further information available from the survey about firms' characteristics include their location, industry activity (by SIC code), firm size (based on employee numbers), among others.

[21]See Woodford, 2003 section B.27 and Appendix B.7

[22]Industrial Trends Survey (ITS), Distributive Trades Survey (DTS), Financial Services Survey (FSS), and the Services Sector Survey (SSS)

[23]This work focuses on data starting in 2009 given that very few data were collected in 2008

Table 1: Summary of CBI survey data

	Ave. Number of firms/reports			Representation of sector (*)
	2009-2014	2015-2020	2021	
ITS	373	353	175	2.71%
DTS	107	92	68	2.54%
SSS	128	143	69	1.98%
FSS	71	74	46	1.92%
All	**679**	**663**	**358**	

(*) Calculated using turnover data reported by firms through the CBI surveys and sector-level statistics from the ONS

To the best of my knowledge, there is only one prior study, Boneva et al., 2020, that has utilized the CBI data on inflation expectations. However, their analysis focuses solely on the manufacturing sector using the ITS survey. In contrast, this work aggregates and examines data from all four CBI surveys, allowing for a comprehensive assessment of heterogeneity across sectors and capturing broader cross-sectional effects. For a more detailed understanding of the CBI survey, please refer to Lee, Mahony, and Mizen, 2020.

4.1.1 Inflation expectations question

The key questions about prices in the four surveys are framed identically. The question about future expectations is "What has been the percentage change over the past 12 months in the general level of output prices in the UK markets that your firm competes in, and what is expected to occur over the next 12 months and the following 12 months?". And the question about past inflation is "What has been the percentage change over the past 12 months in your firm's own average output price for goods sold into UK markets and what is expected to occur over the next 12 months?

Respondents are asked to report their expectations and perceptions about price movements by selecting from one of the ten buckets within the range -10% to 10% (ITS)[24] whereas for DTS, FSS and SSS[25] are -5% to 5%. Additionally, in the four surveys they can answer zero or enter a point estimate manually. The covered range has been of great advantage for the rising inflation in the period 2020-2022, compared to the households survey[26] which had the highest bucket at 5%.

I construct a continuous variable by assigning the midpoint of each price change bin. The

[24]Specifically, the buckets for ITS are -8.1 to-10%;-6.1 to -8%;-4.1 to -6%;-2.1 to -4%;-0.1 to -2%; no change;0.1 to 2%; 2.1 to 4%; 4.1 to 6%; 6.1 to 8% and 8.1 to 10%

[25]The buckets for DTS, FSS and SSS are -4.1 to -5%;-3.1 to -4%;-2.1 to -3%;-1.1 to -2%;-0 to-1%; no change;0.1 to 1%; 1.1 to 2%; 2.1 to 3%; 3.1 to 4% and 4.1 to 5%

[26]Bank of England/Ipsos Inflation Attitudes Survey

full dataset with the sample from 2009q2 to 2022q3 contains 41,300 observations. By keeping only inputs with sector and firm ID information, plus a non-empty report on price movements, the panel is reduced to 33,836. Also, I identified as outliers those expectations reports that are either very far from the other firms' reports in the same sector or are very far from the same firm's reports through time. This is explained in detail in Appendix D. Using this conservative method, only 363 observations are identified as outliers and thereby removed.

The respondents in the CBI dataset encompass 65 sectors classified at the 2-digit SIC level. However, for my analysis, I focus on 45 sectors for which I have a time series spanning more than 45 quarters.

4.1.2 Stylised facts from CBI survey data

The CBI data shows evidence of noticeable discrepancy in sectoral inflation expectations among sectors in line with the assumptions I am imposing to the sector-specific parameters of the Phillips Curve. Figure 1 shows that sectoral inflation expectations for services firms were centered between -2% and 4% in 2010, with sectors 79, 87, 93 and 96 close to the upper bound. More recently, the entire distribution of services expectations has shifted to the right. Figure 3 shows that inflation expectations for services firms are centered between 0% and 6%. The new upper bound is flanked by sectors 55, 56, 63, 72, and 81.

By comparing expectations between services and manufacturing firms (Figure 3 and Figure 4), the data suggests that services firms have shown minimal response to the shocks endured by the UK over the past decade (Brexit, the pandemic, Ukraine war, and the resulting unstable inflation) compared to the response from manufacturing firms. This highlights the importance of adopting a heterogeneous approach in the estimation of the Phillips Curve.

Figure 1

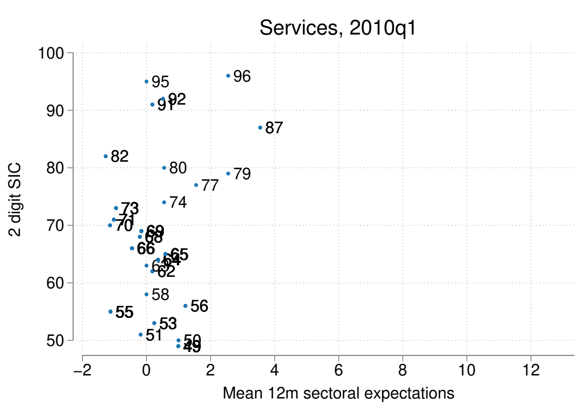


Figure 2

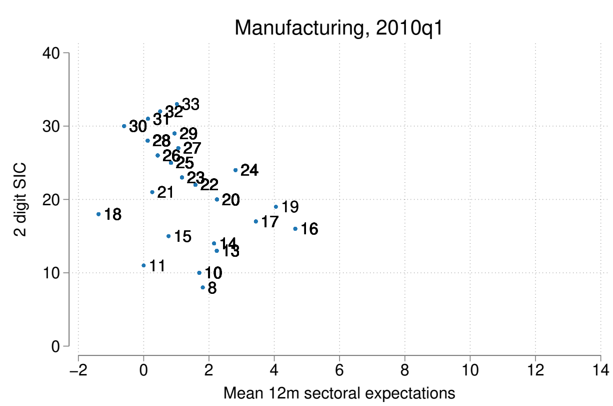


Figure 3

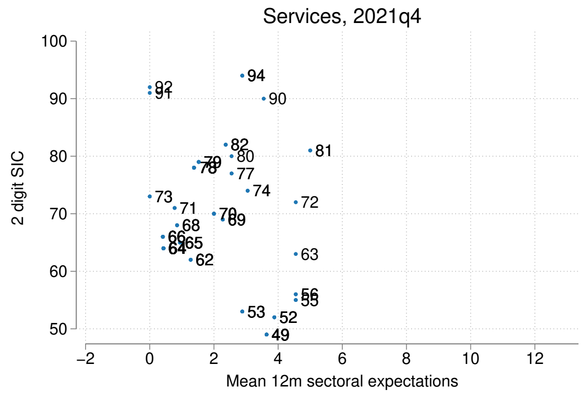


Figure 4

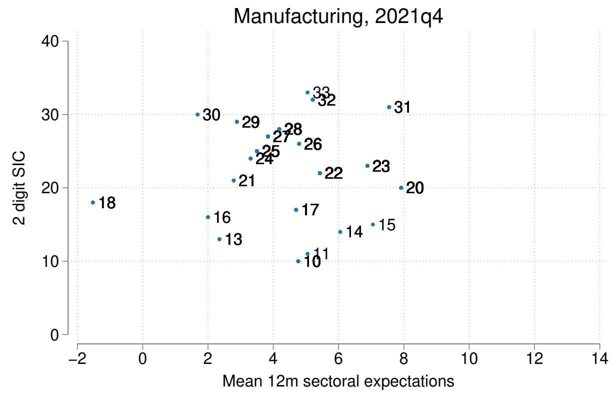


Table 2: Number of firms in each of the sectors used in the panel

	2009-2014	2015-2020	2021-2022
Manufacturing firms			
Fabricated metal	52	46	20
Machinery and equip.	61	38	9
Rubber and plastic	30	27	12
Electrical equipment	21	24	12
Computer; electronic	23	19	5
Non-metallic mineral	19	16	7
Food products	19	14	5
Basic metals	17	13	7
Chemicals	15	12	5
Paper and paper	15	11	4
Textiles	13	11	3
Motor vehicles	11	13	5
Other Manuf.	12	9	2
Wood	10	8	2
Furniture	8	8	2
Other vehicles	8	6	2
Printing and Media	7	7	2
Wearing apparel	7	6	1
Beverages	5	8	1
Footwear, luggage	5	5	2
Pharmaceutical	4	4	3
Other mining	5	3	1
Distributive firms			
Retail (non vehicles)	55	39	21
Wholesale (non vehicles)	38	35	15
WS & retail of vehicles	9	7	2

	2009-2014	2015-2020	2021-2022
Services firms			
Fin service act	30	35	13
Act. aux to fin serv.	20	16	3
Legal and accounting	16	13	3
Insurance and pension	19	12	4
Land transport	13	10	2
Accommodation	11	7	2
Real estate	6	6	3
Postal and courier	6	5	1
Architect. and engin.	8	4	2
Advertis. and mkt res	7	4	0
Mangmnt. Consult.	5	5	2
Employment acts.	6	4	2
Sporting activities	5	4	2
Computer program.	4	4	1
Restaurants & food	3	5	2
Recreational,cultural	4	3	1
Private security	2	4	3
Water transport	3	3	1
Travel agents	3	5	0
Cleaning	4	2	1
Renting and leasing	2	4	2
Travel agency	2	3	2
Other service activities	1	2	0
Medical, optical	2	2	1

The CBI elicits firms' expectations about "changes in the general level of output prices in the UK markets that your firm competes in" without specification about the sector. However, the firms are asked to enter the business activity covered by their reports, and to refer to the SIC listed at the end of the questionnaire. I use their self-reported 4-digit SIC to aggregate firms' expectations and perceptions and construct 2-digit SIC data for the sector-level Phillips Curve analysis.

4.2 Actual inflation rates vs. perceived change in prices

There are at least two sources of prices that I can utilize to analyze sector-level price setting: the actual inflation rates reported by the Office for National Statistics (ONS) and the reports from CBI firms regarding past changes in sectoral prices. While neither source is perfect, I will explain why the CBI reports may be less biased or more suitable for the analysis of sectoral Phillips Curve.

One issue with using the Office for National Statistics (ONS) inflation data is that the price indices are not available at the level of disaggregation (4-digit SIC) that is observed in the CBI reports. The ONS provides disaggregated Producers Price Indices (PPI[27]) by SIC code for industrial sectors. For non-industrial sectors, the Consumers Price Indices (CPI) and Services Producer Prices Indices (SPPI) could be used. However, further details on the mapping between these indices and the specific sectors can be found in Appendix C.

The second issue arises from the fact that the CBI elicits firms' expectations regarding "changes in the general level of output prices in the UK markets that your firm competes in", without specifying the sector. This lack of specification raises the challenge of precisely identifying the exact "markets" with which each firm competes. While one could assume that these markets align with the 4-digit SIC code that firms report at the end of the questionnaire, this assumption may introduce bias. The interpretation of these markets by firms could be related to the locations where they sell their goods or services, where they source their inputs, or where they recruit their labour force.

Using the perceived change in sectoral prices from the CBI survey is a good proxy for the actual inflation rates. As shown in figures 5 and 6, the average of CBI inflation reports follows quite closely the average of 2-digit SIC inflation rates[28].

Figure 5

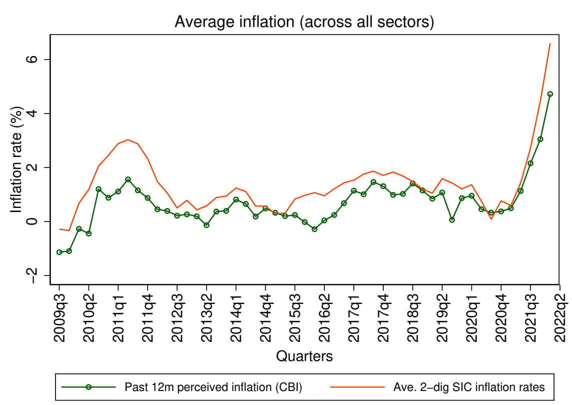
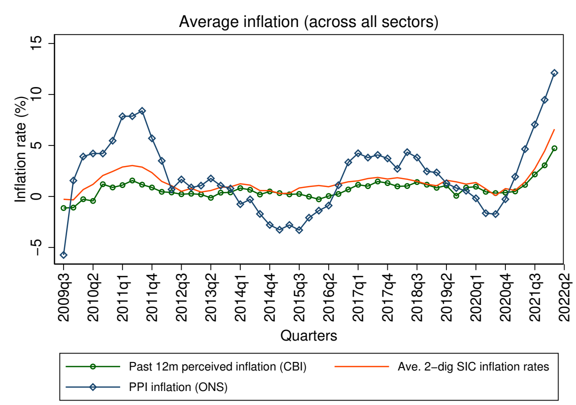


Figure 6



[27]For the PPI I use the output price index. The prices of goods sold by UK manufacturers i.e. the price of goods output (produced) by the UK manufacturer and sold within the UK market. These are commonly known as 'factory gate' prices to reflect the fact that they measure the price of goods before they reach the distribution or retail sectors.

[28]This average is built using all inflation indices from the mapping of 4-digit SIC sectors and PPI, CPI, SPPI data as explained in Appendix C.

4.3 Input-output tables

The ONS produces annual input-output tables with the amount of expenses as a share of income spent on employees and spent on intermediate inputs bought from other industries. From these tables I obtain the share of labour expenses and the share of intermediate goods expenses for each 2-digit SIC industry. I also use the information on how much an industry k buys from industry j to build the matrix with sectoral linkages.

4.4 Slack measures

The measure of real activity in the Phillips Curve literature are usually proxied by either the output gap or some measure of real marginal costs.

For the sectoral labour costs, I tried two measures: the CBI self-reported changes in salary costs and a measure of the unit labour cost (ULC) provided by the ONS. The former is shown in figure 7 and it yields the expected statistical and economic estimates as predicted by the Phillips Curve theory (see the regressions section). The alternative measure, the ULC, measures the nominal cost of labour input per unit of real (inflation-adjusted) economic output. It is the ratio of total nominal employment costs relative to output (divided by real gross value added (GVA)). The ULC data is not available at the 2-digit SIC level. The ONS provides 20 industry categories at the 2 digits SIC grouped as follows: 05to39, 45to98, 01to03, 05to09, 10to33, 35, 36to39, 41to43, 45to47, 49to53, 54to56, 58to63, 64to66, 68, 69to75, 77to82, 84, 85, 86to88, 90to93, 94to96, 97to98. I mapped these categories to the closest 2-digit SIC in the dataset. Yet, this measure is not statistically significant in the Phillips Curve estimation. See in Figure 9 an average measure of these series using the corresponding sectors from the sample.

Obtaining sector-level output gaps is not an easy task given the lack of activity data at the sector level and quarterly frequency. Additionally, even at the national level, the way of calculating the output gap is largely debated in the literature. None of the output gap measures tried yield significant coefficients. Some of the measures of output gap used were constructed using the methodology proposed by Garratt et al., 2008. For the data I used two alternatives: the Gross Domestic Product (GDP) index and the Index of Production (IoP). See Figure 10 for the former.

The other measure I used as proxy for the slack measure is the UK output gap calculated and provided by the Bank of England[29]. See the time series in Figure 8.

[29]This data was provided by the colleagues at the Bank of England and is publicly available in the BoE monetary policy reports

Figure 7

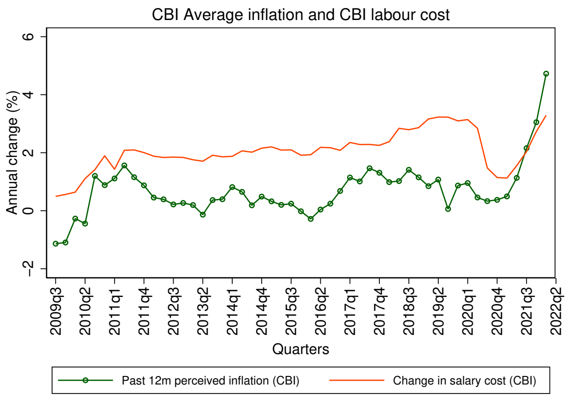


Figure 8

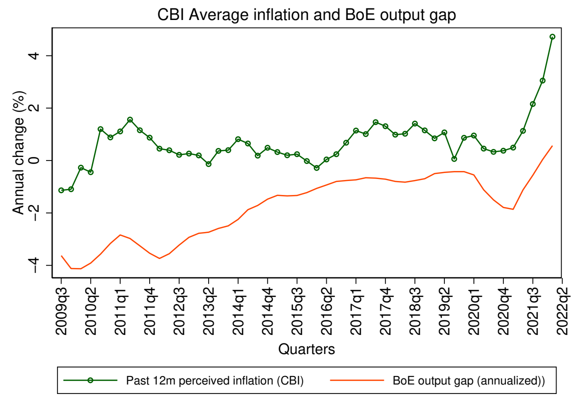


Figure 9

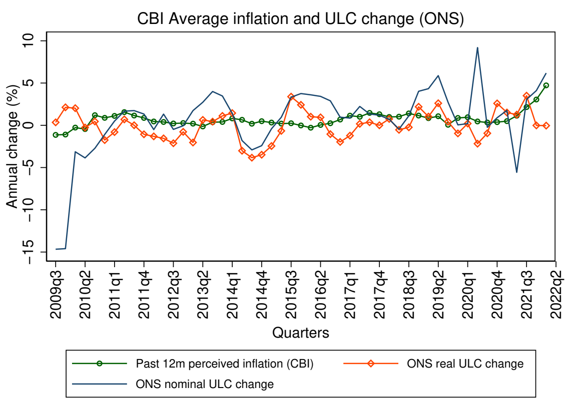
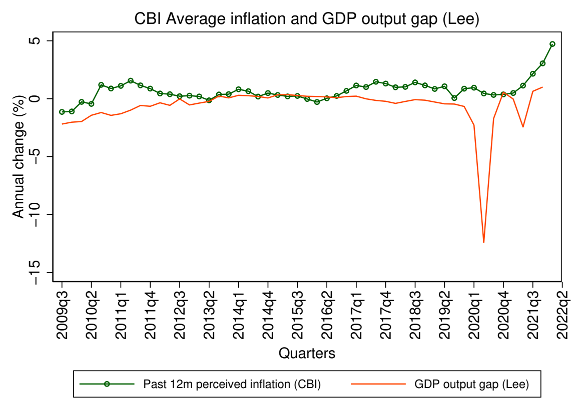


Figure 10



4.5 Other data

The real oil price inflation is the change in oil price adjusted by bilateral FX change. This measure is based on Roberts, 1995, calculated as DCOILBRENTEU - DEXUSUK. DCOILBRENTEU is the FRED series for Crude Oil Prices: Brent - Europe, Percent Change, Quarterly (average of the quarter), Not Seasonally Adjusted. DEXUSUK is the FRED series for U.S. Dollars to U.K. Pound Sterling Spot Exchange Rate, Percent Change, Quarterly (End of period), Not Seasonally Adjusted

Labour share is also used in the estimations, calculated as suggested by the ONS[30]: real ULC = ULC/GVAdeflator[31].

An alternative measure for the labour share used in the estimations, as suggested by BJN:

[30]https://www.ons.gov.uk/economy/economicoutputandproductivity/productivitymeasures/bulletins/labourcostsandlabourincomeuk/latest

[31]GVA deflator: Gross Value Added at basic prices, Implied deflator, Seasonally Adjusted, provided by the ONS

ln[((HAEA*A)/ABML)*100], where A = (E + SE)/E. E is given by BCAJ[32], the number of employee workforce jobs (seasonally adjusted), while SE is given by DYZN, the number of self-employment workforce jobs (seasonally adjusted).

Relative price of imports = ln[(IKBI/IKBL)*100] − GVA deflator, where IKBI is total imports (current prices), and IKBL is total imports (constant prices).

4.5.1 Market concentration (Herfindahl-Hirschman Index and Concentrarion ratio)

To identify the industrial structure, previous studies like Domberger, 1979 utilized the five-firm concentration ratios and estimated the Herfindahl-Hirschman Index (HHI) using employment data. However, I am not aware of any ongoing production of these indices for UK firms. Therefore, I constructed the HHI using turnover data from FAME BvD[33], as described in Brezina et al., 2016 and Naldi and Flamini, 2018.

Let n represent the number of entities operating in a given industry k and q_i represent turnover (net sales) of an i-th entity operating in a given industry (i=1,2,. . . n), then the market share (s_i) of the i-th entity operating on given market can be defined as: $s_i = \frac{q_i}{\sum_{i=1}^{n} q_i}$.

The HHI for each sector is equal to $\sum_{i=1}^{n} (s_i)^2$ (summing up all firms i in each sector). HHI< 0.1 suggests an unconcentrated industry, $0.1 <$HHI< 0.2 moderately concentrated and HHI> 0.2 highly concentrated.

4.6 Other relevant aspects about the data

In the estimations of the Phillips Curve I set the data as annual changes with quarterly frequency. This choice is commonly made by researchers because it enables the calculation of price adjustments at a finer time scale than just the year, as empirical evidence suggests. Modelling annual changes also eliminates the need to adjust the survey data for seasonal effects. Additionally, converting 4-quarter ahead expectations to 1-quarter ahead expectations would require making assumptions about the revision process.

As an example, suppose I want to construct 1-quarter ahead expectations. Dividing the 4-quarter ahead expectations by 4 is not enough, since there are four overlapping forecasts containing information about each quarter. As an example, a constructed 1-quarter ahead report from Q3-2020 should capture expectations about changes in prices from Q3-2020

[32] Four letter codes refer to series produced by the ONS

[33] Bureau van Dijk is a provider of company and business information throughout the UK and Ireland

to Q4-2020. Those expectations have been elicited in the four preceding 4-quarter ahead forecasts: Q4-2019, Q1-2020, Q2-2020 and Q3-2020; since all them contain information about changes between Q3-2020 and Q4-2020. However, it is not straightforward in the literature how to proceed with the conversion from 4-quarter ahead to 1-quarter ahead. Some assumptions should be made regarding the different information sets in each of the preceding forecasts as well as regarding the revisions made among them. For the sake of simplicity and accuracy, I decided to use the original 4-quarter ahead expectations and express all macroeconomic data as annual changes, thereby holding consistency.

5 Sectoral Phillips Curve: empirical estimation

The sector-level Phillips Curve is estimated for 52 sectors, and the expectations variable is calculated as the sector-weighted average of firms' reports using the number of employees as weights. One advantage of this approach is that it yields a balanced sample without any outliers from individual firms. Furthermore, the Phillips Curve has been microfounded at the sector level, providing greater theoretical structure to the estimations.

Based on Imbs, Jondeau, and Pelgrin, 2011, I will estimate the reduced-form parameters using the following expression:

$$\pi_{kt} = \gamma_k^b \, \pi_{k\,t-1} + \gamma_k^f \, E_t \, \pi_{k\,t+1} + \gamma_k^s \, \hat{s}_{kt} + \varepsilon_{kt}^{\pi} \tag{9}$$

where $\hat{s}_{kt} = \hat{w}_{kt} - \hat{p}_{kt}$, being $\hat{w}_{kt}$ the log deviation of wage from the sectoral sample mean.

Based on Rubbo, 2023:

$$\pi_{kt} = \gamma_k^f \, E_t \, \pi_{k\,t+1} + \gamma_k^s \, s_{kt}^R + \varepsilon_{kt}^{\pi} \tag{10}$$

And its hybrid version:

$$\pi_{kt} = \gamma_k^b \, \pi_{k\,t-1} + \gamma_k^f \, E_t \, \pi_{k\,t+1} + \gamma_k^s \, s_{kt}^R + \varepsilon_{kt}^{\pi} \tag{11}$$

5.1 Previous evidence in the UK

The validity of the Phillips Curve in UK data has been confirmed by Batini, Jackson, and Nickell, 2005 using system-based expectations. To the best of my knowledge, the sector-level Phillips Curve has not yet been estimated using direct measures of firms' expectations.

Incorporating some of the variables proposed by Batini, Jackson, and Nickell, 2005 into the estimation of the aggregate Phillips Curve reveals that oil price inflation and labour share are significant in some specifications. In Section 6, I also examine whether these variables are more relevant in explaining the price-setting behaviour of certain sectors over others. For instance, it may be expected that manufacturing firms would be more sensitive to changes in oil prices, whereas labour-intensive sectors such as services firms may be more sensitive to labour share and salary costs.

5.2 Does the panel dimension help identify the Phillips Curve?

Remarkably, exploiting the sector-level micro data and estimating a dynamic panel for the Phillips Curve appears to yield superior results. To address the potential endogeneity of inflation expectations and the slack variable, I use the Stata command xtdcce2 developed by Ditzen, 2021. This toolkit estimates dynamic panel data models with common correlated effects (CCE) and allows for instrumental variable estimation to deal with potential endogeneity issues.

In table 3 I present results of the estimation of the sectoral Phillips Curve with the forcing variable based only on labour costs. Column 1 assumes homogeneous slopes for all sectors, while columns 2 and 3 assume heterogeneous slopes. All models have sector-level fixed effects and 3 accounts also for CCEs. Upon comparing various model specifications, the Root Mean Squared Errors (RMSE)[34] indicate that allowing for heterogeneous coefficients across sectors and partialling out the unobservable common correlated effects (CCE) lead to substantially lower average residual magnitudes. Specifically, model 3 exhibits lower RMSEs compared to models 1 and 2.

Model 3 from both Imbs and Rubbo indicates an average coefficient on the role of expectations at around 0.6 and on lagged expectations at around 0.2. The estimates are consistent with the theory, which predicts that γ^f must be larger than γ^b, suggesting that firms set prices in a more forward- than backward- looking way. Despite not exactly comparable, other papers that have estimated Phillips Curves for the UK have found similar parameters: Meeks and Monti, 2022: $\gamma^b : 0.2$; $\gamma^f : 0.8^{***}$ & Byrne, Kontonikas, and Montagnoli, 2013: $\gamma^b : 0.1^{***}$ $\gamma^f : 0.9^{***}$ & Batini, Jackson, and Nickell, 2005: $\gamma^b 0.3^{***}$; $\gamma^b : 0.7^{***}$. Also, these are similar to recent findings in the US (Meeks and Monti, 2022: $\gamma^b : 0.1$ $\gamma^f : 1.6^{***}$ McLeay and Tenreyro, 2019: $\gamma^b : 0.1^{***}$ $\gamma^f : 0.22$). Moreover, Boneva et al., 2020 estimated firm-level pricing equations using CBI expectations about own prices and obtained $\gamma^f : 0.2 - 0.3$ (γ^b not explicitly reported).

[34] The RMSE is calculated as the square root of the average of squared errors, and it represents the average distance between the observed and predicted values of the dependent variable.

The slopes differ between IJP and Rubbo's framework, consistent with their differing underlying parameters. The slope from IJP framework is 0.1 whereas the slope from Rubbo's framework is 0.9. The former is only capturing the responsiveness of prices to labour costs whereas the latter is capturing the responsiveness to intermediate goods costs as well.

Overall, the results suggest that allowing for heterogeneous coefficients and partialling out the CCEs proxied by the cross-sectional averages leads to better results.

Table 3: Labour cost based Sectoral Phillips Curve

	2SLS Pooled FE	2SLS MG	2SLS CCEMG
		Dependent variable: CBI sectoral inflation	
Expected inflation	1.02***	0.80***	0.63***
	(0.21)	(0.08)	(0.11)
Lagged inflation	0.35***	0.23***	0.17***
	(0.10)	(0.04)	(0.04)
Labour cost	0.06**	0.07*	0.13***
	(0.02)	(0.04)	(0.04)
Heter./Homog. Coeff	Homog.	Heterog.	Heterog.
FE/CCE	FE	FE	FE + CCE
Observations	2,507	2,507	2,507
Number of groups	52	52	52
RMSE	2.24	2.16	1.64
CD test	0.00	0.01	0.42

Note: S.E. in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. Expectations are calculated as weighted averages among all firms in each sector. Labour costs and expectations are instrumented out with: lags (1, 2, 3) of expectations and lags (1, 3) of labour costs. CCEs are proxied with ave. expectations (0 to 3 lags), and up to 2 lags of ave. labour cost and oil inflation; CCEs are partialled out. RMSE is the square root of the ave. of squared errors and is defined in terms of the dependent variable. CD test: null hypothesis of weak Cross Sectional Dependence. Data 2009q1-2022q2.

5.3 Can we unmask the heterogeneity in the price setting behaviour across sectors?

The sector-level estimations reveal a broad heterogeneity across sectors, with manufacturing firms, on average, being more backward-looking than services. More importantly, there is noticeable heterogeneity across industries within groups. This suggests that there are other industry-characteristics that might be driving these differences.
Estimates from model 3 are used in the next section to obtain the γ_k (for each sector). By using these parameters, I investigate the determinants of the asymmetries across sectors.

6 Determinants of the sectoral heterogeneity in price setting

Having unmasked the degree of forward-lookingness for each sector in section 5, the next goal is to investigate its main sources. In this section I use the estimated sector-specific

Table 4: Rubbo cost based Sectoral Phillips Curve

	2SLS Pooled FE	2SLS MG	2SLS CCEMG
	Dependent variable: CBI sectoral inflation		
Expectations	0.87***	0.57***	0.56***
	(0.20)	(0.07)	(0.10)
Lagged inflation	0.32***	0.23***	0.16***
	(0.08)	(0.04)	(0.04)
Composite cost	0.32***	0.86***	0.89***
	(0.10)	(0.17)	(0.24)
Heter./Homog. Coeff	Homog.	Heterog.	Heterog.
FE/CCE	FE	FE	FE + CCE
Observations	2,436	2,436	2,436
Number of groups	52	52	52
RMSE	2.03	1.64	1.46
CD test	0.00	0.00	0.42

Note: S.E. in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. Expectations are calculated as weighted averages among all firms in each sector. Costs and expectations are instrumented out with: lags (1, 2, 3) of expectations and lags (1, 3) of costs. CCEs are proxied with ave. expectations (0 to 3 lags), and up to 2 lags of oil inflation; CCEs are partialled out. RMSE is the square root of the ave. of squared errors and is defined in terms of the dependent variable. CD test: null hypothesis of weak Cross Sectional Dependence. Data 2009q1-2022q2.

parameters of forward-lookingness from the Phillips Curve to understand how responsive they are to the market structure and other industry-characteristics. In order to do so I need to first adjust the estimates by their estimation precision.

6.1 Estimated parameters weighted by their standard error

Some of the parameters estimated for the sector-specific forward-looking coefficients of the Phillips Curve are not significant. To account for the various degrees of precision or imprecision of the estimates, I use a similar approach to the so called weighted least squares (WLS)[35]. Given that the standard errors are obtained from the OLS estimation of the Phillips Curve (see section 5), these are used to adjust the imprecise parameters. The weights are obtained by first calculating the inverse of the standard errors, and then, these weights are rescaled to sum up to one.

$$\overline{w}_k = \frac{w_k}{\sum_k w_k}$$

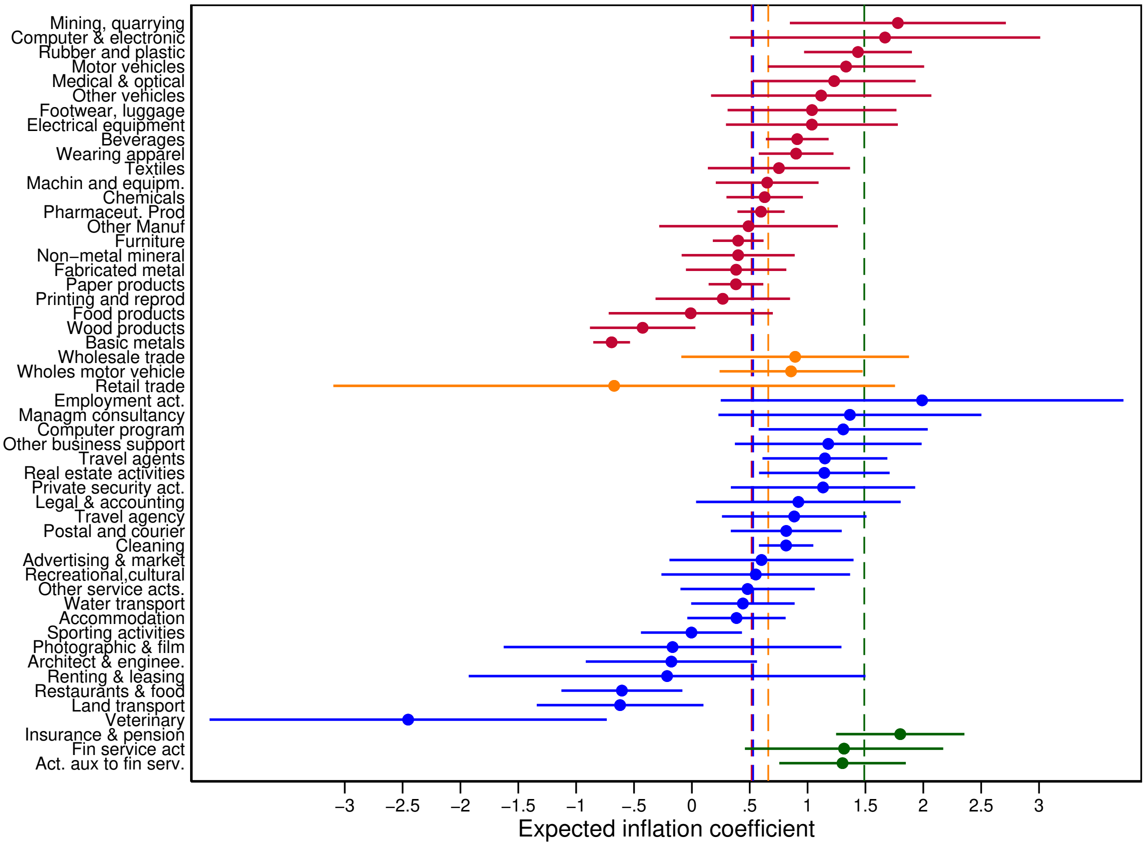
$$\widetilde{X}_k^j = X_k^j * \overline{w}_k$$

The weighted regression is expressed as follows

$$\widetilde{\gamma}_k^f = \beta_0 \widetilde{X}_k^0 + \beta_1 \widetilde{X}_k^1 + ... + \widetilde{u}_k$$

[35]See Domberger, 1979 for an application that deals with the presence of serial correlation revealed in the OLS results and Stock and Watson, 2019 (section 18) for further reference.

Figure 11: Role of expectations by sector (Imbs framework)



Note: Estimations of sectoral expectations coefficients from model 3 (Table 3, through dynamic panels with CCE and IV). These coefficients are net from the effect of the common factor effects. Intervals are calculated as the mean +/- s.e. The labels indicate the mean estimated coefficient for each sector. The dashed vertical lines highlight the mean coefficient across each of the groups. Red colour for manufacturing, Orange for Retail, Blue for services and Green for Financial Services.

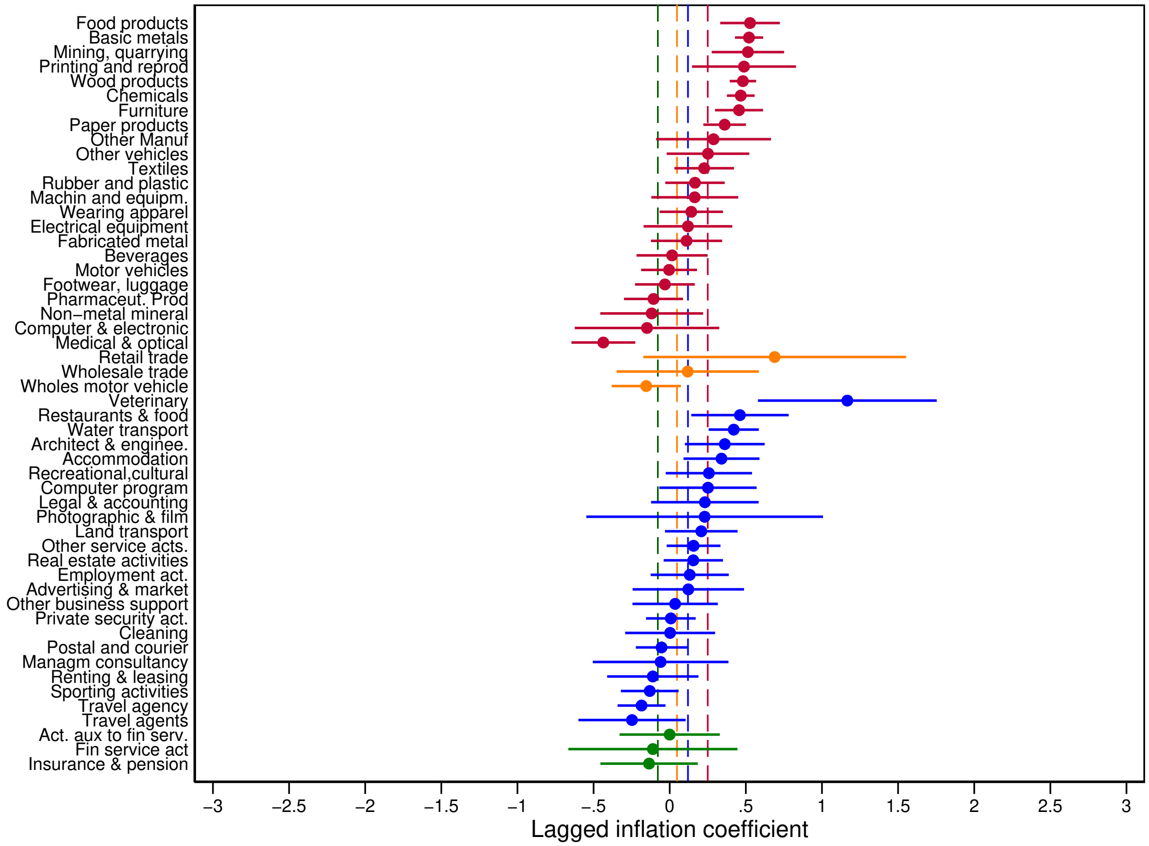
By adjusting the dependent variable and regressors by the precision of the estimates I am giving more weight to the less biased estimated sectors.

6.2 Regression estimation results

Given the relatively limited existing work on what determines the degree of forward-lookingness and the degree of backward-lookingness, the precise regression specification is unclear. Regressions in Table 5 present the association between the sector-specific Phillips Curve parameters and some industry characteristics.

The results indicate a positive relationship and highly statistically significant between the role of expectations and the degree of concentration measured by the HHI. These results are in favour of the hypothesis that firms facing less competition (higher degree of concentration)

Figure 12: Role of lagged inflation by sector (Imbs framework)

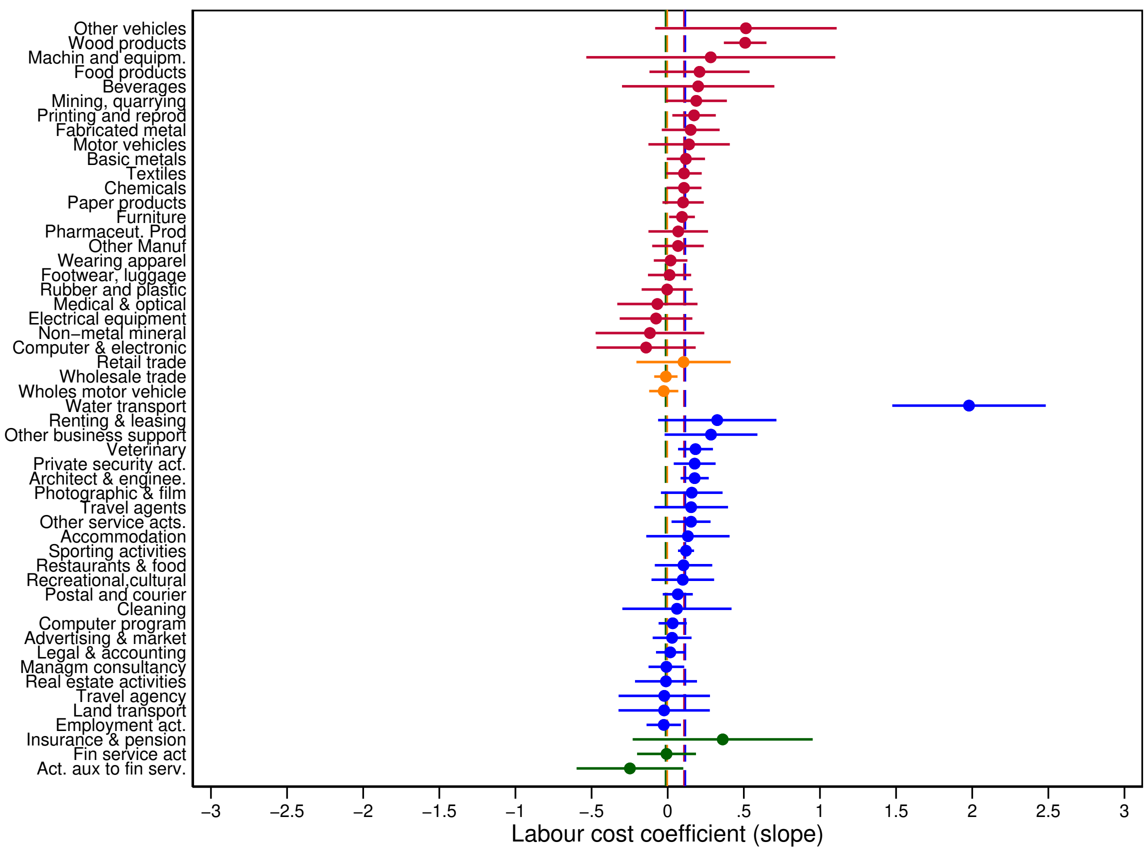


Note: Estimations of sectoral lagged expectations coefficients from model 3 (Table 3, through dynamic panels with CCE and IV). These coefficients are net from the effect of the common factor effects. Intervals are calculated as the mean +/- s.e. The labels indicate the mean estimated coefficient for each sector. The dashed vertical lines highlight the mean coefficient across each of the groups. Red colour for manufacturing, Orange for Retail, Blue for services and Green for Financial Services.

will update prices less frequently (higher stickiness). One way to explain this could be by considering the low demand elasticity of highly-concentrated sectors. When a firm faces only a few competitors, the demand elasticity is low. However, in a highly competitive sector, setting a price slightly below others can result in reduced sales or even no sales. Thus, firms in sectors with a low degree of concentration (high competition) tend to simply follow their competitors' prices, attaching little importance to their own expectations.

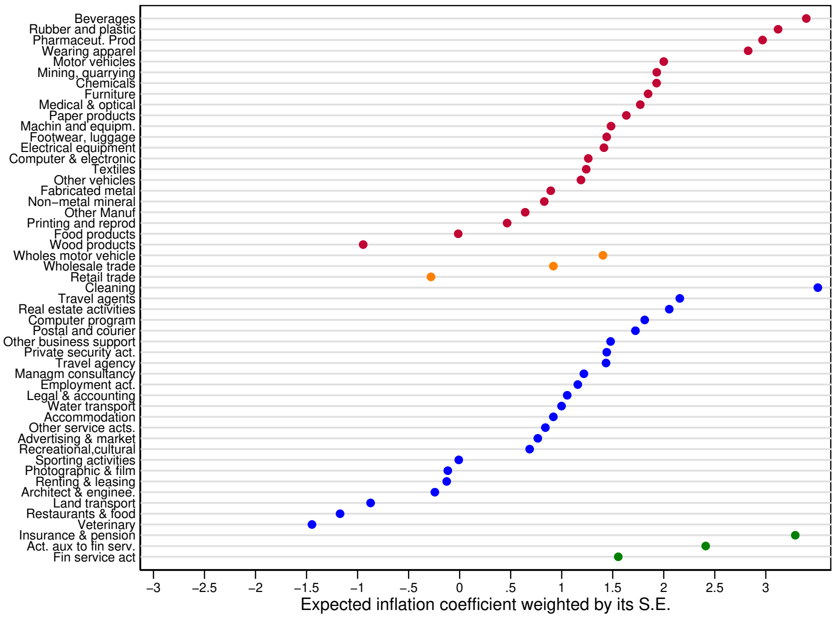
In sectors characterised by both high degrees of concentration and price stickiness, firms often opt to raise prices by more than the optimal level when they have the opportunity to update them. This strategic decision aims to compensate for potential future losses during periods of unchanged prices. This highlights the increased significance of expectations for firms facing greater price rigidities.

Figure 13: Slope by sector (Imbs framework)



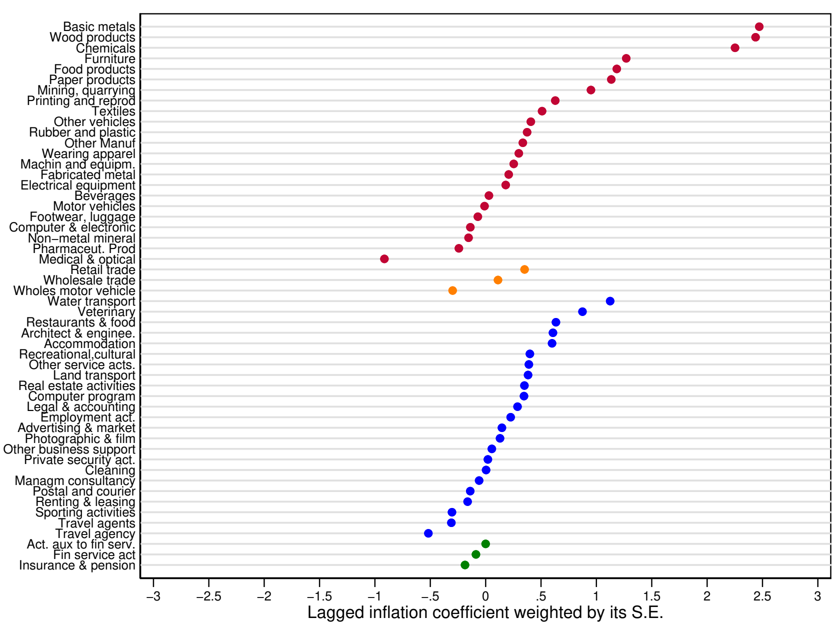
Note: Estimations of sectoral coefficients on labour costs from model 3 (Table 3, through dynamic panels with CCE and IV). These coefficients are net from the effect of the common factor effects. Intervals are calculated as the mean +/- s.e. The labels indicate the mean estimated coefficient for each sector. The dashed vertical lines highlight the mean coefficient across each of the groups. Red colour for manufacturing, Orange for Retail, Blue for services and Green for Financial Services.

Figure 14: Weighted coefficient on expected inflation (Imbs framework)



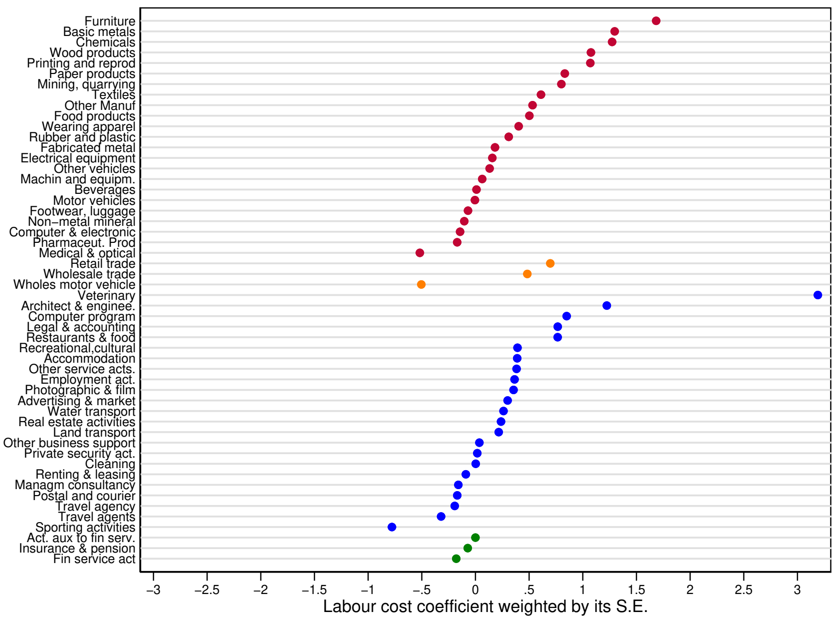
Note: Coefficients on expected inflation from Imbs framework are weighted by their S.E. Industry 24 (Basic metals) has a weighted coefficient of -4.4 and is not displayed in the graph.

Figure 15: Weighted coefficient on lagged inflation (Imbs framework)



Note: Coefficients on expected inflation from Imbs framework are weighted by their S.E.

Figure 16: Weighted coefficient on labour cost (Imbs framework)



Note: Coefficients on labour cost from Imbs framework are weighted by their S.E.

Table 5: Regressions estimations

	IJP's framework			Rubbo's framework		
	γ_f	γ_b	γ_s	γ_f	γ_b	γ_s
	(1)	(2)	(3)	(4)	(5)	(6)
HHI	1.31**	-0.58*	0.42	1.67	-0.19	-0.62
	(0.64)	(0.31)	(0.45)	(1.51)	(0.34)	(0.53)
Imports over supply	-0.32	0.65**	0.14	-0.29	-0.14	-0.15
	(0.42)	(0.31)	(0.10)	(0.68)	(0.21)	(0.26)
Energy over costs	-8.51	7.92***	5.92	32.25*	8.15***	17.74**
	(5.63)	(2.47)	(4.90)	(18.16)	(2.84)	(8.26)
Petrol over costs	-10.64**	2.22	0.61	35.34**	0.31	1.62
	(4.00)	(1.54)	(2.91)	(13.77)	(1.37)	(3.57)
ULC variability	1.42	0.37	-0.92	-7.66**	-0.22	-0.61
	(1.79)	(0.61)	(0.69)	(3.22)	(0.47)	(1.05)
Dummy Services	-0.89**	0.11	0.29	1.24	-0.05	0.05
	(0.34)	(0.16)	(0.23)	(0.94)	(0.14)	(0.14)
Observations	51	51	51	51	51	51
R-squared	0.36	0.61	0.10	0.36	0.28	0.54

Note: S.E. in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. All variables are weighted by the inverse of the S.E. from the corresponding Sectoral Phillips Curve estimated parameters.

7 Conclusions

Using survey-data of firms' expectations allows to identify the Phillips Curve parameters as predicted by the theory. The CBI survey data reveals a broad heterogeneity across sectors, in line with the assumptions I impose to the sector-specific parameters of the Phillips Curve. Also, exploiting the micro data at the sector level by estimating a dynamic panel for the Phillips Curve seems to yield better results than ignoring the cross-sectional effects.

I estimate industry-level Phillips Curves for 52 sectors and find: positive and significant coefficients on lagged inflation, expected inflation and on the labour cost, consistent with the theory. Results also show that including the intermediate goods into the measure of costs, the slope not only remains statistically significant but it also becomes larger. This suggests that there are some sectoral interactions through nominal rigidities across industries that can be captured by Rubbo's framework, and, hence ignored in the traditional Phillips Curve setting.

The findings of this study contribute to ongoing policy discussions regarding the importance of inflation expectations in firms' price-setting behavior and shed light on the variations among different sectors. It also sheds light on the importance of the production network effects in the sectoral inflation process.

Appendix A Sectoral Phillips Curve derivation by Imbs, Jondeau, and Pelgrin, 2011

The sector-level Phillips Curve framework will assume, among others, that there is a continuum of firms i within each sector k. Each firm produces a different variety of a good k, with same technology within the sector but different labour intensity. It is also assumed that there is monopolistic competition among these firms and that each supplier understands that its sales depend upon the price charged for its good relative to its sector-level price, according to the demand function

$$Y_{ikt} = Y_{kt} \left(\frac{P_{ikt}}{P_{kt}} \right)^{-\eta} \tag{12}$$

where P_{ikt} is the price of firm i of good k chosen taking P_{kt} (the price index in the sector k) and Y_{kt} (the aggregate demand) as given, $\eta > 1$ is the elasticity of substitution across varieties within sector k.

The demand for good k, Y_{kt}, is defined through the Dixit and Stiglitz CES aggregator across a continuum of firms i on a unit interval producing differentiated goods:

$$Y_{kt} = \left[\int_0^1 Y_{ikt}^{\frac{\eta-1}{\eta}} \, di \right]^{\frac{\eta}{\eta-1}} \tag{13}$$

Each firm produces a differentiated good with a production function

$$Y_{ikt} = Z_{kt} \, f(h_{ikt}) \tag{14}$$

where Z_{kt} is a time-varying sector-specific exogenous technology factor, labour is the only factor of production and h_{ikt} denotes hours worked.

Price setting decisions are governed by the Calvo, 1983 mechanism. A fraction $0 < \alpha_k < 1$ of firms keep their prices unchanged each period, whereas new prices are chosen for the other $1 - \alpha_k$ of the firms. Each supplier that chooses a new price for its goods in period t faces exactly the same decision problem. In equilibrium, all prices that are chosen in period t have the common optimal price ${P_{ikt}}^*$.

The firms optimising in t will choose ${P_{ikt}}^*$ that solves:

$$\max_{{P_{ikt}}^*} E_t \sum_{j=0}^{\infty} (\alpha_k \beta)^j \, \left[Y_{ik\,t,t+j} \, P^*_{ikt} - \Psi \left(Y_{ik\,t,t+j} \right) \right] \tag{15}$$

where $Y_{ik\,t,t+j}$ is real output produced in t+k by firms that changed their prices at t and

$\Psi(Y_{ik\,t,t+j})$ are the total nominal costs of supplying good k.

The optimising firms will take into account that with probability α_k, they won't update prices for the next k periods.

By taking the first order condition of Equation 15 and working on the algebra, I get the following expression:

$$\sum_{j=0}^{\infty}(\alpha_k\beta)^j\,E_t\left[Y_{ik\,t,t+j}\,\left(P^*_{ikt}-\eta\,S_{ik\,t,t+j}P_{ik\,t,t+j}\right)\right]=0 \tag{16}$$

where real marginal cost is $S_{ik\,t,t+j}=\Psi'(Y_{ik\,t,t+j})/P_{ik\,t,t+j}$

The sector is assumed to be a collection of suppliers that always change their prices at the same time and hire inputs in common factor markets as well. We assume that in equilibrium each supplier in the same sector always chooses the same price. Also, in steady state $P_{ik\,t,t+j}=P_{ikt}, P_{ik\,t,t+j}=P^*_{ikt}$, $P_{ik}=P^*_{ikt}$, $P_{t+j}=P_t$, $Y_{ik\,t,t+j}=Y_{ikt}$, $S_{ik\,t,t+j}=S_k=\eta/(\eta-1)$

A first order Taylor expansion around the steady states gives

$$\hat{p}^*_{ikt}=(1-\alpha_k\beta)\sum_{j=0}^{\infty}(\alpha_k\beta)^j E_t\left[\hat{s}_{ik\,t,t+j}+\hat{p}_{ik\,t,t+j}\right] \tag{17}$$

where $\hat{s}_{ik\,t,t+j}=s_{ik\,t,t+j}-\overline{s}_{ik}$ and $\hat{p}_{ik\,t+j}=p_{ik\,t+j}-\overline{p}_{ik}$

Next, I will present the derivation of the equation that determines price setting at the sector level. According to Imbs, Jondeau, and Pelgrin, 2011, when there are no specific shocks affecting individual firms, all firms capable of adjusting their prices at time t will choose the same optimal price. This assumption guarantees a symmetric equilibrium across firms within each sector. Consequently, for simplicity, firms' indices i will be omitted from the succeeding steps.

Based on the Calvo sticky prices mechanism, prices in sector k will be comprised by $(1-\alpha_k)$ share of firms that have updated prices at t and α_k share of firms that will have last period's prices. Hence, the sectoral price level in t is calculated as:

$$\hat{p}_{kt}=\alpha_k\,\hat{p}_{k\,t-1}+(1-\alpha_k)\,\hat{p}^*_{kt} \tag{18}$$

Also, there's a proportion of firms ω among the $(1-\alpha)$ that are updating prices who will do so in a purely backward-looking manner. This is similar to Gali and Gertler, 1999, in the sense that the price in t for backward-looking firms depends only on information dated $t-1$ or earlier.

Then, newly set prices will be defined as:

$$\hat{p}^*_{kt} = \omega_k \, \hat{p}^b_{kt} + (1 - \omega_k) \, \hat{p}^f_{kt} \tag{19}$$

where p^b_{kt} refers to prices set by backward-looking firms, who adjust for inflation the prices they set the last time they could, i.e.:

$$\hat{p}^b_{kt} = \hat{p}^*_{k\,t-1} + \hat{\pi}_{k\,t-1} \tag{20}$$

and p^f_{kt} refers to prices set by forward-looking firms according to Equation 17.

Combining Equation 17 and 20, they get the following linearised hybrid sectoral Phillips Curve:

$$\hat{\pi}_{kt} = \frac{\omega_k}{\phi_k} \, \hat{\pi}_{k\,t-1} + \frac{\beta \alpha_k}{\phi_k} \, E_t \hat{\pi}_{k\,t+1} + \frac{(1 - \omega_k)(1 - \alpha_k)(1 - \beta \alpha_k)}{\phi_k} \, h_k \, \hat{s}_{kt} \tag{21}$$

$$\text{where} \quad \phi^k = \alpha_k + \omega^k [1 - \alpha_k (1 - \beta)]$$

Lastly, ε^π_{kt} is added to capture an i.i.d. shock to real marginal costs in sector k, which may embed measurement error. The reduced-form expression is expressed as follows:

$$\hat{\pi}_{kt} = \gamma^b_k \, \hat{\pi}_{k\,t-1} + \gamma^f_k \, E_t \hat{\pi}_{k\,t+1} + \gamma^s_k \, \hat{s}_{kt} + \varepsilon^\pi_{kt} \tag{22}$$

Appendix B Two sector illustration based on Rubbo, 2023's framework

I will first express Equation 3 and Equation 4 in matrix form for two sectors for illustrative purposes:

$$\begin{pmatrix} \pi_{1t} \\ \pi_{2t} \end{pmatrix} = \begin{pmatrix} \hat{\alpha}_1 & 0 \\ 0 & \hat{\alpha}_2 \end{pmatrix} \begin{pmatrix} mc_{1t} - p_{1\,t-1} \\ mc_{2t} - p_{2\,t-1} \end{pmatrix} + \beta \begin{pmatrix} 1 - \hat{\alpha}_1 & 0 \\ 0 & 1 - \hat{\alpha}_2 \end{pmatrix} \begin{pmatrix} E_t \pi_{1\,t+1} \\ E_t \pi_{2\,t+1} \end{pmatrix} \tag{23}$$

$$\begin{pmatrix} mc_{1t} \\ mc_{2t} \end{pmatrix} = \begin{pmatrix} (1 - a_1) w_{1t} + \lambda_{11t} \, p_{1t} + \lambda_{12t} \, p_{2t} \\ (1 - a_2) w_{2t} + \lambda_{21t} \, p_{1t} + \lambda_{22t} \, p_{2t} \end{pmatrix} - \begin{pmatrix} logZ_{1,t} \\ logZ_{2,t} \end{pmatrix} \tag{24}$$

where $\hat{\alpha_k}(\alpha_k, \beta)$ is the following increasing and convex function:

$$\hat{\alpha_k} = \frac{\alpha_k(1-\beta(1-\alpha_k))}{1-\beta\,\alpha_k(1-\alpha_k)}$$

Now, I will combine Equation 23 and 24, and ignore the productivity term just for brevity. This omission won't affect the results.

$$\begin{pmatrix}\pi_{1t}\\ \pi_{2t}\end{pmatrix} = \begin{pmatrix}\hat{\alpha}_1 & 0\\ 0 & \hat{\alpha}_2\end{pmatrix}\begin{pmatrix}(1-a_1)w_{1t} + \lambda_{11t}\,p_{1t} + \lambda_{12t}\,p_{2t} - p_{1\,t-1}\\ (1-a_2)w_{2t} + \lambda_{21t}\,p_{1t} + \lambda_{22t}\,p_{2t} - p_{2\,t-1}\end{pmatrix} + \beta\begin{pmatrix}1-\hat{\alpha}_1 & 0\\ 0 & 1-\hat{\alpha}_2\end{pmatrix}\begin{pmatrix}E_t\pi_{1\,t+1}\\ E_t\pi_{2\,t+1}\end{pmatrix}$$

Adding and subtracting $\Lambda\,p_{t-1}$ to obtain expressions π_t for both sectors, and then combine these with the left hand side inflation term.

$$\begin{aligned}\begin{pmatrix}1-\lambda_{11t}\,\hat{\alpha}_1 & -\lambda_{12t}\,\hat{\alpha}_1\\ -\lambda_{21t}\,\hat{\alpha}_2 & 1-\lambda_{22t}\,\hat{\alpha}_2\end{pmatrix}\begin{pmatrix}\pi_{1t}\\ \pi_{2t}\end{pmatrix} &= \begin{pmatrix}\hat{\alpha}_1 & 0\\ 0 & \hat{\alpha}_2\end{pmatrix}\begin{pmatrix}(1-a_1)w_{1t} + \lambda_{12t}\,p_{2\,t-1} - (1-\lambda_{11t})\,p_{1\,t-1}\\ (1-a_2)w_{2t} + \lambda_{21t}\,p_{1\,t-1} - (1-\lambda_{22t})\,p_{2\,t-1}\end{pmatrix}\\ &+ \beta\begin{pmatrix}1-\hat{\alpha}_1 & 0\\ 0 & 1-\hat{\alpha}_2\end{pmatrix}\begin{pmatrix}E_t\pi_{1\,t+1}\\ E_t\pi_{2\,t+1}\end{pmatrix}\end{aligned}$$

Further combining terms to get expressions for the inflation rates:

$$\begin{aligned}\begin{pmatrix}\pi_{1t}\\ \pi_{2t}\end{pmatrix} &= \begin{pmatrix}1-\lambda_{11t}\,\hat{\alpha}_1 & -\lambda_{12t}\,\hat{\alpha}_1\\ -\lambda_{21t}\,\hat{\alpha}_2 & 1-\lambda_{22t}\,\hat{\alpha}_2\end{pmatrix}^{-1}\begin{pmatrix}\hat{\alpha}_1 & 0\\ 0 & \hat{\alpha}_2\end{pmatrix}\begin{pmatrix}(1-a_1)w_{1t} + \lambda_{12t}\,p_{2\,t-1} - (1-\lambda_{11t})\,p_{1\,t-1}\\ (1-a_2)w_{2t} + \lambda_{21t}\,p_{1\,t-1} - (1-\lambda_{22t})\,p_{2\,t-1}\end{pmatrix}\\ &+ \begin{pmatrix}1-\lambda_{11t}\,\hat{\alpha}_1 & -\lambda_{12t}\,\hat{\alpha}_1\\ -\lambda_{21t}\,\hat{\alpha}_2 & 1-\lambda_{22t}\,\hat{\alpha}_2\end{pmatrix}^{-1}\beta\begin{pmatrix}1-\hat{\alpha}_1 & 0\\ 0 & 1-\hat{\alpha}_2\end{pmatrix}\begin{pmatrix}E_t\pi_{1\,t+1}\\ E_t\pi_{2\,t+1}\end{pmatrix}\end{aligned}$$

The expression obtained above assumes for simplicity that there two sectors: 1, 2. If I would try to extend it to include every sector j from where any sector k buys intermediate goods, the number of terms on the right hand side would expand as long as $\lambda_{kj} \neq 0$.

$$\begin{aligned}\begin{pmatrix}\pi_{1t}\\ \pi_{2t}\end{pmatrix} =& (I-\Lambda\,\hat{A})^{-1}\hat{A}\begin{pmatrix}(1-a_1)w_{1t} + \lambda_{12t}\,p_{2\,t-1} - (1-\lambda_{11t})\,p_{1\,t-1}\\ (1-a_2)w_{2t} + \lambda_{21t}\,p_{1\,t-1} - (1-\lambda_{22t})\,p_{2\,t-1}\end{pmatrix}\\ &+ (I-\Lambda\,\hat{A})^{-1}\beta(1-\hat{A})\begin{pmatrix}E_t\pi_{1\,t+1}\\ E_t\pi_{2\,t+1}\end{pmatrix}\end{aligned}$$

Finally, I will express inflation rates in reduced form in terms of Rubbo's measure of cost,

S^R_{kt}, and inflation expectations:

$$\pi_{kt} = (I - \Lambda\,\hat{A})^{-1}\hat{A}\,(S^R_{kt}) + (I - \Lambda\,\hat{A})^{-1}\beta\,(1 - \hat{A})\,E_t\pi_{k\,t+1} \tag{25}$$

where $\hat{A}$ refers to the diagonal matrix of $\hat{\alpha_k}$, and Λ refers to the input-output matrix which elements are λ_{kj}.

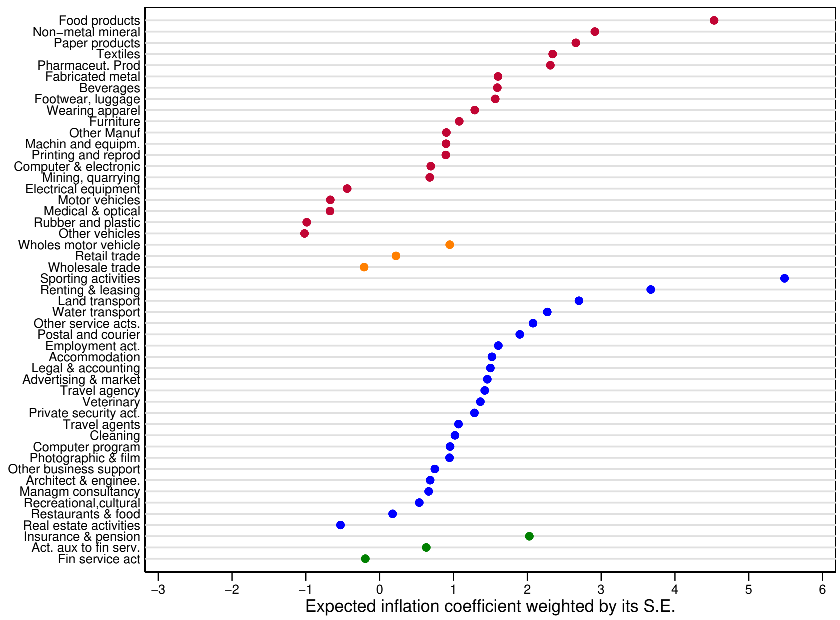
Appendix C Additional Figures and Tables

Table 6: Relevance of instruments

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	*Expectations*	*Expectations*	*Labour cost*	*Labour cost*	*Rubbo cost*	*Rubbo cost*
Expectations (1st lag)	0.23***	0.20***		0.01		-0.09***
	(0.03)	(0.03)		(0.01)		(0.01)
Expectations (2nd lag)	0.13***	0.11***		-0.04***		0.01
	(0.03)	(0.03)		(0.01)		(0.01)
Expectations (3rd lag)	0.07**	0.11***		-0.02**		-0.02**
	(0.03)	(0.03)		(0.01)		(0.01)
Cost (1st lag)		0.29**	0.98***	0.97***	0.73***	0.81***
		(0.12)	(0.04)	(0.04)	(0.04)	(0.05)
Cost (2nd lag)		-0.07	-0.00	-0.06	0.08*	0.02
		(0.15)	(0.06)	(0.06)	(0.05)	(0.05)
Cost (3rd lag)		0.28***	-0.22***	-0.15***	-0.09**	-0.02
		(0.10)	(0.04)	(0.03)	(0.04)	(0.04)
FE	Time and Sector	Time and Sector	Time and Sector	Time and Sector	Time and Sector	Time and Sector
Observations	2,070	2,070	2,146	2,086	2,028	2,028
R-squared	0.44	0.47	0.77	0.78	0.59	0.64

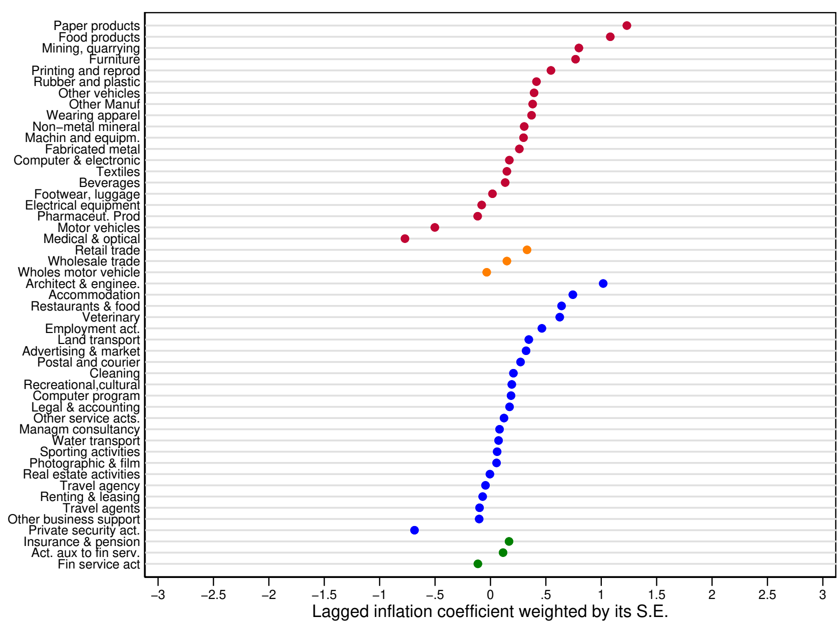
Note: OLS estimations. S.E. in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. Intercepts were included in the estimations but omitted in the table.

Figure 17: Weighted coefficient on expected inflation (Rubbo framework)



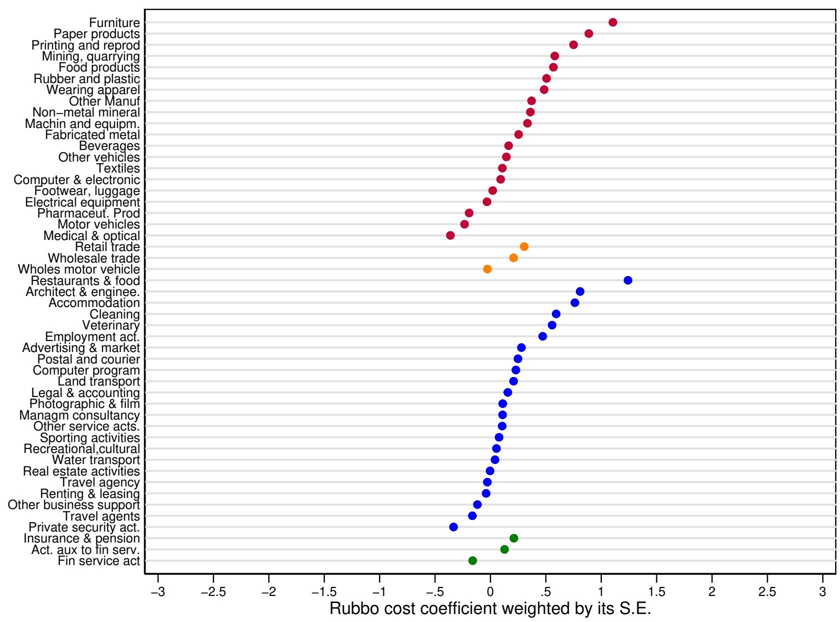
Note: Coefficients on expected inflation from Rubbo framework are weighted by their S.E.

Figure 18: Weighted coefficient on lagged inflation (Rubbo framework)



Note: Coefficients on expected inflation from Rubbo framework are weighted by their S.E.

Figure 19: Weighted coefficient on Rubbo cost (Rubbo framework)



Note: Coefficients on the composite cost from Rubbo framework are weighted by their S.E.

References

Abbas, Syed K., Prasad Sankar Bhattacharya, and Pasquale Sgro (May 2016). "The new Keynesian Phillips curve: An update on recent empirical advances". In: *International Review of Economics & Finance* 43, pp. 378–403. ISSN: 1059-0560. DOI: 10.1016/J.IREF.2016.01.003.

Adam, Klaus and Mario Padula (Jan. 2011). "Inflation dynamics and subjective expectations in the united states". In: *Economic Inquiry* 49.1, pp. 13–25. ISSN: 00952583. DOI: 10.1111/j.1465-7295.2010.00328.x.

Alvarez, Luis and Ignacio Hernando (Sept. 2007). "Pricing decisions in the euro area: How firms set prices and why". DOI: 10.1093/acprof:oso/9780195309287.001.0001.

Andrade, Philippe et al. (Jan. 2022). "No firm is an island? How industry conditions shape firms' expectations". In: *Journal of Monetary Economics* 125, pp. 40–56. ISSN: 03043932. DOI: 10.1016/j.jmoneco.2021.05.006.

Barro, Robert J (1972). *A Theory of Monopolistic Price Adjustment*. Tech. rep. 1, pp. 17–26. URL: https://about.jstor.org/terms.

Batini, Nicoletta, Brian Jackson, and Stephen Nickell (Sept. 2005). "An open-economy new Keynesian Phillips curve for the U.K". In: *Journal of Monetary Economics* 52.6, pp. 1061–1071. ISSN: 03043932. DOI: 10.1016/j.jmoneco.2005.08.003.

Bils, Mark and Peter J Klenow (2004). *Some Evidence on the Importance of Sticky Prices*. Tech. rep. 5.

Boneva, Lena et al. (Apr. 2020). "Firms' Price, Cost and Activity Expectations: Evidence from Micro Data". In: *Economic Journal* 130.627, pp. 555–586. ISSN: 14680297. DOI: 10.1093/ej/uez059.

Brezina, I. et al. (Mar. 2016). "Herfindahl–Hirschman index level of concentration values modification and analysis of their change". In: *Central European Journal of Operations Research* 24.1, pp. 49–72. ISSN: 16139178. DOI: 10.1007/s10100-014-0350-y.

Byrne, Joseph P., Alexandros Kontonikas, and Alberto Montagnoli (Aug. 2013). "International evidence on the new keynesian phillips curve using aggregate and disaggregate data". In: *Journal of Money, Credit and Banking* 45.5, pp. 913–932. ISSN: 00222879. DOI: 10.1111/jmcb.12030.

Calvo, Guillermo A. (Sept. 1983). "Staggered prices in a utility-maximizing framework". In: *Journal of Monetary Economics* 12.3, pp. 383–398. ISSN: 0304-3932. DOI: 10.1016/0304-3932(83)90060-0.

Candia, Bernardo, Olivier Coibion, and Yuriy Gorodnichenko (2021). "The Inflation Expectations of U.S. Firms: Evidence from a New Survey". URL: www.iza.org.

Carvalho, Carlos (2006). "Heterogeneity in Price Stickiness and the Real Effects of Monetary Shocks Heterogeneity in Price Stickiness and the Real Effects of Monetary Shocks". In.

Chudik, Alexander and M. Hashem Pesaran (Oct. 2015). "Common correlated effects estimation of heterogeneous dynamic panel data models with weakly exogenous regressors". In: *Journal of Econometrics* 188.2, pp. 393–420. ISSN: 18726895. DOI: 10.1016/j.jeconom.2015.03.007.

Clarida, Richard, Jordi Galí, and Mark Gertler (1999). *The Science of Monetary Policy: A New Keynesian Perspective*. Tech. rep., pp. 1661–1707.

Coibion, Olivier and Yuriy Gorodnichenko (Feb. 2012). "What can survey forecasts tell us about information rigidities?" In: *Journal of Political Economy* 120.1, pp. 116–159. ISSN: 00223808. DOI: 10.1086/665662.

— (2015). "Is the phillips curve alive and well after all? Inflation expectations and the missing disinflation". In: *American Economic Journal: Macroeconomics* 7.1, pp. 197–232. ISSN: 19457715. DOI: 10.1257/mac.20130306.

Coibion, Olivier, Yuriy Gorodnichenko, and Rupal Kamdar (Dec. 2018). "The formation of expectations, inflation, and the Phillips curve". In: *Journal of Economic Literature* 56, pp. 1447–1491. ISSN: 00220515. DOI: 10.1257/jel.20171300.

Coibion, Olivier, Yuriy Gorodnichenko, and Saten Kumar (Sept. 2018). *How do firms form their expectations? New survey evidence*. DOI: 10.1257/aer.20151299.

DelNegro, Marco et al. (2020). *What's Up with the Phillips Curve?* Tech. rep.

Dhyne, Emmanuel et al. (2006). "Price Changes in the Euro Area and the United States: Some Facts from Individual Consumer Price Data". In: *Journal of Economic Perspective*.

Ditzen, Jan (Sept. 2021). "Estimating long-run effects and the exponent of cross-sectional dependence: An update to xtdcce2". In: *Stata Journal* 21.3, pp. 687–707. ISSN: 15368734. DOI: 10.1177/1536867X211045560.

Domberger, Simon (1979). *Price Adjustment and Market Structure*. Tech. rep. 353, pp. 96–108.

Eberhardt, Markus (Aug. 2022). "Democracy, growth, heterogeneity, and robustness". In: *European Economic Review* 147. ISSN: 00142921. DOI: 10.1016/j.euroecorev.2022.104173.

Friedman, Milton (1968). "The role of monetary policy". In: *American Economic Review*.

Gagliardone, Luca et al. (2023). *Anatomy of the Phillips Curve: Micro Evidence and Macro Implications*. Tech. rep.

Gali, Jordi and Mark Gertler (1999). *Inflation dynamics: A structural econometric analysis*. Tech. rep., pp. 195–222.

Gali, Jordi, Mark Gertler, and J David Lopez-Salido (2001). *European inflation dynamics*. Tech. rep., pp. 1237–1270.

Garratt, Anthony et al. (2008). *Real-Time Representations of the Output Gap*. Tech. rep. 4, pp. 792–804. URL: https://www.jstor.org/stable/40043115.

Hazell, Jonathon et al. (2022). *The Slope of the Phillips Curve: Evidence from U.S. States*. Tech. rep.

Imbs, Jean, Eric Jondeau, and Florian Pelgrin (May 2011). "Sectoral Phillips curves and the aggregate Phillips curve". In: *Journal of Monetary Economics* 58.4, pp. 328–344. ISSN: 03043932. DOI: 10.1016/j.jmoneco.2011.05.013.

IMF (Oct. 2022). *World Economic Outlook*. Tech. rep. IMF. URL: www.imfbookstore.org.

Kato, Ryo, Tatsushi Okuda, and Takayuki Tsuruga (Dec. 2021). "Sectoral inflation persistence, market concentration, and imperfect common knowledge". In: *Journal of Economic Behavior and Organization* 192, pp. 500–517. ISSN: 01672681. DOI: 10.1016/j.jebo.2021.10.026.

Klenow, Peter J. and Benjamin A. Malin (Jan. 2010). "Microeconomic Evidence on Price-Setting". In: *Handbook of Monetary Economics* 3.C, pp. 231–284. ISSN: 1573-4498. DOI: 10.1016/B978-0-444-53238-1.00006-5.

Lee, Kevin, Michael Mahony, and Paul Mizen (2020). "The CBI Suite of Business Surveys". In: ISSN: 2631-3588. URL: www.escoe.ac.uk.

Leith, Campbell and Jim Malley (May 2007). “A sectoral analysis of price-setting behavior in U.S. manufacturing industries”. In: *Review of Economics and Statistics* 89.2, pp. 335–342. ISSN: 00346535. DOI: 10.1162/rest.89.2.335.

Maćkowiak, Bartosz, Emanuel Moench, and Mirko Wiederholt (Oct. 2009). “Sectoral price data and models of price setting”. In: *Journal of Monetary Economics* 56.SUPPL. ISSN: 03043932. DOI: 10.1016/j.jmoneco.2009.06.012.

Mann, Catherine (Sept. 2022). *Inflation expectations, inflation persistence, and monetary policy strategy – speech by Catherine L. Mann _ Bank of England*. Tech. rep.

Mavroeidis, Sophocles, Mikkel Plagborg-Møller, and James H. Stock (2014). “Empirical evidence on inflation expectations in the New Keynesian Phillips curve”. In: *Journal of Economic Literature* 52.1, pp. 124–188. ISSN: 00220515. DOI: 10.1257/jel.52.1.124.

McLeay, Michael and Silvana Tenreyro (May 2019). *Optimal Inflation and the Identification of the Phillips Curve*. Tech. rep. Cambridge, MA: National Bureau of Economic Research. DOI: 10.3386/w25892.

Meeks, Roland and Francesca Monti (2022). *Heterogeneous beliefs and the Phillips curve **. Tech. rep.

Naldi, Maurizio and Marta Flamini (Sept. 2018). “Dynamics of the Hirschman–Herfindahl Index under New Market Entries”. In: *Economic Papers* 37.3, pp. 344–362. ISSN: 17593441. DOI: 10.1111/1759-3441.12222.

Nason, James M and Gregor W Smith (2005). *Identifying the New Keynesian Phillips Curve*. Tech. rep. URL: www.frbatlanta.org.

Pesaran, M. Hashem (July 2006). *Estimation and inference in large heterogeneous panels with a multifactor error structure*. DOI: 10.1111/j.1468-0262.2006.00692.x.

Pesaran, M. Hashem and Ron Smith (July 1995). “Estimating long-run relationships from dynamic heterogeneous panels”. In: *Journal of Econometrics* 68.1, pp. 79–113. ISSN: 0304-4076. DOI: 10.1016/0304-4076(94)01644-F.

Reis, Ricardo (2023). *The burst of high inflation in 2021–22: how and why did we get here?* Ed. by Michael D. Bordo, John H Cochrane, and John B. Taylor. Hoover Institution Press, pp. 203–252. ISBN: 9780817925642.

Roberts, John M (1995). *New Keynesian Economics and the Phillips Curve*. Tech. rep. 4, pp. 975–984. URL: https://about.jstor.org/terms.

Rubbo, Elisa (2023). “Networks, Phillips Curves, and Monetary Policy”. In: *Econometrica* 91.4, pp. 1417–1455. ISSN: 0012-9682. DOI: 10.3982/ECTA18654. URL: https://www.econometricsociety.org/doi/10.3982/ECTA18654.

Rudd, Jeremy and Karl Whelan (Mar. 2006). *Can Rational Expectations Sticky-Price Models Explain Inflation Dynamics?* Tech. rep.

Sbordone, Argia M (2002). *Prices and unit labor costs: a new test of price stickiness*. Tech. rep., pp. 265–292.

Sheedy, Kevin D. (Nov. 2007). “Inflation Persistence When Price Stickiness Differs Between Industries”.

Stock, James and Mark Watson (2019). *Introduction to Econometrics, Global Edition*. Pearson Education.

Vermeulen, Philip et al. (2007). *Price setting in the euro area : some stylised facts from individual producer price data*. Tech. rep. URL: http://www.nbb.be.

Werning, Iván (2022). “Expectations and the rate of inflation”. URL: http://www.nber.org/papers/w30260.

Woodford, Michael (Sept. 2003). *Interests and prices: foundations of a theory of monetary policy*. Princeton University Press. ISBN: 9780691010496.