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

Cristina Griffa*

October 2, 2023

Preliminary and Incomplete

Please do not cite or circulate

LINK TO THE LATEST VERSION

Abstract

The recent inflation surge has renewed interest in understanding its primary drivers. This has prompted a search for enhanced empirical methods and more sophisticated data to estimate the Phillips Curve. In this study, I examine price-setting behaviour across 52 sectors in the UK and study the potential sources of the uncovered heterogeneity. I first estimate Sectoral Phillips Curves using heterogeneous panel methods, using direct measures of firms' inflation expectations. This novel feature addresses a very common weak identification issue discussed in the literature. Additionally, I account for unobserved time-varying heterogeneity. This approach enables me to identify a significant and positive Phillips Curve slope when considering the traditional setting based on only labour costs. Moreover, the inclusion of production networks through intermediate goods costs yields a significant, albeit larger slope, suggesting the importance of sectoral linkages typically overlooked in traditional Phillips Curve settings. Substantial heterogeneity across industries is uncovered in terms of forward- and backward-looking behaviour and cost responsiveness. After uncovering this asymmetry, I delve into their main drivers, focusing on sector-specific costs and market structures. The results reveal a positive association between the level of concentration and the role 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 also want to thank Galina Potjagailo for her comments and helpful conversations. I extend my gratitude to Omar Licandro, Nacho Vizcaino, Markus Eberhardt, Jan Ditzen, my colleagues at the University of Nottingham, my colleagues at the Bank of England, and the 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 their insightful discussions. Additionally, I would like to 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.

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[2]. 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[3]. Finally, potential measurement errors may arise from using indirect measures of expectations, such as forecasts from professionals or households expectations[4], actual inflation as an instrument, or assuming rational expectations.

I estimate the Sectoral Phillips Curves based on two frameworks, with the main difference lying on the production function, one assuming that labour is the only source of costs and the other including intermediate goods alongside labour. Notably, I will show that, on average, the structural parameters from both frameworks are quite similar when it comes to the role of expectations and lagged inflation. However, the responsiveness of prices to costs is significantly smaller when labour costs are considered alone compared to when intermediate goods costs are also taken into account. Incorporating intermediate goods costs introduces sectoral linkages and additional nominal rigidities within the supply chain. This is particularly relevant during periods of recent inflation spikes, as it adds a crucial layer to our understanding of the inflation process. My findings from 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. The microfoundation of the Sectoral Phillips Curve predicts heterogeneity in price-stickiness, in the price responsiveness to costs and in the degree of backward-lookingness without providing a specific theoretical framework for the sources of these heterogeneities. I will then explore certain industry-characteristics that might be associated with the heterogeneity observed across sectors. 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[5].

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

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

[4]Coibion, Gorodnichenko, and Kamdar, 2018.

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

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 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

[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).

effects of production networks. Therefore, the results might not be directly comparable to previous evidence.

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 3 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

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

In this section, I will discuss two frameworks for studying sectoral inflation dynamics. First, I will introduce the labour cost-based Sectoral Phillips Curve, which is based on IJP's work. This framework extends the traditional microfoundation approach used to derive the aggregate Phillips Curve. It does so by incorporating distinct key assumptions that enable it to explain sectoral inflation processes instead of aggregate inflation dynamics.

One notable limitation of IJP's framework is its omission of sectoral interactions within the theoretical setting. IJP empirically approximate the presence of production linkages by utilising econometric techniques, which allow them to account for potential correlations in sectoral shocks and capture any cross-sectoral interdependencies that may exist in the data.

In my analysis, I will 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 emphasised the explicit inclusion of the production network within the microfoundations of the Phillips Curve. In line with this approach, the second framework is based on the Sectoral Phillips Curve derived by Rubbo, 2023. Leveraging input-ouput tables, I will use the micro level intermediate input shares to capture the sectoral linkages, presenting novel empirical evidence on how sectoral interconnections influence the inflation process. A more detailed exploration of this framework will be undertaken in the second part of this section.

In the final part of this section, I will discuss additional industry-characteristics not considered in the studied theoretical frameworks but are nonetheless linked to 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.

[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.

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:

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

Additionally, among the firms that are able to adjust prices within a specific period, only a portion represented as $1-\omega_k$ follows optimal pricing strategies, i.e. they set prices based on their expectations of future marginal costs. Conversely, a fraction ω_k use a simple rule of thumb: they set prices based on past inflation data $\pi_{k,t-1}$. By introducing this concept, we arrive at a hybrid Phillips curve that encompasses the purely forward-looking Calvo model as a particular case.

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], 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:

$$\pi_{kt} = \gamma^b_k\, \pi_{k\,t-1} + \gamma^f_k\, E_t\, \pi_{k\,t+1} + \gamma^s_k\, h_{kt}\, \hat{s}_{kt} + \varepsilon^{\pi}_{kt} \tag{2}$$

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^{π}_{kt}, is a cost-push shock.

$$\mu = 1.1$$

[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.

[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.

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

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.

2.2 The Labour and Intermediate Goods Cost-Based Sectoral Phillips curve

A widely accepted consensus attributes the recent surge in inflation in most advanced economies to a combination of demand and supply shocks, impacting sectors heterogeneously, followed by deanchoring and an increase in inflation expectations [14]. This intricate inflation process necessitates a more sophisticated theoretical framework that integrates the production network into the microfoundations of the Phillips Curve. In the following section, I discuss the second framework, rooted in the Sectoral Phillips Curve model introduced by Rubbo, 2023.

By leveraging data from input-output tables, the estimation of this framework allows us to capture intermediate goods costs and sectoral linkages. This provides 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.

[14] For an in-depth analysis of the primary factors behind the recent rise in inflation in most Western advanced economies, see Reis, 2023.

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.

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

- 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]:

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

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 6. In Appendix B I show the derivation of the system with 2 sectors for illustrative purposes.

$$\pi_{kt} = [(I - \Lambda \, \tilde{A})^{-1} \tilde{A}] \, \hat{s}_{kt}^{R} + (I - \Lambda \, \tilde{A})^{-1} \beta \, (1 - \tilde{A}) \, E_t \pi_{k\,t+1} \tag{5}$$

[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.

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

$$s^R_{kt} \equiv (1 - a_{kt})\, \hat{w}_{kt} + \sum_j \lambda_{kjt}\, \hat{p}_{jt} - (1 - \lambda_{kkt})\hat{p}_{k\,t-1} \tag{6}$$

I approximate the Rubbo's cost measure, s^R_{kt} [17], by using: the labour share for each sector, $(1 - a_{kt})$, the intermediate goods share bought by sector k from sector j, λ_{kjt}, and sector j's intermediate goods' prices, $\hat{p}_{jt}$ [18].

By further reducing the expression in Equation 6, I obtain the equivalent to the Sectoral Phillips Curve:

$$\pi_{kt} = \gamma^s_k\, \hat{s}^R_{kt} + \gamma^f_k\, E_t\, \pi_{k\,t+1} + \varepsilon^\pi_{kt} \tag{7}$$

Despite the similarity between Equation 7 and the reduced form from IJP, the underlying structural parameters derived from Rubbo incorporate sectoral linkages. Sectoral inflation in a given sector is influenced by both wages and intermediate goods prices. Additionally, the responsiveness of prices to costs will be explained by sectoral interconnections through the input-output table (Λ) and nominal rigidities (A). The role of expectations will be explained by the same structural parameters, as well as β.

Let's compare the sets of structural parameters from IJP and Rubbo and temporarily ignore the discount factor and the indexation rate (ω in IJP) for simplicity: One interesting difference is that in the traditional Sectoral Phillips Curve setting, firms pricing behaviour in sector k respond to expected inflation and costs based on their own degree of price stickiness. However, in the extended version of the Sectoral Phillips Curve that incorporates production networks, the responsiveness of prices to expected inflation and to marginal costs is influenced not only by the nominal rigidities within the sector itself but also by its suppliers, considering the extent of sector k's purchases from these suppliers. I discuss this further in section 4.3.

2.3 Industry Characteristics and Cross-Section Heterogeneity

In the previous sections, I described the microfoundations of the Sectoral Phillips Curves, which emphasise differences in parameters without providing structural explanations. While both frameworks reveal variations in price stickiness among industries, they lack a structural rationale. This section introduces industry-specific characteristics, drawn from existing research, to address the cross-section heterogeneity. It explores various determinants that shed light on the relationship between price stickiness and industry characteristics.

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

[18] Matching the notation used in IJP's section, variables with the hat symbol ($\hat{}$), such as $\hat{p}_{jt}$ and $\hat{w}_{kt}$, represent the log deviation of price and wage, respectively, from the sectoral sample mean.

The results of this "second-stage" analysis hold significant value for future research, aiding in addressing gaps in microfoundations for better specifying and identifying structural parameters. Additionally, these findings also provide insights for policymakers, especially concerning expectations management and communication. Monetary policy (MP) has more substantial and enduring effects when accounting for the asymmetries across sectors (Carvalho, 2006). These asymmetries in price change frequencies across sectors result in varying speeds of reaction to economic shocks. Moreover, 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).

2.3.1 Understanding the Positive Relationship Between γ^f and Price Stickiness

Most academic analysis has predominantly centred around the concept of price stickiness (α). However, the estimation of the Phillips Curve provides sector-specific values for γ^f. To further understand this relationship, I will delve into the underlying parameters that constitute γ^f. These parameters include β (the discount factor), α (representing price stickiness), and ϕ (ultimately influenced by α, β, and ω)[19]. Typically, β is assumed to be close to 1. In my analysis, I will focus on the forward-looking behaviour, with the understanding that the backward-looking (γ_b or ω) and forward-looking (γ_f) behaviour move in opposite directions.

The NKPC setting claims that the greater the price stickiness in sector k, the more firms are unable to adjust prices in each period (t). Consequently, they assign more weight to expected future markups, leading to a higher value of γ^f. This positive relationship between γ^f and price stickiness arises because firms, facing greater price stickiness, are compelled to maintain the same price for a more extended period.

This line of reasoning is consistent with Werning, 2022, who argues that firms initially set their prices above their ideal price, but as time progresses, their prices tend to fall below the ideal level. Consequently, when firms expect higher inflation, they adjust their prices more substantially above the currently ideal price. Thus, sectors with lower price change frequencies will overshoot inflation proportionally more as a compensatory response. Higher values of α result in a stronger pass-through effect from expectations of future inflation to current inflation.

2.3.2 Determinants of Cross-Sector Heterogeneity

Understanding the factors contributing to cross-sector heterogeneity in the forward-looking parameter (γ^f) of the Sectoral Phillips Curve is essential. Various determinants come into

[19] The parameter ω is introduced in the IJP derivation to capture sectoral inflation persistence.

play, shedding light on the relationship between price stickiness and industry characteristics. In the following subsection, I will review industry-specific characteristics studied in the existing literature. Klenow and Malin, 2010 provides a (non-exhaustive) list of factors affecting the frequency of price changes, based on research available up to 2010. These factors include: inflation variability, the frequency and magnitude of cost and demand shocks, the structure and degree of market competition, and the statistical methods used to collect price data.

Market Concentration: Leith and Malley, 2007 conducted a study estimating NKPC structural parameters for US industries. They found a positive correlation between market concentration (Herfindahl-Hirschman index) and price stickiness. They argue that higher concentration, indicating less competition, results in stickier price-setting behaviour and a greater tendency to respond in a forward-looking manner. Relatedly, Bils and Klenow, 2004 found 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.

External Competition: In addition to market concentration, Vermeulen et al., 2007 studied the impact of external competition through an indicator of "import penetration" derived from input–output tables. Alvarez and Hernando, 2007 also investigated this aspect and found a significant, albeit weak, positive effect of import penetration on the frequency of price changes. Import penetration is calculated as total imports over total resources (production plus total imports), using the Input–Output tables.

Inflation Variability: Dhyne et al., 2006 revealed that sectors with higher inflation variability tend to have significantly higher price change frequencies. This suggests that firms may adjust prices more frequently when facing greater volatility in inflation to stay closer to their optimal prices.

Cost Structure: Vermeulen et al., 2007 and Alvarez and Hernando, 2007 explored the impact of cost structure on price change frequencies. They found that firms in labour-intensive sectors tend to adjust prices less frequently, possibly because wages adjust less frequently than other input prices. Conversely, firms with a higher share of energy and intermediate inputs in total costs have a positive correlation with the frequency of price changes. This is because the prices of raw materials, such as energy, change very frequently.

Other Relevant Factors: Additional factors have been studied by researchers examining price changes. For instance, Bils (2004) found an inverse relationship between the concen-

tration ratio and the frequency of price changes, suggesting that more competition leads to more frequent price adjustments. Moreover, Kato (2021) reported a negative correlation between sectoral inflation persistence and market concentration, implying that increased market concentration is associated with an increase in γ^f. This correlation is due to changes in pricing complementarity as markets become more concentrated.
In contrast, Domberger, 1979 reports opposing findings: a positive relationship between the speed of price adjustment and market concentration. The author considers two plausible hypotheses: the first suggests that price coordination in concentrated industries is easier due to relatively low information and communication costs among sellers, potentially accelerating price adjustments. The second hypothesis relates to "administered prices" and posits that sellers in highly concentrated markets tend to adjust prices unilaterally either due to difficulties in oligopolistic collusion or through the use of mark-up pricing. While Domberger provides evidence supporting the first hypothesis, it is important to note that his study period (1963-1974) coincided with a period of rising inflation, characterised by mostly upward price movements. Furthermore, his sample predominantly consists of industrial sectors, whereas my sample includes also services and distributive sectors, reflecting a wider range of market structures.

These findings collectively contribute to our understanding of why different sectors exhibit varying levels of price stickiness, providing valuable insights into cross-sector heterogeneity within the Sectoral Phillips Curve. These determinants will be further tested in Section 6 to comprehensively analyze their impact on the Sectoral Phillips Curve parameters.

2.4 Open Economy Features

The Sectoral Phillips Curves presented in the previous sections do 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.

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.

$$\pi_t = \gamma^f\, E_t\{\pi_{t+1}\} + \gamma^b\, \pi_{t-1} + \gamma^s\, s_t + \alpha_1\, z_{p,t} + \alpha_2\, (p_t^W - p_t) + \alpha_3\, s_{L,t} + \alpha\Delta n_t + \varepsilon_t^\pi \tag{8}$$

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 IJP and Rubbo, 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.

3 Sectoral Phillips Curve: An Empirical Investigation

In the following empirical analysis, I employ a partial equilibrium approach to estimate the Sectoral Phillips Curve, drawing from the frameworks developed by IJP and Rubbo. In this section, I will first provide a brief overview of the key identification issues that have been discussed in the literature concerning Phillips Curve estimation. For a more comprehensive review, please refer to Mavroeidis, Plagborg-Møller, and Stock, 2014 and Abbas, Bhattacharya, and Sgro, 2016.

In the second part, I ellaborate on how these identification issues are addressed in this study. This includes the use of direct measures of expectations, sectoral data, and the application of panel methods, among other considerations.

Finally, in the third part, I will delve into the tradeoff between using marginal cost and the output gap as proxies for the forcing variable.

3.1 Challenges in Estimating the Phillips Curve

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.

Sectoral Heterogeneity in the Phillips Curve Framework: The Phillips Curve has typically been estimated at the aggregate level, assuming homogeneity across firms and sectors. However, when data reveals heterogeneity across sectors, imposing homogeneity can introduce aggregation bias. To address these issues, research papers such as IJP and Byrne, Kontonikas, and Montagnoli, 2013 have turned to the Sectoral New Keynesian Phillips Curve (NKPC) framework, which reveals lower persistence of inflation and significantly larger coefficients on real marginal costs compared to the aggregate level. This highlights the empirical importance of sector-level heterogeneity.

Addressing Cross-Sectoral Interdependencies: Factors such as input-output production linkages and integrated factor markets can lead to cross-sectoral interdependencies. To account for these interdependencies, IJP implement the Seemingly Unrelated Regression Equations (SURE) correction, aimed at capturing cross-sector interdependencies. They assert that the SURE correction is a robust technique that accommodates common macroeconomic shocks, cross-sector linkages, and other factors influencing sectoral prices or marginal costs with contemporaneous correlations across industries. To enhance robustness, they also employ an alternative estimator proposed by Pesaran, 2006, which introduces a correction technique to account for unobserved common factors[20], potentially correlated with sector-specific regressors.

While Byrne, Kontonikas, and Montagnoli, 2013 also utilise the CCE technique, they employ the weighted mean group (WMG) estimator which utilises observed sectoral weights. Both IJP and Byrne (2013) assume an exogenous autoregressive process for real marginal costs to identify the forward-looking term of inflation in the NKPC model, as direct measures of expectations are lacking.

It's worth noting that while these research papers employ powerful tools to address cross-sector interdependencies, they do not explicitly model linkages between sectors, such as through an input-output structure. Therefore, I enhance the estimation of Sectoral Phillips Curves by accounting for production networks through input-output tables and eliminating any remaining cross-sectional dependence through CCEs. Another way my approach improves estimation is through the use of direct measures of inflation expectations.

The Simultaneity Challenge in Phillips Curve Estimation: 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. Additionally, the dependent variable (prices) may be jointly determined with the explanatory variables (salary and expectations). To address the common simultaneity problem, I will employ instrumental variable techniques, including lagged explanatory variables, and present relevance tests and alternative instruments for robustness.

The Impact of Endogenous Monetary Policy Response on Phillips Curve Slope: Another challenge faced in estimating the aggregate Phillips Curve arises from the disconnection between inflation and real economic activity due to the dynamic response of

[20] I will provide a more detailed explanation of CCE in Section 3.2.2.

monetary policy to inflationary pressures. As ellaborated in McLeay and Tenreyro, 2019, the slope of the Phillips Curve is the result of the interplay between Aggregate Supply (AS) and Aggregate Demand (AD). While AS represents the positive correlation between inflation and real activity, AD reflects the central bank's objective to offset demand shocks through monetary policy.

When the central bank successfully mitigates these demand shocks, the AD would offset the AS effect. Consequently, what becomes apparent is a negative slope, reflecting the endogenous response of monetary policy to inflationary pressures. In practical terms, this means that when inflation rises, the central bank takes measures to slow down the economy.

This argument sheds light on the observed empirical evidence of flat Phillips Curves when using aggregate data. To address this challenge, researchers have explored the use of cross-sectional data, such as regional or sectoral data, as a means to overcome the simultaneity issue. See McLeay and Tenreyro, 2019 for an example with regional data. In the following sections, I will delve into how leveraging sectoral data can effectively tackle the simultaneity issue and estimate sector-specific price-setting behaviour after eliminating cross-sectional dependencies.

3.2 Solutions Proposed to the Described Challenges

3.2.1 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. That work 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. 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[21] 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.

3.2.2 Utilising Common Correlated Effects (CCE) Estimation in Dynamic Panel Mean Group Analysis

In the context of Dynamic Panel Mean Group Estimation, this study employs the Common Correlated Effects (CCE) estimator, a method closely aligned with the approach introduced by Chudik and Pesaran, 2015. The CCE estimator, initially proposed by Pesaran, 2006 and extended by Chudik and Pesaran, 2015[22] is designed to address the challenge of cross-

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

[22] 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.

sectional dependence (CSD) and enhance the efficiency of estimations. This section explores its application in the context of the estimation of the Sectoral Phillips Curve.
When analysing sectoral inflation dynamics, it's essential to account for various factors. For instance, the conventional Sectoral Phillips Curve framework assumes that labour is the sole factor of production, ignoring the production network linkages discussed in the previous section. Additionally, there are potential omissions of common shocks—a factor not explicitly considered in both the IJP and Rubbo models. Failure to account for the impact of these shocks across sectors can lead to their mistakenly incorporation into the model residuals, consequently losing estimation efficiency.

To mitigate these limitations I incorporate CCEs into the estimation framework. Notably, the inclusion of CCEs serves to mitigate the aforementioned risks and is expected to reduce CSD. While Rubbo's model incorporates intermediate goods within the production function alongside labour, thereby facilitating the inclusion of some sectoral linkages through input-output tables, empirical results reveal remaining CSD even after the incorporation of the production network.

To provide some intuition: it could be that some shocks that hit the UK economy such as Brexit and Covid affected several sectors simultaneously and differently, and are not necessarily captured by the production network. We should however think of these omitted factors not just as omitted variables, which we could in principle have included in the model, but also as a set of unknown and time-varying determinants correlated with inflation and independent variables. Therefore, CCEs will also be included in Rubbo's estimation equation.

The inclusion of CCEs is achieved by considering time-varying covariates, which play a crucial role in accounting for sectoral linkages, unobserved factors, and common shocks that may affect sectors heterogeneously. These common elements are complemented by sector-specific "factor loadings" designed to capture various sector-specific shocks using a more concise set of variables. This approach[23] effectively reduces data dimensionality and prevents overfitting by concentrating on the most influential factors affecting the variables of interest.

In general terms, the model can be expressed as follows:

$$\begin{aligned} y_{kt} &= \zeta_k \, y_{k,t-1} + \iota_k \, x_{kt} + u_{kt} \\ x_{kt} &= \xi_{x,1k} \, f_{1t} + \xi_{x,2k} \, f_{2t} + \varepsilon_{x,kt} \\ u_{kt} &= \xi_{u,1k} \, f_{1t} + \xi_{u,2k} \, f_{2t} + \varepsilon_{u,kt} \end{aligned}$$

[23]See Eberhardt and Presbitero, 2015 for an empirical application of these methods

In this representation, we observe variables such as y_{kt}, x_{kt}, the common factors f_{It}, while the factor loadings ξ_{Ik} are unobserved. The error terms $\varepsilon_{x,kt}$ and $\varepsilon_{u,kt}$ are both independently and identically distributed (IID). Not accounting for the CSD[24] potentially leads to (i) Ommited variable bias if $\xi_{x,k} \neq 0$ indicating that sectors are exposed to the same common factor or shock, and ordinary least squares becoming inconsistent; (ii) Residuals can be correlated across sectors if $\xi_{u,k} \neq 0$.

Then, in the case of the IJP Sectoral Phillips Curve, I augment Equation 2 as follows:

$$\pi_{kt} = \alpha_k + \gamma_k^b \, \pi_{k\,t-1} + \gamma_k^f \, E_{kt} \, \pi_{k\,t+1} + \gamma_k^s \, h_{kt} \, \hat{s}_{kt} + u_{kt} \tag{9}$$

$$u_{kt} = g_k \, f_t + \varepsilon_{kt}^{\pi} \tag{10}$$

where π_{kt}, $\pi_{k\,t-1}$ and $E_{kt}\,\pi_{k\,t+1}$ are current, lagged, and expected sectoral inflation, respectively, all expressed in annual percentage change; $\hat{s}_{kt}$ is detrended real marginal cost, expressed in logarithm terms. These variables constitute the observable part of the model, with their parameter coefficients γ_k^b, γ_k^f, and γ_k^s allowed to differ across industries k. Equation 9 also includes sector fixed-effects, α_k, and a set of unobserved common factors f_t with sector-specific factor loadings g_k. These common factors not only drive inflation but also expected inflation and real marginal costs. As explained in Eberhardt and Presbitero, 2015, the parameters γ_k^b, γ_k^f, and γ_k^s are not identified unless I find some way to approximate the unobservable factors in the error term u. Following Chudik and Pesaran, 2015, I compute cross-sectional averages z_t to approximate the time-varying covariates.

Equation 9 is then estimated using various sets of covariates to eliminate strong CSD while monitoring regression dimensionality, considering the limitations of the sample size. The initial set of cross-sectional averages, following the methodology's literature, are computed on the model's explanatory variables: inflation, expected inflation, and the cost measure. Due to the high correlation between the first two variables[25], including just one is sufficient. Additionally, in line with empirical evidence mentioned in the previous section, I incorporate additional time-varying covariates, specifically real import prices and oil price inflation.

Next, I provide an illustrative specification framework for estimating Equation 9, which effectively mitigates strong cross-sectional dependence (CSD) by utilising the following variables for z_t: average expectations (lags zero to three), average labor costs (lags zero to two), and oil inflation (lags zero to two). For detailed results, please refer to the regression outputs in Table 3.

[24]This is explained in detail in Ditzen, 2021, based on Everaert and De Groote, 2016.
[25]See details in Correlation Table 7.

$$\begin{aligned}\pi_{kt} &= \alpha_k + \gamma_k^b\, \pi_{k\,t-1} + \gamma_k^f\, E_{kt}\, \pi_{k\,t+1} + \gamma_k^s\, h_{kt}\, \hat{s}_{kt} \\ &\quad + \sum_{t=0}^{3} g_{1\,k}\, \overline{E_{kt}\, \pi_{k\,t+1}} + \sum_{t=0}^{2} g_{2\,k}\, \overline{\hat{s}_{kt}} + \sum_{t=0}^{2} g_{3\,k}\, \pi_t^{oil} + \varepsilon_{kt}^{\pi}\end{aligned} \tag{11}$$

3.2.3 Heterogeneous Sector-specific Coefficients

Ignoring the heterogeneity across sectors in dynamic panel analyses and opting for a pooled (homogeneous) model may result in inconsistent and potentially misleading coefficient estimations, as discussed in Pesaran and Smith, 1995. Furthermore, Byrne, Kontonikas, and Montagnoli, 2013 presents evidence that overlooking data heterogeneity can lead to an aggregation bias, which, in turn, can amplify inflation persistence and diminish the significance of real marginal costs, particularly when these costs exhibit high persistence.

$$\pi_{kt} = \gamma^f\, E_{kt}\pi_{k\,t+1} + \gamma^b\, \pi_{k\,t-1} + \gamma_k^s\, h_{kt}\, \hat{s}_{kt} + \varepsilon_{kt} \tag{12}$$

By estimating Equation 12 instead of Equation 9, upon any of the following being true: $\gamma_k^f \neq \gamma^f$, $\gamma_k^b \neq \gamma^b$ or $\gamma_k^s \neq \gamma^s$, then the errors ε_{kt} will be correlated with the explanatory variables and the estimated coefficients will be biased.

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

3.2.4 Sectoral Linkages Through Input-Output Tables

In sharp contrast to the one-sector benchmark, within a multi-sector framework, industries may be differentially exposed to wage and productivity fluctuations, in a direct way through labour costs and in an indirect way through the production network. Rubbo's multi-sector theoretical framework incorporates intermediate goods as an additional source of cost variability. When firms integrate intermediate goods into their cost minimisation process, they include sectoral linkages in their price-setting decisions. Each firms' cost structure is influenced by its interactions with other industries and the resulting adjustments due to price changes in those industries.

Furthermore, by considering production networks using input-output tables, it reveals additional nominal rigidities within the supply chain. The responsiveness of industry k to changes in costs has a direct effect through wages, and an indirect effect of inflationary pressures through the production network. A shock to industry j will impact industry k proportionally to the share of expenditures of sector k spent in industry j and the degree of stickiness of sector j.

Therefore, the degree of price stickiness in industry k is directly explained by the same-industry characteristics, i.e. reasons for having low-frequency in price adjustment, or indirectly by the price stickiness coming from the supplier. Intuitively, a non-sticky industry is willing to update prices every quarter but buys goods only from a very rigid industry which only updates prices annually. Hence, the non-sticky industry will exhibit low-frequency price updates. A non-sticky industry could be thought of as an industry not tied to annual contracts or an industry with very high market power. Conversely, a sticky industry could be due to using annual contracts/indexation or being part of a very competitive market.

By omitting the sectoral linkages, the estimation of the Phillips Curve will be biased. See Appendix B for an illustrative example of an economy with 2 sectors.

This aspect gains particular significance in light of the recent surge in inflation, as production networks and sectoral interdependencies add a critical layer to our understanding of the inflationary process.

3.2.5 Other Potential Identification Concerns

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

Time Series Properties: One common challenge in this literature 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, I employ lagged variables[26] to instrument out the regressors.

Another commonly concern is the potential nonstationarity of the inflation series. In Table 6 I carried out panel unit root tests following Pesaran, 2007. Results reject the panel unit root test hypothesis, indicating that a statistically significant proportion of the units are stationary.

It is also the case that inflation expectations are simultaneously determined along with the current inflation rates. By conducting a first-stage regression, the resulting fitted value

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

mitigates the endogeneity issue. I show in Table 8 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 an annual to a quarterly measure. This is reflected in the short-dated correlation, 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 vice versa.

Finally, I include sector fixed effects to the empirical specification to mitigate any measurement error in the proxies used for the marginal cost or any error coming from the survey-based data.

3.3 Proxy for the 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 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 Sectoral Phillips Curve by Woodford, 2003 contains both relative prices and aggregate output gap[27] whereas the

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

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. Therefore, I will use firm-reported data of salary costs from the survey as proxy for the slack measure.

4 Data and Descriptives

4.1 Survey of Firms' Expectations

The Confederation of British Industry (CBI) suite of business surveys comprises four surveys[28] 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.

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

Although the CBI survey began in 1958, the quantitative question on past and expected future price movements started being collected in 2008[29]. 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.

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

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

To the best of my knowledge, there is only one prior study, Boneva et al., 2020, that has utilised 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)[30] whereas for DTS, FSS and SSS[31] are -5% to 5%. Additionally, in the four surveys they can answer zero or enter a point estimate manually. The range studied in this work, which spans from -10% to 10% has proven to be highly advantageous in capturing the rising inflation period 2020-2022, compared to the households survey[32] which had the highest bucket at 5%.

I construct a continuous variable by assigning the midpoint of each price-change bin. By retaining only data points with sector and firm ID information, and removing empty reports on price movements, the full dataset from 2009q2 to 2022q3 contains 36,299 observations. Also, I identified as outliers and winsorised[33] those expectations reports that are very far from the other firms' reports in the same sector. This is explained in detail in Appendix D. Using this conservative method, only 750 observations are identified as outliers and thereby replaced through the winsorising method.

The respondents in the CBI dataset encompass 65 sectors classified at the 2-digit SIC level. However, for my analysis, I focus on 52 sectors for which I have a time series spanning more than 45 quarters.

[30]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%

[31]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%

[32]Bank of England/Ipsos Inflation Attitudes Survey

[33]Winsorising is the transformation of extreme values by capping them at a specified percentile of the data; in this case I cap the low extreme values at percentile 25 -6*IQR and the high extreme values at percentile 75 + 6IQR.

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 centred 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, Covid, 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

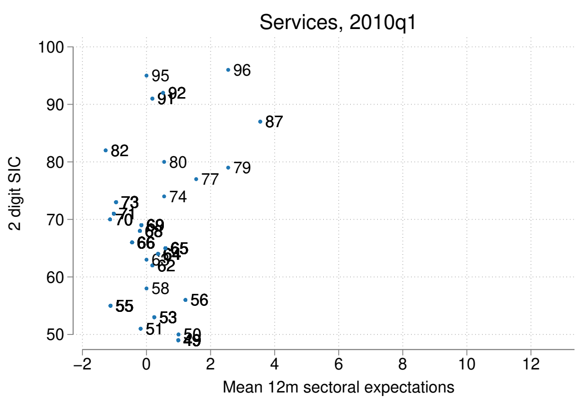


Figure 2

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 utilise 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,

Figure 3

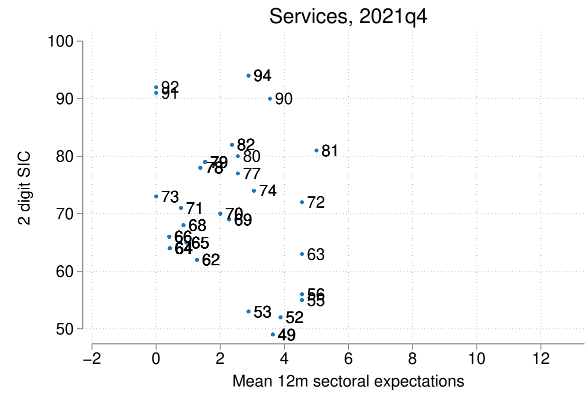


Figure 4

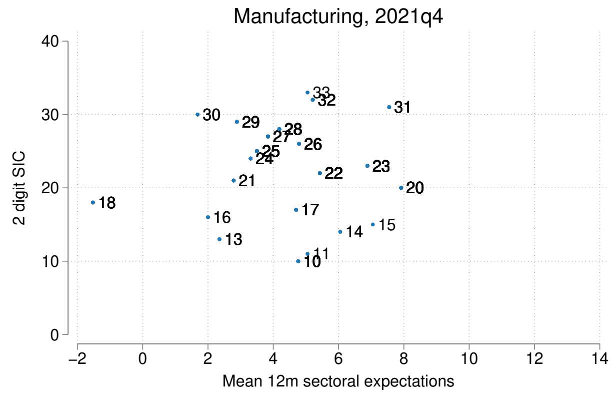


Table 2: Number of firms in each of the sectors used in the panel

	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

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[34]) by SIC code for industrial sectors. For non-industrial sectors, the Consumers Price Indices (CPI) and Services Producer Prices Indices (SPPI) could be used[35].

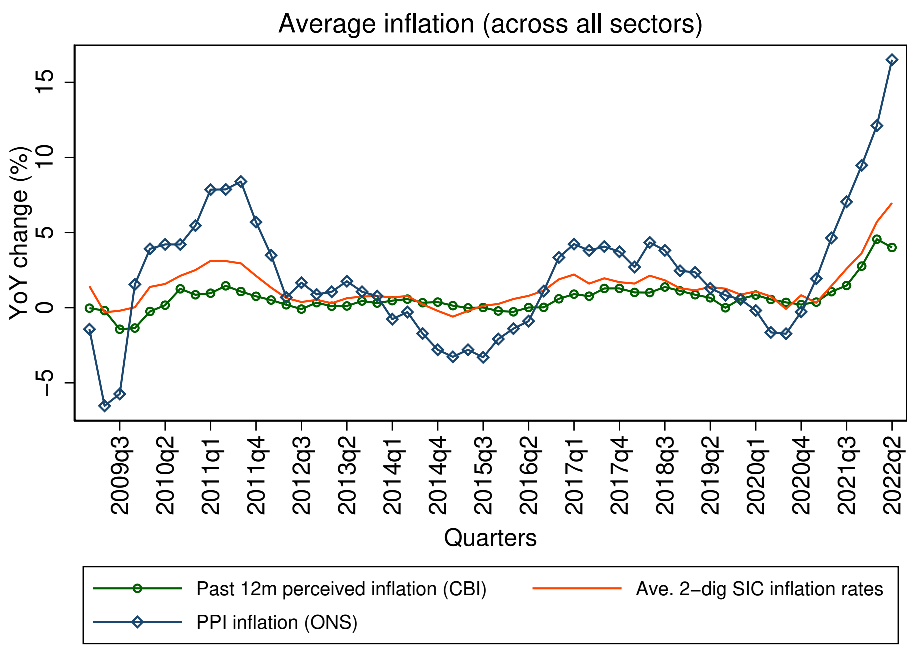
[34]For the PPI I use the output price index. The prices of goods sold by UK manufacturers i.e. the price of goods output (produced) by the UK manufacturer and sold within the UK market. These are commonly known as 'factory gate' prices to reflect the fact that they measure the price of goods before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

[35]The mapping of 4-digit SIC sectors and PPI, CPI, SPPI data is detailed in Table 10.

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 figure 6, the average of CBI inflation reports follows quite closely the average of 2-digit SIC inflation rates.

Figure 5: Measures of sectoral inflation



Note: "Past 12m perceived inflation" refers to perceived changes in prices reported by firms to the CBI survey. "Ave. 2-dig SIC inflation rates" is constructed as the average across all sectors using inflation series from PPI, SPPI and CPI series provided by the ONS.

4.3 Input-Output Tables

The ONS produces 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. The input-output tables are available at an annual frequency. From these tables I derive the share of labour expenses and the share of intermediate goods expenses for each 2-digit SIC industry to build the production network matrix.

Share of labour cost and share of intermediate inputs costs:

$$Totalcost_k = Intermediatecosts_k + CompensationtoEmployees_k$$

$$LS_k = \frac{CompensationtoEmployees_k}{Totalcost_k}$$

$$ICshare_{kj} = \frac{IC_{kj}}{Totalcost_k}$$

where $IC_{k,j}$ refers to the annual amount bought by industry k to sector j and LS_k refers to the annual Labour costs share in sector k.

4.4 Slack Measures

In the Phillips Curve literature, the measure of real economic activity is typically proxied by either the output gap or some measure of real marginal costs. As discussed in Section 3.3, variations in production costs are considered the most theoretically sound representation of the slack measure. For the sake of robustness, I have used both marginal cost and the output gap in the estimation of the Phillips Curve. Notably, statistically significant results were obtained when employing the CBI measure of labour cost. Below, I will provide a detailed explanation of the data sources and methodological approach used for each of these measures.

4.4.1 Labour Cost

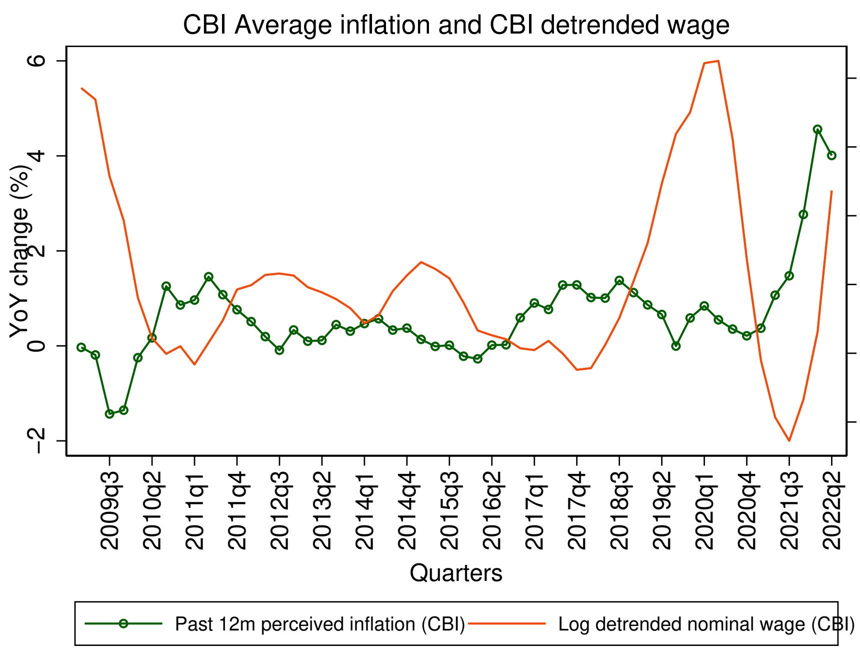
For the sectoral labour costs, I tried two measures: the log detrended nominal wage, constructed using the CBI self-reported changes in salary costs, and a measure of the unit labour cost (ULC) provided by the ONS[36]. The former is shown in Figure 6 and yields the expected statistical and economic estimates 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)). This measure is not statistically significant when using it as a forcing variable in the estimation of the Phillips Curve based on Equation 2.

[36] See more details on how I constructed these two measures in Appendix D. I calculated the log deviation of wage from the sectoral sample mean, $\hat{s}_{kt}$ using the self-reported change in each firm's "wage/salary cost per person employed"

4.4.2 Output Gap

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). The other measure I used as proxy for the slack measure is the UK output gap calculated and provided by the Bank of England. See the time series in Figure 7. This measure was not statistically significant when used as a slack measure of the Phillips Curve.

Figure 6: Inflation and CBI nominal wage

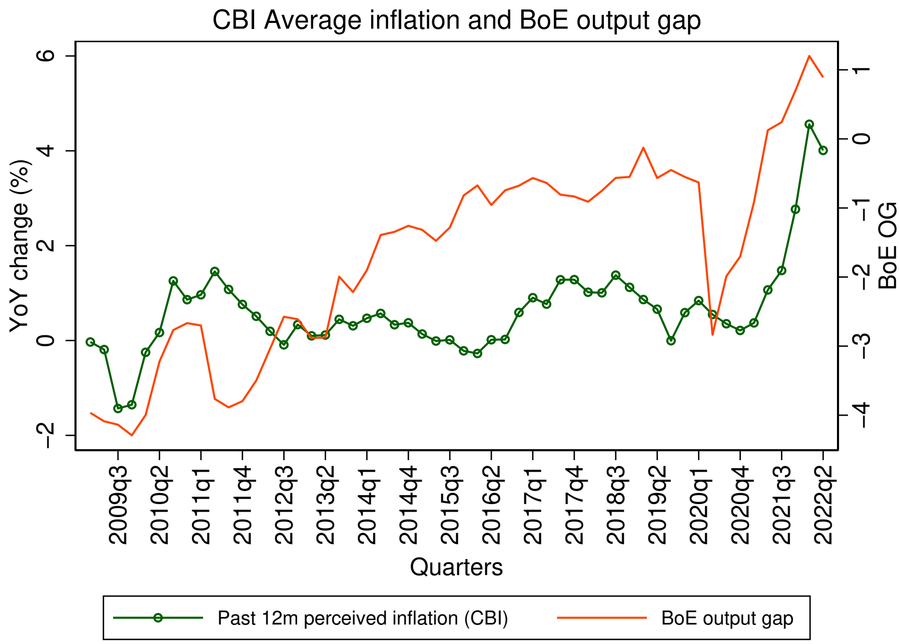


Note: I calculated the log detrended nominal wage as the deviation of wage from the sectoral sample mean using the self-reported change in each firm's "wage/salary cost per person employed" from the CBI.

4.4.3 Composite Cost

In order to construct Rubbo's composite cost measure for the estimation of Equation 6, I need the following data: the labour share for each sector, $(1 - a_{kt})$, the intermediate goods share bought by sector k from sector j, λ_{kjt}, and sector j's intermediate goods' prices, $\hat{p}_{jt}$. I have explained in Section 4.3 how I obtain the first two from the input-output table, LS_k

Figure 7: Inflation and BoE output gap



Note: The data for the Bank of England output gap was provided by staff from the Bank of England and is publicly available in the BoE monetary policy reports.

and $ICshare_{kj}$, respectively. Below, I will explain how I calculate the intermediate goods' prices.

I first compute quarterly sectoral prices by dividing the past 12 months CBI perceived sectoral inflation by four, $\pi^q_{kt} \equiv \frac{\pi^y_{kt}}{4}$. By indexing the first quarter in the series as 100 and applying the quarterly changes throughout the series, I obtain a price level series for each sector at the quarterly basis. Lastly, I compute the log of the series and detrend it by subtracting the sample mean price for each sector and obtain $\hat{p}_{kt}$.

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

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

ln[((HAEA*A)/ABML)*100], where A = (E + SE)/E. E is given by BCAJ[37], 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[38], where IKBI is total imports (current prices), and IKBL is total imports (constant prices).

4.5.1 Market Concentration (Herfindahl-Hirschman Index)

To identify the industrial structure, I calculate the standard measure of concentration, the Herfindahl-Hirschman Index (HHI). As I am not aware of any ongoing production of these indices for UK firms, I constructed the HHI using turnover data from FAME BvD[39]. I show the series for each industry from 2009 to 2021 in Figure 22, but I use only the 2021 series for the panel analysis as it is the latest available and it does not vary much from previous years.

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

I then define the HHI for a given sector k as follows: $HHI_k = \sum_{f=1}^{n} (s_f)^2$ (summing up all firms f in each industry). 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

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

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

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

report from Q3-2020 should capture expectations about changes in prices from Q3-2020 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 sector-level microfoundation of the Phillips Curve provides greater theoretical structure to the estimations.

Based on Imbs, Jondeau, and Pelgrin, 2011 (IJP), I will estimate the reduced-form parameters using Equation 2:

$$\pi_{kt} = \gamma_k^b \, \pi_{k\,t-1} + \gamma_k^f \, E_t \, \pi_{k\,t+1} + \gamma_k^s \, h_{kt} \, \hat{s}_{kt} + \varepsilon_{kt}^{\pi} \tag{13}$$

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

Remember the derived Equation 7:

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

being the hybrid version as follows:

$$\pi_{kt} = \gamma_k^b \, \pi_{k\,t-1} + \gamma_k^f \, E_t \, \pi_{k\,t+1} + \gamma_k^s \, s_{kt}^R + \varepsilon_{kt}^{\pi} \tag{14}$$

5.1 Previous Research on Phillips Curve Estimation in the UK

The validity of the aggregate Phillips Curve in UK data has been confirmed by Batini, Jackson, and Nickell, 2005 through econometric techniques to estimate unobserved expectations and by Meeks and Monti, 2022 using households expectations. In the UK context, Byrne, Kontonikas, and Montagnoli, 2013 represents the only available evidence of Sectoral Phillips

Curve estimation, also relying on econometric methods to proxy unobserved expectations. To the best of my knowledge, this is the first study to estimate Sectoral Phillips Curve using direct measures of expectations from UK firms.

Incorporating some of the variables proposed by Batini, Jackson, and Nickell, 2005 into the estimation of the aggregate Phillips Curve, as identified by their study, I found that oil price inflation and real import prices were not statistically significant as sector-specific parameters when added to the Sectoral Phillips Curve. However, adding oil inflation as a common factor was helpful in eliminating cross-sectional dependence in both IJP and Rubbo's frameworks.

In Section 6, I will further investigate whether some industry characteristics, as well as common factors, play a significant role in explaining the price-setting behaviour of specific sectors. Some of the factors tested include labour share, the share of imports, and the share of costs that are accounted for by energy/petrol.

5.2 Does the Panel Dimension Help Identify the Phillips Curve?

Remarkably, exploiting the sector-level microdata and estimating a dynamic panel for the Phillips Curve while controlling for CCEs yields superior results. To address potential endogeneity issues concerning inflation expectations and the slack variable, I use the Stata command xtdcce2 developed by Ditzen, 2021, which estimates dynamic panel data models with CCEs and allows for instrumental variable estimation.

In table 3 I present the results of the Sectoral Phillips Curve estimation using only labour costs as a forcing variable, and in Table 4, I incorporate labour costs with micro-level intermediate goods costs, thereby accounting for production network effects in the inflation process. In both cases, Column 1 assumes homogeneous slopes for all sectors, while Columns 2 and 3 assume heterogeneous slopes. All models have sector-level fixed effects, and Model 3 is augmented with common factors to control for CCEs.

Upon comparing various model specifications, the third model consistently yields the lowest Root Mean Squared Errors (RMSE)[40] in both frameworks. This suggests that allowing for heterogeneous coefficients across sectors and accounting for unobservable CCEs results in substantially lower average residual magnitudes. Additionally, considering production networks in Rubbo's framework leads to a lower RMSE compared to the IJP framework.

In Model 3 from both IJP and Rubbo, the average coefficient coefficient for the role of expectations is approximately 0.6, and for lagged expectations, it's around 0.2. These

[40]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.

estimates align with economic theory, which predicts that γ^f should be larger than γ^b, indicating that firms set prices in a more forward- than backward- looking way. Although not exactly comparable, similar parameters have been found in other studies that estimated Phillips Curves for the UK and the US.

In the UK, Meeks and Monti, 2022 found $\gamma^b : 0.2$ and $\gamma^f : 0.8^{***}$; Byrne, Kontonikas, and Montagnoli, 2013 obtained $\gamma^b : 0.1^{***}$ and $\gamma^f : 0.9^{***}$; while Batini, Jackson, and Nickell, 2005 reported $\gamma^b 0.3^{***}$ and $\gamma^b : 0.7^{***}$. Moreover, Boneva et al., 2020 estimated firm-level pricing equations using CBI expectations about their own prices and obtained $\gamma^f : 0.2 - 0.3$ (γ^b not explicitly reported).

Some recent evidence using US data: Meeks and Monti, 2022 found $\gamma^b : 0.1$ $\gamma^f : 1.6^{***}$ and McLeay and Tenreyro, 2019 reported $\gamma^b : 0.1^{***}$ $\gamma^f : 0.22$.

The slopes differ between IJP and Rubbo's framework, consistent with their differing underlying parameters. In the IJP framework, the slope is around 0.1, capturing the responsiveness of prices solely to labour costs. In Rubbo's framework, the slope is around 0.9, indicating a larger responsiveness of prices to a composite measure of costs which arise from both labour and intermediate goods.

In summary, these results suggest that allowing for heterogeneous coefficients and controlling for CCEs using cross-sectional averages leads to improved outcomes in both frameworks. Moreover, they indicate that the slope plays a larger role in explaining sectoral inflation dynamics when intermediate goods are incorporated into the cost function.

While these results speak about the average parameters, we are interested in examining the heterogeneity among those and the sources that may be driving these asymmetries. In the next section I will discuss this.

5.3 Can we Unmask the Heterogeneity in the Price Setting Behaviour Across Sectors?

While the average parameters obtained in the previous section tell us how the industries behave on average, behind the averages there is broad heterogeneity across sectors. In this section I will break down the results and focus on the sector-specific parameters and in the Section 6 I will focus on the potential sources, i.e. industry-characteristics and other common factors, that might explain the asymmetries.

Sector-specific parameters are obtained using Model 3 from both frameworks. In this section, I will show only the parameters from IJP, and in Appendix C, I will present the parameters from Rubbo's framework.

Table 3: Labour cost based Sectoral Phillips Curve (IJP)

	Pooled OLS, IV (1)	MG OLS, IV (2)	CCEMG OLS, IV (3)
	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 (k)/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 (p-value)	0.00	0.01	0.42

Note: This table presents the OLS panel time-series estimation results using the IV method. The averages of sector-specific parameters are reported. Expectations are calculated as weighted averages among all firms in each sector. Labour costs and expectations are instrumented using: lags (1, 2, 3) of expectations and lags (1, 3) of labour costs. The CCEMG estimator is implemented using cross-section averages proxied by ave. expectations (0 to 3 lags), and up to 2 lags of ave. labour cost and oil inflation; these proxies of 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. S.E. in parenthesis (robust in model 1). *** p<0.01, ** p<0.05, * p<0.1.

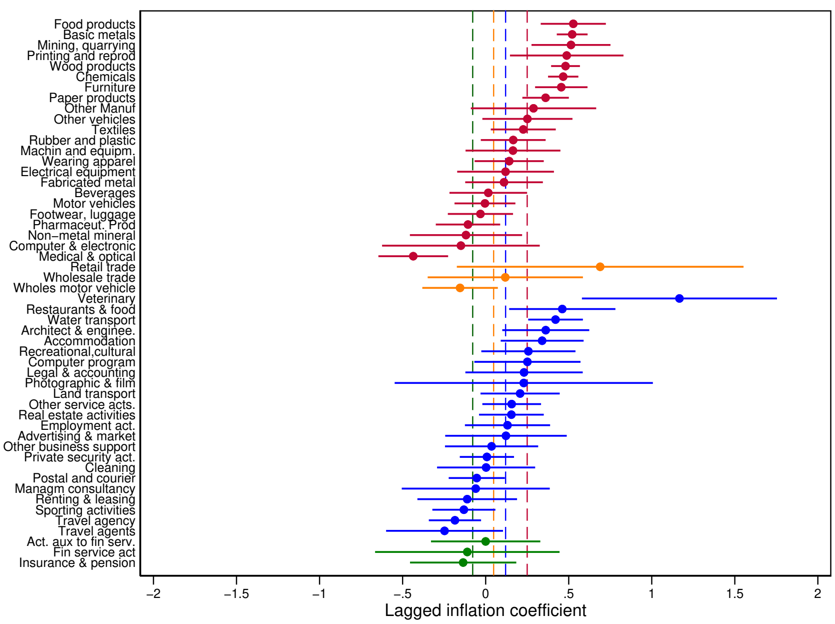
Table 4: Rubbo cost based Sectoral Phillips Curve

	Pooled OLS, IV (1)	MG OLS, IV (2)	CCEMG OLS, IV (3)
	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 (k)/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 (p-value)	0.00	0.00	0.42

Note: This table presents the OLS panel time-series estimation results using the IV method. The averages of sector-specific parameters are reported. Expectations are calculated as weighted averages among all firms in each sector. Costs and expectations are instrumented using: lags (1, 2, 3) of expectations and lags (1, 3) of costs. The CCEMG estimator is implemented using cross-section averages proxied by ave. expectations (0 to 3 lags), and up to 2 lags of oil inflation; these proxies of 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. S.E. in parenthesis (robust in model 1). *** p<0.01, ** p<0.05, * p<0.1.

In Figure 8, we can observe that the estimated parameters related to lagged inflation are mostly located between -0.5 and 0.5 with quite narrow standard errors intervals. Some estimates are not statistically or not economically significant, suggesting that there might be industry-specific characteristics that the model is not accounting for. By comparing the sector-specific coefficients across groups[41], it doesn't seem to be a large difference on the average parameters across groups, i.e. the average among Manufacturing is 0.25 while the average among Services is 0.12. Yet, there's a wider heterogeneity across industries within each group, being the most persistent across Manufacturing: Food Products, and the least, Medical and Optical.

Figure 8: Role of lagged inflation by sector (IJP framework)

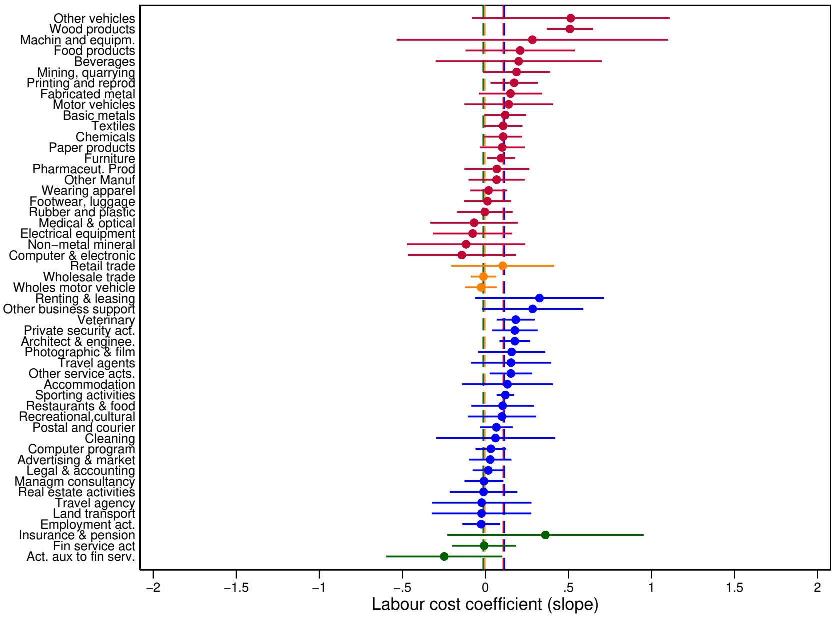


Note: Sector-specific parameters related to lagged expectations coefficients from Model 3 (Table 3, through dynamic panels with CCE). These coefficients are net from common factor effects. Intervals are calculated as the mean +/- s.e. The labels indicate the mean estimated coefficient for each sector. 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 9 displays estimated sector-specific parameters very close to zero, ranging between -0.3 and 0.5. Only the estimated parameter for the Water Transport industry appears to deviate from the others (not included in the figure). These results are particularly relevant to the widely discussed point that labour is considered the only source of costs in these models. When including production networks, these estimated parameters are much further away from zero. See Figure 15 with parameters obtained from Rubbo's framework.

[41] With groups I refer to: Manufacturing, Distributive/Retail, Services, Financial Services.

Figure 9: Slope by sector (IJP framework)

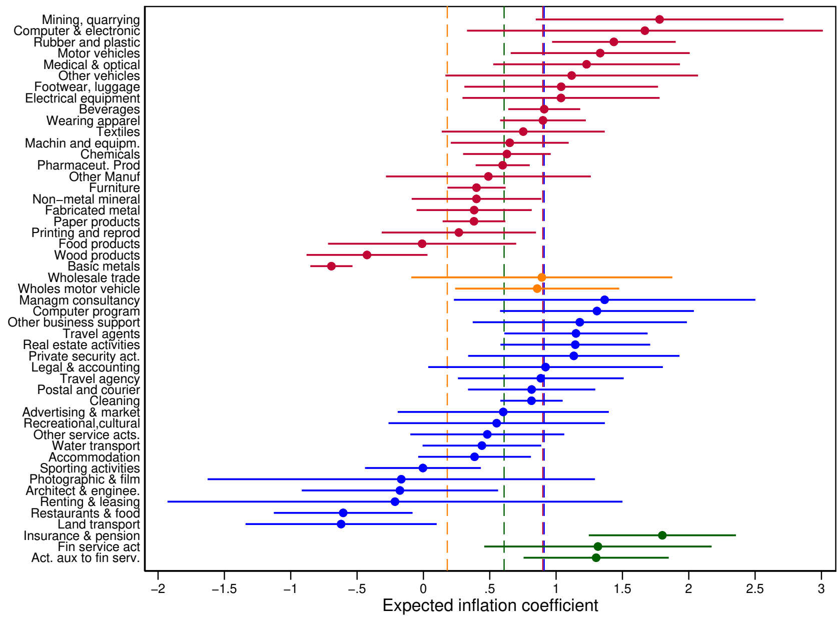


Note: Sector-specific parameters related to labour costs from Model 3 (Table 3, through dynamic panels with CCE). These coefficients are net from common factor effects. Intervals are calculated as the mean +/- s.e. The labels indicate the mean estimated coefficient for each sector. The dashed vertical lines highlight the mean coefficient across each of the groups. The Water Transport industry was excluded due to parameter values falling outside the range between -2 to 2, which would have distorted the axis scales. This adjustment was made to ensure comparability across figures. Red colour for manufacturing, Orange for Retail, Blue for services and Green for Financial Services.

Finally, based on Figure 10, we can see that while there is not a significant difference in the average estimate between Manufacturing and Services firms, both at around 0.9, there are large differences within the groups. Certain Manufacturing sectors, such as Mining, Computer and Rubber have sector-specific parameters of around 1.4, suggesting that they are as forward looking as firms in Management Consultancy activities and the industries within the Financial Services group. This suggests that industry-specific characteristics may be responsible for these differences rather than their broad classification as Manufacturing or Services.

Overall, the findings show an interesting degree of heterogeneity across sectors which I will investigate in the next section.

Figure 10: Role of expectations by sector (IJP framework)



Note: Sector-specific parameters related to expectations coefficients from Model 3 (Table 3, through dynamic panels with CCE). These coefficients are net from 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. Certain industries, such as Veterinary, Retail, and Employment Activities, were excluded due to parameter values falling in the range of -3 to -2 or 3 to 4, which would have distorted the axis scales. This adjustment was made to ensure comparability across figures. Red colour: Manufacturing; Orange: Retail; Blue: Services; and Green: Financial Services.

6 Determinants of Price Setting Heterogeneity Across Sectors

After unveiling the heterogeneity in sector-specific parameters in Section 5, the next goal is to investigate certain factors that may contribute to these asymmetries. In this section, I will utilise the estimated parameters of forward- and backward-looking behaviour, as well as the Phillips Curve slope to understand how they respond to market structure and other industry characteristics. To ensure comparability, I will initially adjust the estimates based on their estimation precision.

6.1 Estimated Parameters Weighted by their Standard Error

The estimated sector-specific parameters exhibit various levels of estimation precision due to being estimated as a panel, without accounting for potentially certain characteristics or shocks that may affect particular sectors. To address this unequal precision distribution, I will apply weights to the parameters based on their standard errors. This approach is similar to weighted least squares (WLS)[42]. Since the standard errors are derived from the OLS estimation of the Phillips Curve, they will be used to adjust the imprecise parameters. The weights will be determined by first calculating the inverse of the standard errors and then rescaling them to sum up to one.

$$w_k^p = \frac{\gamma_k^p}{s.e._k^p}$$

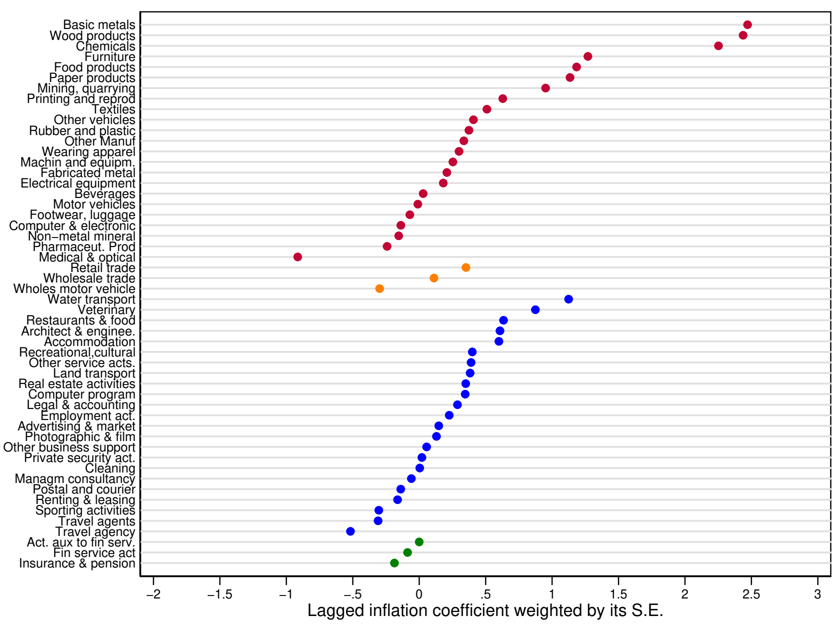
where p represents the Phillips Curve parameters (f for forward-looking, b for backward-looking, and s for slope).

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

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

I show in Figures 11, 12, and 13 the weighted parameters by sector from IJP framework[43].

Figure 11: Weighted parameter on lagged inflation (IJP framework)

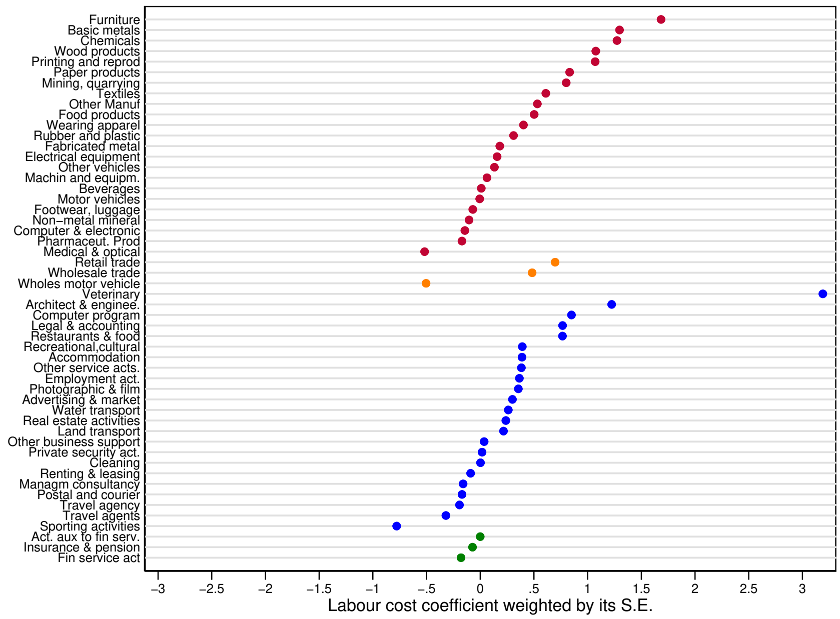


Note: The coefficients presented in the figure have been weighted based on their respective S.E. from IJP framework. Red colour: Manufacturing; Orange: Retail; Blue: Services; and Green: Financial Services.

[42]For an application dealing with the presence of serial correlation revealed in OLS results and implementing WLS, see Domberger, 1979. For further reference, please refer to Stock and Watson, 2019 (section 18).

[43]In Appendix C I will show the estimated parameters from Rubbo's framework.

Figure 12: Weighted parameter on labour cost (IJP framework)



Note: The coefficients presented in the figure have been weighted based on their respective S.E. from IJP framework. Red colour: Manufacturing; Orange: Retail; Blue: Services; and Green: Financial Services.

In the next section I will study the potential sources of heterogeneity using these weighted parameters. In order to do so, I will adjust the regression dependent variable and regressors by the precision of the estimates. By doing this, I am giving more weight to the less biased estimated sectors.

The weighted regression used is expressed as follows:

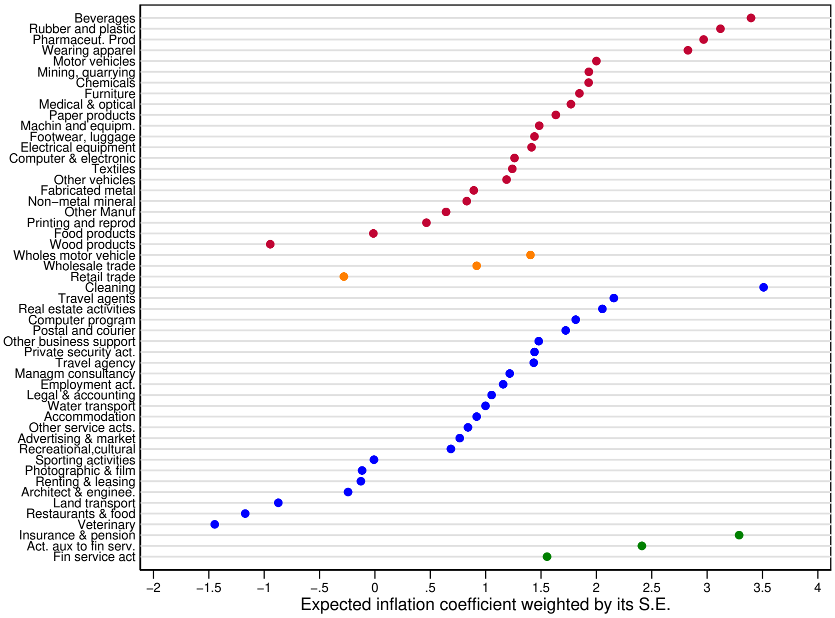
$$\widetilde{\gamma}_k^p = \beta_0 \widetilde{X}_k^0 + \beta_1 \widetilde{X}_k^1 + ... + \widetilde{u}_k$$

6.2 Regression Estimation Results

As previously discussed, the microfoundation of the Phillips Curve predicts heterogeneity in price-stickiness, in the price responsiveness to costs (i.e. the slope) and in the degree of backward-lookingness (sometimes referred to as “persistence”) without providing a specific theoretical framework for the sources of these heterogeneities. In this section, I will explore certain industry-characteristics that might be associated with the heterogeneity observed across sectors, drawing from existing research and the extensive discussion in Section 2.3. However, due to the absence of a specific theoretical framework explaining the sources of cross-sectional heterogeneity, the exact regression specifications remain unclear.

The following regressions in Table 5 will shed light on the association between the sector-

Figure 13: Weighted parameter on expected inflation (IJP framework)



Note: The coefficients presented in the figure have been weighted based on their respective S.E. from IJP framework. The Basic Metals industry was excluded due to parameter values falling outside the range between -2 to 4, which would have distorted the axis scales. This adjustment was made to ensure comparability across figures. Red colour: Manufacturing; Orange: Retail; Blue: Services; and Green: Financial Services.

specific Phillips Curve parameters (γ_f corresponds to the role of expectations, γ_b corresponds to the degree of backward-lookingness, and γ_s refers to the slope) and selected industry characteristics, providing insights into potential sources of heterogeneity.

The results reveal a noteworthy pattern in the relationship between the role of expectations and the degree of concentration measured by the HHI. In the IJP framework, we observe a positive and highly statistically significant relationship, while in Rubbo's framework is positive but not statistically significant. These findings support the hypothesis that firms operating in less competitive sectors (higher degree of concentration) tend to update prices less frequently, indicating higher price stickiness. One possible explanation lies in the demand elasticity of highly-concentrated sectors. When a firm faces only a few competitors, the demand elasticity tends to be low. In highly competitive sectors, however, setting a price even slightly below competitors can result in reduced sales or even no sales. Consequently, firms in sectors with lower degrees of concentration (high competition) are more inclined to simply follow their competitors' prices, attaching less importance to their own expectations.

In sectors characterised by both high degrees of concentration and price stickiness, firms

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.

often choose 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.

Regarding backward-looking behaviour (i.e. price adjustment based on past inflation), the results differ between the two frameworks. In the IJP framework, firms tend to update prices more in a backward-looking manner when exposed to a larger share of imports. In Rubbo's framework, this relationship is negative but statistically insignificant. Yet, it is worth noting that the IJP framework does not account for the production network, which might lead to imports capturing certain omitted variables in the model. This issue might be rectified in Rubbo's estimation.

The effect of energy costs is consistently positive and statistically significant in both frameworks concerning the backward-looking parameter. This suggests that firms update prices based on past inflation when they are exposed to a larger share of energy costs as part of their cost structure.

Finally, the slope parameter exhibits statistical significance and a positive association with the share of energy costs over total costs in Rubbo's framework but lacks significance in IJP model.

In conclusion, these findings align with previous evidence suggesting that market concentration might be one of the sources of heterogeneity in the Phillips Curve price stickiness.

They also imply that some of these sources may be better captured in Rubbo's model, based on the enhanced specification which captures the sectoral linkages, thereby yielding less scope for second-stage analysis.

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

$$Y_{ikt} = Y_{kt} \left(\frac{P_{ikt}}{P_{kt}} \right)^{-\eta} \tag{15}$$

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:

$$Y_{kt} = \left[\int_0^1 Y_{ikt}^{\frac{\eta-1}{\eta}} \, di \right]^{\frac{\eta}{\eta-1}} \tag{16}$$

Each firm produces a differentiated good with a production function

$$Y_{ikt} = Z_{kt} \, f(h_{ikt}) \tag{17}$$

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:

$$\max_{{P_{ikt}}^*} E_t \sum_{j=0}^{\infty} (\alpha_k \beta)^j \; \left[Y_{ik\,t,t+j} \, P_{ikt}^* - \Psi \left(Y_{ik\,t,t+j} \right) \right] \tag{18}$$

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 18 and working on the algebra, I get the following expression:

$$\sum_{j=0}^{\infty}(\alpha_k\beta)^j\, E_t\left[Y_{ik\,t,t+j}\ (P^*_{ikt} - \eta\, S_{ik\,t,t+j}P_{ik\,t,t+j})\right] = 0 \tag{19}$$

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

$$\hat{p}^*_{ikt} = (1-\alpha_k\beta)\sum_{j=0}^{\infty}(\alpha_k\beta)^j E_t\left[\hat{s}_{ik\,t,t+j} + \hat{p}_{ik\,t,t+j}\right] \tag{20}$$

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:

$$\hat{p}_{kt} = \alpha_k\,\hat{p}_{k\,t-1} + (1-\alpha_k)\,\hat{p}^*_{kt} \tag{21}$$

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:

$$\hat{p}^*_{kt} = \omega_k \, \hat{p}^b_{kt} + (1 - \omega_k) \, \hat{p}^f_{kt} \tag{22}$$

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.:

$$\hat{p}^b_{kt} = \hat{p}^*_{k\,t-1} + \hat{\pi}_{k\,t-1} \tag{23}$$

and p^f_{kt} refers to prices set by forward-looking firms according to Equation 20.

Combining Equation 20 and 23, they get the following linearised hybrid sectoral Phillips Curve:

$$\hat{\pi}_{kt} = \frac{\omega_k}{\phi_k} \, \hat{\pi}_{k\,t-1} + \frac{\beta\alpha_k}{\phi_k} \, E_t\hat{\pi}_{k\,t+1} + \frac{(1-\omega_k)(1-\alpha_k)(1-\beta\alpha_k)}{\phi_k} \, h_k \, \hat{s}_{kt} \tag{24}$$

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

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:

$$\hat{\pi}_{kt} = \gamma^b_k \, \hat{\pi}_{k\,t-1} + \gamma^f_k \, E_t\hat{\pi}_{k\,t+1} + \gamma^s_k \, \hat{s}_{kt} + \varepsilon^{\pi}_{kt} \tag{25}$$

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:

$$\begin{pmatrix} \pi_{1t} \\ \pi_{2t} \end{pmatrix} = \begin{pmatrix} \tilde{\alpha}_1 & 0 \\ 0 & \tilde{\alpha}_2 \end{pmatrix} \begin{pmatrix} mc_{1t} - p_{1\,t-1} \\ mc_{2t} - p_{2\,t-1} \end{pmatrix} + \beta \begin{pmatrix} 1-\tilde{\alpha}_1 & 0 \\ 0 & 1-\tilde{\alpha}_2 \end{pmatrix} \begin{pmatrix} E_t\pi_{1\,t+1} \\ E_t\pi_{2\,t+1} \end{pmatrix} \tag{26}$$

$$\begin{pmatrix} mc_{1t} \\ mc_{2t} \end{pmatrix} = \begin{pmatrix} (1-a_1)w_{1t} + \lambda_{11t}\, p_{1t} + \lambda_{12t}\, p_{2t} \\ (1-a_2)w_{2t} + \lambda_{21t}\, p_{1t} + \lambda_{22t}\, p_{2t} \end{pmatrix} - \begin{pmatrix} logZ_{1,t} \\ logZ_{2,t} \end{pmatrix} \tag{27}$$

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

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

Now, I will combine Equation 26 and 27, and ignore the productivity term just for brevity. This omission won't affect the results.

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

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.

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

Further combining terms to get expressions for the inflation rates:

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

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

This 2-sector matrix illustration shows that inflation in sector 1 depends on a composite cost measure, which I will call "Rubbo cost's measure". This includes wages weighted by the share of labour, lagged prices in sector 1 and lagged prices in sector 2. By extending this expression to all sectors $j: 1, 2, ...N$ from where k buys intermediate goods, all price level terms would be included on the right hand side, as long as $\lambda_{kj} \neq 0$.

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

S^R_{kt}, and inflation expectations:

$$\pi_{kt} = (I - \Lambda\,\tilde{A})^{-1}\tilde{A}\,(S^R_{kt}) + (I - \Lambda\,\tilde{A})^{-1}\beta\,(1 - \tilde{A})\,E_t\pi_{k\,t+1} \tag{28}$$

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

Appendix C Additional Figures and Tables

Table 6: Panel Stationarity Test: Pesaran (2007) CIPS

Specification with constant

Lags	CBI inflation	*(p)*	Labour cost	*(p)*	Expected inflation	*(p)*	Composite cost	*(p)*
0	-24.1	0.0	-7.4	0.0	-26.9	0.0	-13.8	0.0
1	-13.8	0.0	-8.9	0.0	-16.3	0.0	-9.9	0.0
2	-8.3	0.0	-8.8	0.0	-10.4	0.0	-8.3	0.0
3	-5.2	0.0	-7.9	0.0	-8.0	0.0	-6.2	0.0
4	-3.2	0.0	-6.2	0.0	-4.5	0.0	-4.5	0.0

Specification with constant and trend

Lags	CBI inflation	*(p)*	Labour cost	*(p)*	Expected inflation	*(p)*	Composite cost	*(p)*
0	-25.9	0.0	-3.2	0.0	-27.9	0.0	-10.4	0.0
1	-14.4	0.0	-4.9	0.0	-15.8	0.0	-6.5	0.0
2	-7.9	0.0	-5.1	0.0	-9.1	0.0	-5.6	0.0
3	-3.3	0.0	-4.2	0.0	-6.3	0.0	-3.4	0.0
4	-0.2	0.4	-2.8	0.0	-1.5	0.1	-1.1	0.1

Note: This table reports the standardised Z-tbar statistic and its p-value from the Pesaran, 2007 test. The null hypothesis is that all series are nonstationary. Lags indicate the lag augmentation in the Dickey Fuller regression employed, with a constant or a constant and trend as indicated. I used the Stata routine *multipurt* by Markus Eberhardt.

Table 7: Correlation table

	CBI Sectoral Inflation	Expected Inflation	Labour Cost	Composite Cost	Oil Price Inflation	Real Import Prices	IG Cost Share	Labour Cost Share
CBI Sectoral Inflation	1.00							
Expected Inflation	0.53	1.00						
Labour Cost	-0.29	-0.08	1.00					
Composite Cost	0.51	0.28	0.09	1.00				
Oil Price Inflation	0.22	0.28	-0.12	0.14	1.00			
Real Import Prices	0.27	0.31	-0.14	0.21	0.79	1.00		
IG Cost Share	-0.01	-0.05	-0.02	0.01	-0.02	-0.02	1.00	
Labour Cost Share	0.01	0.05	0.02	-0.01	0.02	0.02	-1.00	1.00

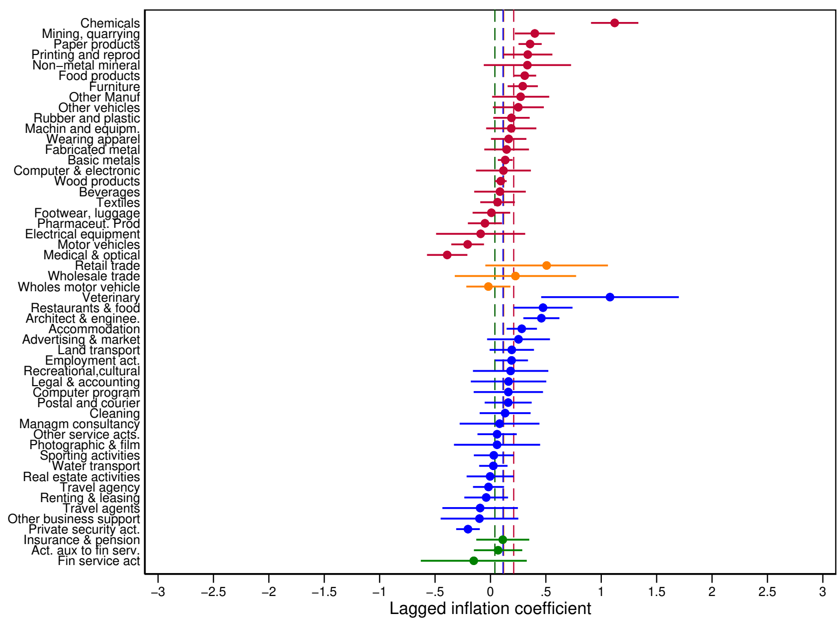
Note: This table reports correlation levels for the main studied variables. “IG” means Intermediate Goods.

Table 8: 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

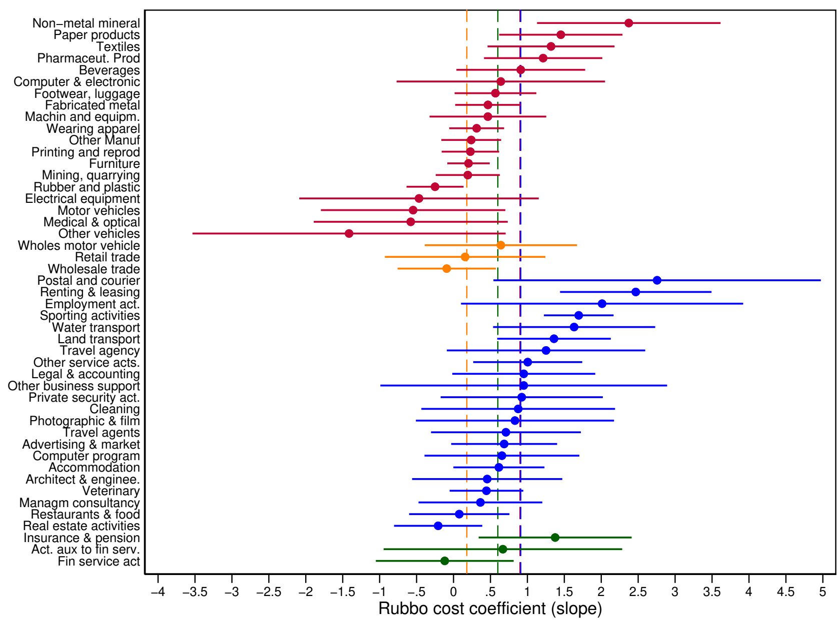
Note: OLS estimations. S.E. in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. Intercepts were included in the estimations but omitted in the table.

Figure 14: Role of lagged inflation by sector (Rubbo's framework)



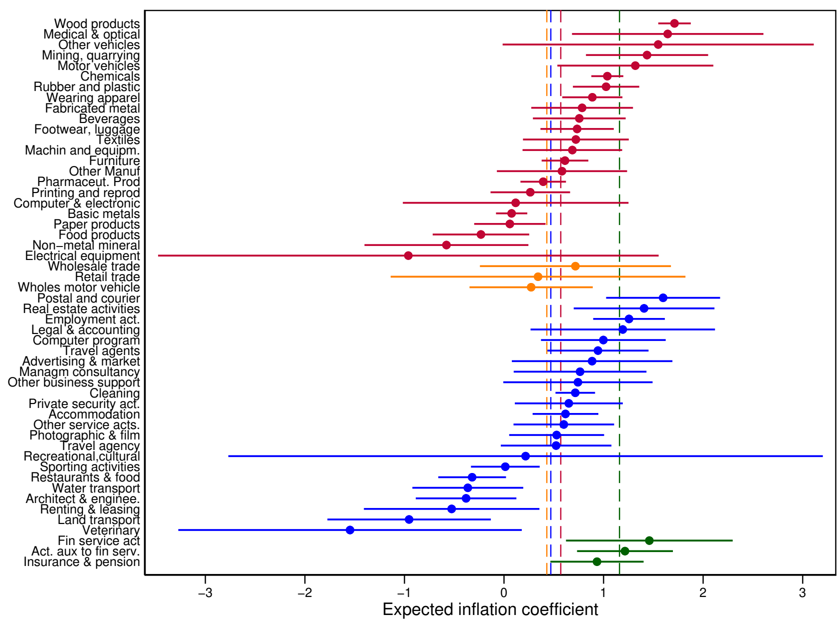
Note: Sector-specific parameters related to expectations coefficients from Model 3 (Table 4, through dynamic panels with CCE). These coefficients are net from common factor effects. Intervals are calculated as the mean +/- s.e. The labels indicate the mean estimated coefficient for each sector. The dashed vertical lines highlight the mean coefficient across each of the groups. Red colour: Manufacturing; Orange: Retail; Blue: Services; and Green: Financial Services.

Figure 15: Slope by sector (Rubbo's framework)



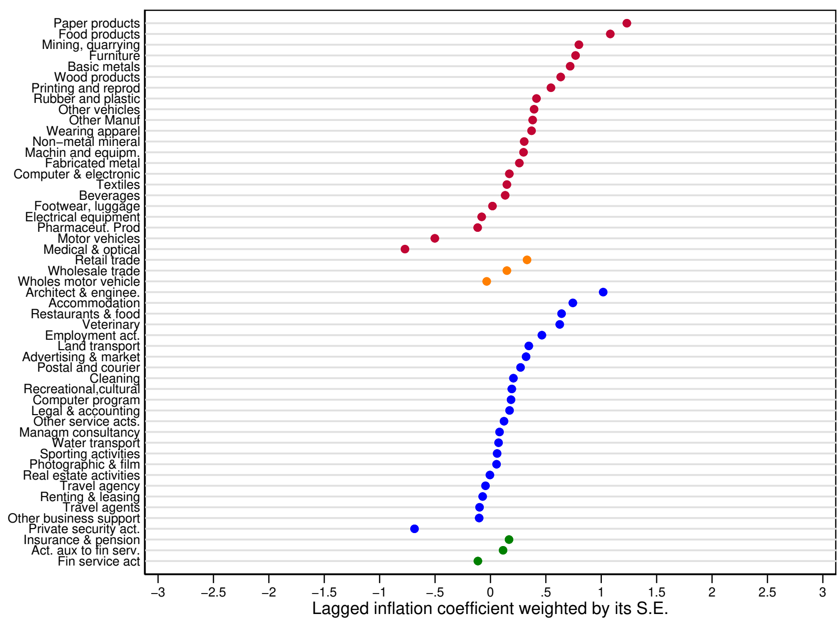
Note: Sector-specific parameters related to expectations coefficients from Model 3 (Table 4, through dynamic panels with CCE). These coefficients are net from common factor effects. Intervals are calculated as the mean +/- s.e. The labels indicate the mean estimated coefficient for each sector. The dashed vertical lines highlight the mean coefficient across each of the groups. Certain industries such as Chemicals, Food Products, Wood Products, Basic Metals, and Recreational Activities were excluded due to the estimated parameters falling outside the range of -4 to 5, adding them would distort the axis scales. This adjustment was made to ensure comparability across figures. Red colour: Manufacturing; Orange: Retail; Blue: Services; and Green: Financial Services.

Figure 16: Role of expectations by sector (Rubbo's framework)



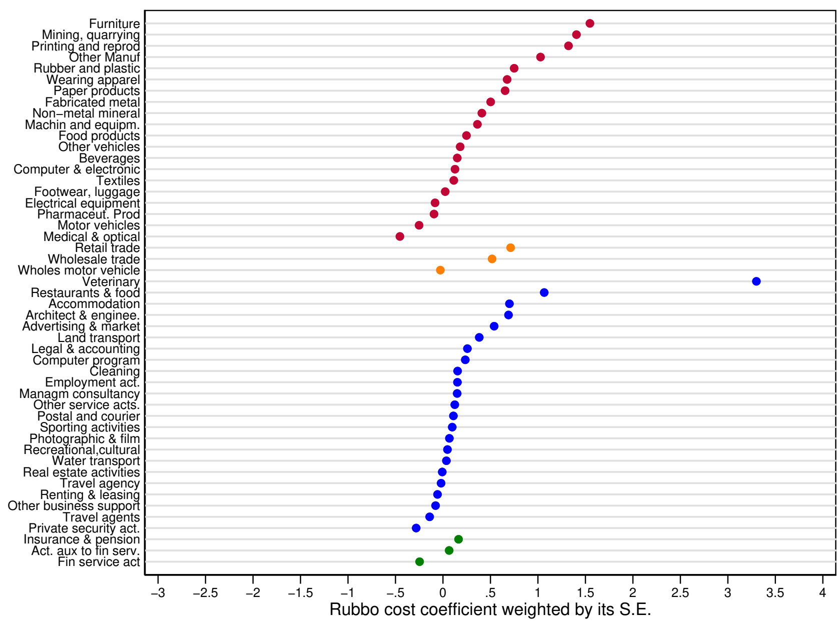
Note: Sector-specific parameters related to expectations coefficients from Model 3 (Table 4, through dynamic panels with CCE). These coefficients are net from common factor effects. Intervals are calculated as the mean +/- s.e. The labels indicate the mean estimated coefficient for each sector. The dashed vertical lines highlight the mean coefficient across each of the groups. Red colour: Manufacturing; Orange: Retail; Blue: Services; and Green: Financial Services.

Figure 17: Weighted coefficient on lagged inflation (Rubbo's framework)



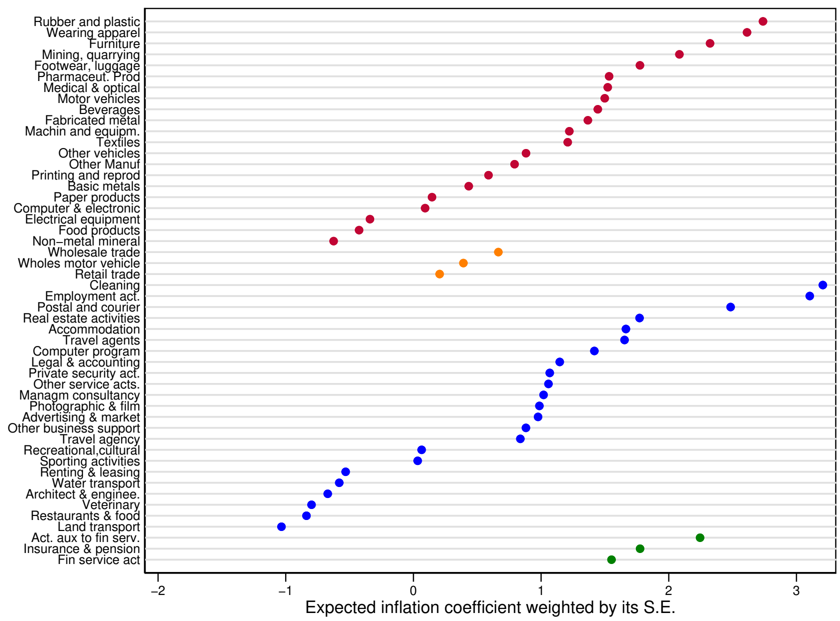
Note: The coefficients presented in the figure have been weighted based on their respective S.E. from Rubbo's framework. The Chemicals industry was excluded due to the estimated parameters falling outside the range of -3 to 3, adding them would distort the axis scales. This adjustment was made to ensure comparability across figures. Red colour: Manufacturing; Orange: Retail; Blue: Services; and Green: Financial Services.

Figure 18: Weighted coefficient on Rubbo cost (Rubbo's framework)



Note: The coefficients presented in the figure have been weighted based on their respective S.E. from Rubbo's framework. Certain industries such as Chemicals, Wood Products, and Basic Metals were excluded due to the estimated parameters falling outside the range of -3 to 4, adding them would distort the axis scales. This adjustment was made to ensure comparability across figures. Red colour: Manufacturing; Orange: Retail; Blue: Services; and Green: Financial Services.

Figure 19: Weighted coefficient on expected inflation (Rubbo's framework)



Note: The coefficients presented in the figure have been weighted based on their respective S.E. from Rubbo's framework. Certain industries such as Chemicals and Wood Products were excluded due to the estimated parameters falling outside the range of -2 to 3, adding them would distort the axis scales. This adjustment was made to ensure comparability across figures. Red colour: Manufacturing; Orange: Retail; Blue: Services; and Green: Financial Services.

Appendix D Data and measurement

D.1 Outliers detection and winsorisation scheme

Table 9 summarises the number of firm-level outliers detected from the sample based on the sectoral inflation and the salary cost questions.

Outliers are identified as

- i. values greater than percentile 75 + 6*IQR, or
- ii. values lower than percentile 25 - 6*IQR
- (i) and (ii) are applied to each of the three variables obtained from the CBI survey data and used in this study:

Past industry prices(pi)

Expected industry prices (ei)

Salary cost (wi)

The percentiles and IQR are calculated through Method 1 for most cases and Method 2 for some special cases where IQR=0 through Method 1.

Method 1: percentiles and IQR are calculated across all firms within the same sector and within a given quarter.
Method 2: percentiles and IQR are calculated across all firms within the same sector and within 2 year rolling windows.
Rule: When Method 1 yields IQR=0, then Method 2 is used. This will be the case in 5 sector&quarters.

IQRs are calculated as:

$$IQR^{pi} = p75^{pi} - p25^{pi}$$
$$IQR^{ei} = p75^{ei} - p25^{ei}$$
$$IQR^{wi} = p75^{wi} - p25^{wi}$$

Once the outliers are identified, I'll proceed with the winsorisation. I will set all data below percentile 25 - 6*IQR to that value, and data above percentile 75 + 6*IQR to that value.

Table 9: Summary of outliers

Industry	**N. of outliers**	**Total N. of reports**	**Industry**	**N. of outliers**	**Total N. of reports**
Mining, quarrying		203	Restaurants & food		214
Food products	15	865	Book publishing		95
Beverages	2	278	TV and Video		36
Textiles	7	624	Radio and TV		13
Wearing apparel	5	338	Wired telecom. Act.	3	53
Footwear, luggage	1	268	Computer program	3	283
Wood products	33	468	Web portals & news	2	71
Paper products	27	694	Fin service act	83	1,910
Printing and reprod	5	363	Insurance & pension	49	762
Coke, petrol prods	3	86	Act. aux to fin serv.	45	907
Chemicals	16	752	Real estate activities	5	369
Pharmaceut. Prod	1	232	Legal & accounting	1	771
Rubber and plastic	24	1,532	Managm consultancy	11	346
Non-metal mineral	12	917	Architect & enginee.	12	354
Basic metals	58	798	Research & developm.		67
Fabricated metal	77	2,717	Advertising & market	4	296
Computer & electronic	15	1,136	Photographic & film	3	115
Electrical equipment	15	1,243	Veterinary		149
Machin and equipm.	53	2,618	Renting & leasing		154
Motor vehicles	6	643	Employment act.	15	323
Other vehicles	6	353	Travel agency	5	145
Furniture	2	420	Private security act.		186
Other Manuf	17	578	Cleaning		161
Medical & optical	2	113	Other business support	1	158
Wholes motor vehicle	1	424	Residential care		79
Wholesale trade	57	2,175	Performing arts		24
Retail trade	24	2,447	Recreational,cultural		206
Land transport	7	642	Gambling		94
Water transport		163	Sporting activities	4	241
Air transport		92	Activ. of member org	1	20
Aux transport activ		182	Repair		42
Postal and courier	1	310	Other service acts.	1	131
Accommodation	10	468			
Total	**750**	**33,917**			

This table shows the number of identified outliers based on the "sectoral inflation perceptions" question from the CBI.

D.2 Price mapping

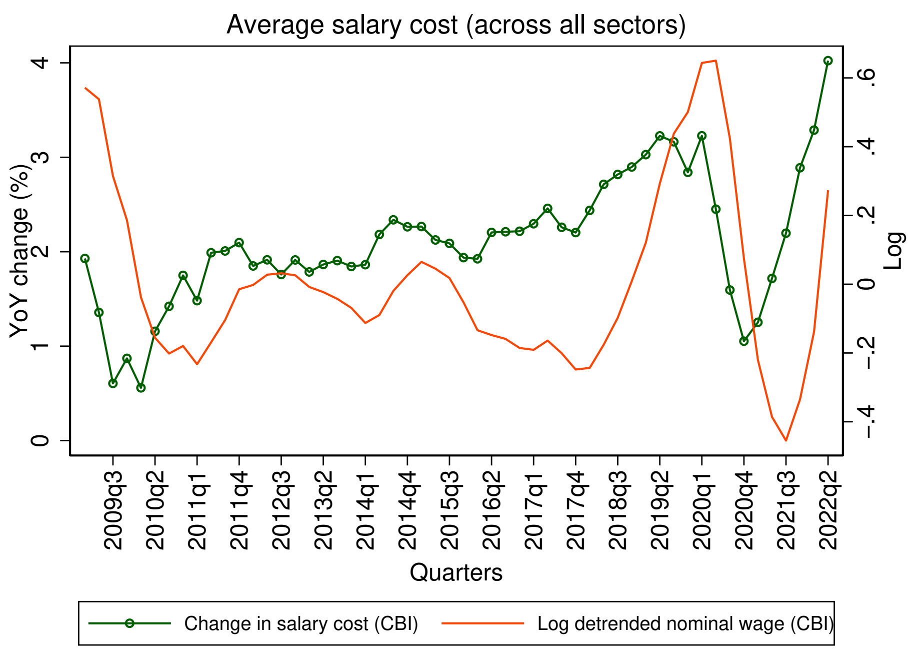
Table 10: Price mapping

2-dig SIC	2-digit SIC description	PPI	SPPI	CPI by COICOP
		Available price indices		
8	Other mining and quarrying	x		
10	Manuf. of food products	x		
11	Manuf. of beverages	x		
13	Manuf. of textiles	x		
14	Manuf. of wearing apparel	x		
15	Manuf. of leather	x		
16	Manuf. of wood and	x		
17	Manuf. of paper	x		
18	Printing and media reproduction	x		
19	Manuf. of refined petroleum	x		
20	Manuf. of chemicals	x		
21	Manuf. of pharmaceutical prods.	x		
22	Manuf. of rubber and plastic	x		
23	Manuf. of non-metallic mineral	x		
24	Manuf. of basic metals	x		
25	Manuf. of metal products	x		
26	Manuf. of computer, electronic	x		
27	Manuf. of electrical equipment	x		
28	Manuf. of machinery and equip.	x		
29	Manuf. of motor vehicles	x		
30	Manuf. of other transport equip.	x		
31	Manuf. of furniture	x		
32	Other manufacturing	x		
33	Repair of machinery and equipm.	x		
45	Wholesale and retail trade		x	
46	Wholesale trade (non vehicles)			Various CPI indices at 5 digit COICOP
47	Retail trade (except vehicles)			Various CPI indices at 5 digit COICOP
49	Land transport		x	Index 0731: Passenger transport by railway
50	Water transport		x	Index 0734: Psger transport by sea and inland
51	Air transport		x	Index 0733: Passenger transport by air
52	Support to transport acts.		x	
53	Postal and courier		x	Index 081: Postal Services
55	Accommodation		x	Index 112: Accommodation services
56	Food and beverage service		x	Index 1111: Restaurants & Cafes
58	Publishing activities		x	
59	Motion picture, video, TV		x	Index 0914: Recording media
60	Programming and broadcasting			Index 0911: Rec and reprod. of sound and pics
61	Telecommunications		x	Index 082/3: Telephone equip. and serv.
62	Computer programming		x	
63	Information service acts.			
64	Financial serv.(no insurance)		x	Index 126: Financial services
65	Insurance and pension			Index 125: Insurance
66	Acts. aux. to financial serv.			Index 1262: Other financial services (nec)
68	Real estate activities		x	
69	Legal and accounting acts.		x	Index 12702: Legal services and accountancy
70	Activities of head offices		x	
71	Architect. and engin. acts.		x	
72	Scientific R and D			
73	Advertising and mkt research		x	
74	Other prof., scient. acts.		x	
75	Veterinary activities			Index 09350: Veterinary services
77	Rental and leasing		x	
78	Employment activities		x	
79	Travel agency			
80	Security and investigation		x	
81	Services to buildings		x	
82	Office administrative ?		x	
87	Residential care			Index 12402: Residences for elderly/disabled
90	Creative, arts and entertmt.			Index 094: Recreational and cultural services
91	Libraries, museums, culture			Index 0942: Cultural services
92	Gambling and betting activities			
93	Sports activities and recreation			Index 0941: Recreational and sporting services
94	Membership organisations			
95	Repair of computers			Index 0533: Repair and household appliances
96	Personal service acts.		x	

D.3 Measures of cost

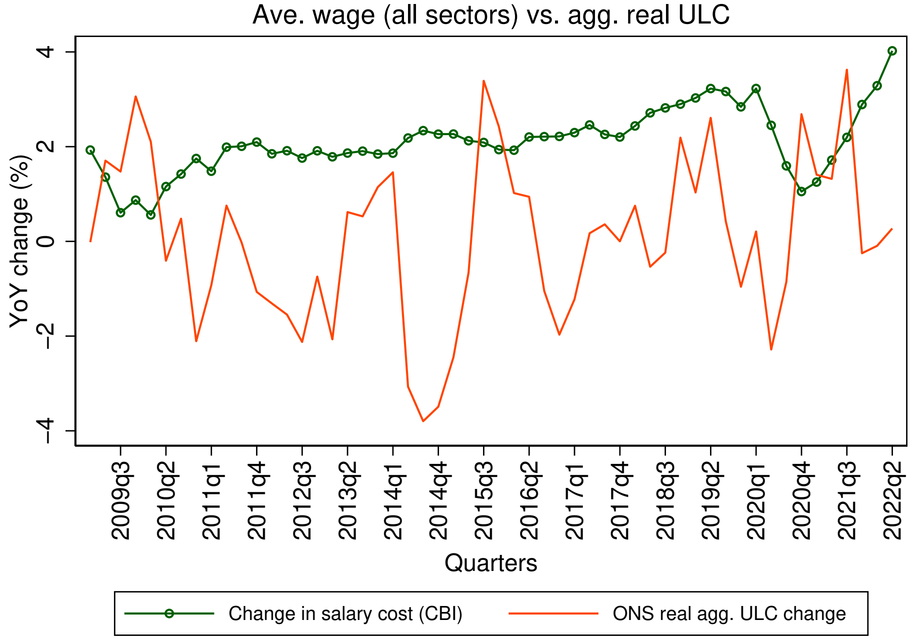
The ULC measure provided by the ONS represents the nominal cost of labour input per unit of real (inflation-adjusted) economic output. It is the ratio of total nominal employment costs relative to output (divided by real gross value added (GVA)). The ULC data is not available at the 2-digit SIC level. 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.

Figure 20: Inflation and CBI nominal wage



Note: The log detrended nominal wage is calculated as the deviation of wage from the sectoral sample mean using the self-reported change in each firm's "wage/salary cost per person employed" from the CBI.

Figure 21: Inflation and CBI nominal wage



Note: Change in salary cost is obtained from the CBI survey. The real aggregate ULC change is the ratio of total nominal employment costs relative to output (divided by real gross value added (GVA), this is provided by the ONS.

Figure 22: Herfindahl-Hirschman index (HHI) series

SIC 2 digits	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Mining, quarrying	0.26	0.26	0.27	0.26	0.25	0.25	0.22	0.21	0.22	0.21	0.21	0.22	0.24
Food products	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Beverages	0.15	0.15	0.14	0.14	0.14	0.15	0.17	0.14	0.13	0.14	0.13	0.12	0.15
Textiles	0.06	0.07	0.05	0.04	0.04	0.04	0.04	0.05	0.04	0.04	0.04	0.04	0.06
Wearing apparel	0.08	0.08	0.09	0.11	0.12	0.13	0.15	0.16	0.20	0.18	0.19	0.27	0.26
Footwear, luggage	0.06	0.06	0.06	0.06	0.06	0.04	0.04	0.06	0.06	0.08	0.09	0.10	0.16
Wood products	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.03
Paper products	0.15	0.16	0.15	0.16	0.16	0.16	0.15	0.18	0.20	0.21	0.21	0.22	0.26
Printing and reprod	0.02	0.02	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.02	0.02	0.03
Chemicals	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.03	0.02	0.02	0.07
Pharmaceut. Prod	0.26	0.25	0.25	0.24	0.23	0.23	0.21	0.22	0.22	0.21	0.22	0.24	0.24
Rubber and plastic	0.04	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.03	0.03	0.01	0.01
Non-metal mineral	0.03	0.03	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Basic metals	0.17	0.13	0.12	0.13	0.13	0.14	0.14	0.14	0.13	0.13	0.12	0.16	0.22
Fabricated metal	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Computer & electronic	0.04	0.04	0.03	0.04	0.04	0.04	0.03	0.03	0.03	0.03	0.03	0.03	0.03
Electrical equipment	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.04	0.05	0.01	0.01	0.01
Machin and equipm.	0.07	0.04	0.06	0.06	0.08	0.07	0.07	0.08	0.08	0.07	0.08	0.06	0.07
Motor vehicles	0.05	0.07	0.05	0.04	0.05	0.09	0.11	0.10	0.09	0.12	0.13	0.15	0.14
Other vehicles	0.23	0.23	0.16	0.15	0.16	0.14	0.15	0.15	0.15	0.14	0.14	0.16	0.18
Furniture	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02
Other Manuf	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Medical & optical	0.13	0.13	0.14	0.15	0.13	0.18	0.15	0.16	0.13	0.14	0.12	0.14	0.15
Wholes motor vehicle	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Wholesale trade	0.06	0.06	0.07	0.06	0.05	0.03	0.02	0.02	0.02	0.02	0.02	0.02	0.01
Land transport	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.02	0.02	0.02	0.02	0.02	0.03
Water transport	0.04	0.05	0.05	0.04	0.04	0.04	0.04	0.04	0.03	0.09	0.14	0.02	0.01
Travel agents	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.04	0.05	0.07	0.10	0.11	0.13
Postal and courier	0.45	0.41	0.39	0.38	0.39	0.31	0.30	0.29	0.30	0.29	0.28	0.27	0.30
Accommodation	0.02	0.02	0.02	0.02	0.02	0.02	0.03	0.03	0.03	0.03	0.02	0.03	0.03
Restaurants & food	0.10	0.11	0.11	0.11	0.10	0.10	0.10	0.11	0.11	0.11	0.11	0.12	0.14
Computer program	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.02
Fin service act	0.02	0.01	0.03	0.03	0.02	0.02	0.02	0.02	0.02	0.01	0.02	0.01	0.01
Insurance & pension	0.10	0.06	0.06	0.05	0.05	0.05	0.03	0.09	0.05	0.06	0.06	0.09	0.08
Act. aux to fin serv.	0.10	0.11	0.11	0.11	0.09	0.09	0.08	0.08	0.10	0.12	0.09	0.05	0.09
Real estate activities	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01
Legal & accounting	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.02	0.02	0.02
Managm consultancy	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Architect & enginee.	0.02	0.06	0.02	0.13	0.19	0.13	0.13	0.08	0.05	0.03	0.04	0.05	0.04
Advertising & market	0.02	0.02	0.02	0.02	0.02	0.02	0.05	0.05	0.05	0.05	0.05	0.03	0.04
Photographic & film	0.01	0.01	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Veterinary	0.22	0.18	0.15	0.13	0.07	0.06	0.05	0.05	0.07	0.07	0.08	0.09	0.09
Renting & leasing	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.04	0.04
Employment act.	0.02	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02
Travel agency	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.02	0.04	0.05	0.03
Private security act.	0.47	0.48	0.47	0.45	0.47	0.45	0.46	0.47	0.47	0.44	0.42	0.38	0.03
Cleaning	0.03	0.02	0.02	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.02	0.02	0.02
Other business support	0.02	0.01	0.02	0.02	0.02	0.02	0.02	0.01	0.01	0.01	0.01	0.01	0.01
Recreational,cultural	0.05	0.02	0.09	0.08	0.08	0.09	0.07	0.07	0.07	0.07	0.08	0.03	0.08
Sporting activities	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Other service acts.	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01

Note: The HHI series for all industries in the UK are own calculations based on turnover data from BvD FAME dataset. The degree of HHI by year is indicated using green shading, with darker green representing a higher index and lighter green indicating a lower index.

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.

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 and Andrea F. Presbitero (Sept. 2015). "Public debt and growth: Heterogeneity and non-linearity". In: *Journal of International Economics* 97.1, pp. 45–58. ISSN: 18730353. DOI: 10.1016/j.jinteco.2015.04.005.

Everaert, Gerdie and Tom De Groote (Mar. 2016). "Common Correlated Effects Estimation of Dynamic Panels with Cross-Sectional Dependence". In: *Econometric Reviews* 35.3, pp. 428–463. ISSN: 15324168. DOI: 10.1080/07474938.2014.966635.

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.

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.

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.

— (Mar. 2007). "A simple panel unit root test in the presence of cross-section dependence". In: *Journal of Applied Econometrics* 22.2, pp. 265–312. ISSN: 08837252. DOI: 10.1002/jae.951.

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.

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.