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

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Abstract

I examine price-setting behaviour across 52 sectors in the UK by estimating Sectoral Phillips Curves (SPCs) — which measure the sectoral inflation responsiveness to sector-level inflation expectations and costs. Using a unique survey-based and micro-level dataset on direct measures of firms' expectations, labour costs, and supplier prices, I establish, at the sector-level, a positive response of inflation to both inflation expectations and costs. Second, accounting for sectoral linkages through input-output tables, I find a significant and larger response of inflation to costs than when these linkages are not explicitly accounted for. Third, I uncover substantial sectoral heterogeneity in responses to costs and expectations. Delving into potential sources of heterogeneity, I find that expectations play a larger role in the price-setting decisions of firms in more concentrated sectors.

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1 Introduction

The recent global surge in prices has brought back general attention to understanding inflation. Central banks rely on the New Keynesian Phillips Curve (NKPC) to understand and ultimately control inflation. The NKPC is a microfounded relationship that captures how inflation responds to firms' expected future inflation and firms' costs. Accurately estimating these responses (the NKPC parameters) is crucial for shaping monetary policy. Although extensively studied, most papers face challenges in identifying the NKPC parameters.

In this paper, I overcome a number of these challenges by estimating Sectoral Phillips Curve (SPCs) based on a theoretical microfounded framework, and by utilising a unique confidential survey dataset. My contribution is threefold: First, I address some commonly encountered weak identification challenges by using direct measures of firms' expectations, industry-level prices, and salary costs. Using this panel dataset, I find a positive response of inflation to expected inflation and marginal costs. I establish that the (positively sloped) Phillips Curve has not disappeared, as it has been claimed in other papers using more aggregated data, such as Coibion and Gorodnichenko (2015) and Del Negro, Lenza, et al. (2020). Second, building on the seminal work by Rubbo (2023), I include micro-level time-varying data on intermediate goods shares using input-output tables, revealing a significantly larger inflation response to costs than when these linkages are not accounted for. This finding underscores the importance of considering intermediate goods and their embedded sectoral linkages, features that are overlooked in traditional output gap- and labour cost-based Phillips Curve settings. To the best of my knowledge, this is the first paper to estimate SPCs using direct measures of firms' expectations and input-output tables.

Third, employing panel time series methods with sector-specific coefficients allows me to uncover large sectoral heterogeneity in the SPC parameters. Delving into potential sources of heterogeneity through market- and cost-structure measures, I find that market concentration is one of the factors driving the sensitivity of inflation to expected future inflation. This might be attributed to less concentrated sectors — i.e. those facing greater competition — tracking their competitors' prices more closely, thus giving less weight to their own expectations.

Identifying the Phillips Curve parameters — i.e. the sensitivity of current inflation to expected future inflation and to firms' costs — presents several challenges. Some are related to the data used as proxies, while others stem from model specification issues. Concerning the data-related issues, a common challenge arises from the general lack of available data on firms' expectations. This makes it difficult to identify the sensitivity of current inflation to expected future inflation. In the literature to date, expectations have primarily been approximated using actual inflation or rational expectations assumptions. However, these proxies have been largely criticised for being weak instruments. Accurately identifying and understanding this parameter is crucial for central banks, given that inflation expectations are a powerful tool for controlling inflation. The relevance of inflation expectations in understanding the recent inflation process is underscored in Reis (2023), which criticises the use of professional forecasts and median household surveys, considering them inadequate instruments for assessing inflation persistence. Prolonged inflationary supply shocks can reduce the effectiveness of monetary policy when the sensitivity of inflation to inflation expectations is lower, as emphasised in the recently released IMF (2023) report.

The second set of challenges relate to the use of aggregate data to identify the sign – expected to be positive – of the sensitivity of inflation to firms' costs, commonly referred to as the "Phillips Curve slope". The positive slope captures the idea that when the economy operates above its potential, increased demand can raise marginal costs, ultimately leading to higher prices. The flat or negative slope obtained when employing aggregate data results from the monetary policy's aim to offset aggregate demand shocks by raising interest rates, leading to lower inflation. This does not hold when using more disaggregate data as the central bank cannot directly offset regional or sectoral shocks. McLeay and Tenreyro (2019), and Hazell et al. (2022) show evidence of significant and positive slopes by employing regional data, while Imbs et al. (2011) and Byrne et al. (2013) obtain significant and positive slopes by employing sectoral data.

The novelty of this paper stems from combining sectoral data with direct measures of firms' expectations, supplier prices and salary costs. These features mitigate against the challenges faced when estimating the Phillips Curve using aggregate data, indirect measures of expectations, and other weak proxies. I use a survey dataset produced by the UK's Confederation of British Industry (CBI) and the Bank of England (BoE), which contains quarterly data of narrowly defined industries in the UK. This dataset is available over a relatively long sample period since 2009 and provides direct measures of firms' inflation expectations, which are not commonly available. Unlike other studies that use proxies like professional or household expectations, actual inflation, or rational expectations assumptions, using survey data mitigates the risk of weak proxies and resulting bias in the estimation, as stated in Coibion, Gorodnichenko, and Kamdar (2018).

The advantage of using salary costs data as forcing variable instead of output has been highlighted in Gagliardone et al. (2023). Most studies resort to proxy measures — such as the output gap or labour share — due to the lack of firm-level labour cost data, and obtain a negative Phillips Curve slope. The negative slope may be indicative of a low elasticity of marginal cost to the output gap and not necessarily a low response of inflation to costs. Therefore, using salary costs mitigates that identification problem. I also employ sector-level prices from the survey to track sectoral inflation over time and to serve as proxies for supplier prices. By integrating these micro-level costs of intermediate goods with input-output tables, the estimation can effectively account for the influence of production networks on the sectoral inflation process. However, it's crucial to note that although survey data provides more realistic insights, it may be prone to measurement errors. I address this concern by showing that, on average, survey-based data on sectoral inflation closely aligns with official aggregate data.

Potential weak identification of the Phillips Curve might also stem from model misspecification. I estimate the SPC based on two microfounded frameworks from Imbs et al. (2011) (henceforth

IJP) and Rubbo (2023). These frameworks primarily differ in their production functions and subsequently affect the transmission of nominal rigidities in Rubbo's framework. IJP primarily focuses on labour costs as the main source of cost variation. They acknowledge the importance of sectoral linkages but don't explicitly model them.[1] I will refer to this SPC as the *Labour-Cost SPC*, to emphasise labour as the main source of cost variation. This expression is equivalent to the New Keynesian Phillips Curve, but with sector-specific coefficients.[2]

My estimation of the *Labour-Cost SPC* differs from that of IJP in several aspects: I study 52 industries in the UK, including those in manufacturing, distributive, retail, and services sectors. Secondly, I use survey-based industry-level prices, direct measures of expectations, and salary costs. Despite these differences, my results align with IJP, revealing positive and statistically significant average SPC parameters. Understanding that sectors in the UK predominantly exhibit forward-looking behaviour is critical for policymakers. This result is achieved through direct measures of firms' expectations, which mitigates the identification issues associated with indirect measures. Moreover, forward-looking price-setting behaviour reduces the risk of price persistence. These findings set the stage for a comparison with the *Full-cost SPC*, where I account for sectoral linkages.

I obtain a *Full-Cost SPC* with equivalent reduced-form parameters as in the *Labour-Cost SPC*, where "Full" is used to emphasise the inclusion of intermediate goods alongside labour into the production function, following Rubbo (2023). The *Labour-Cost SPC* assumes that firms face price stickiness due to not being able to adjust prices every quarter. The *Full-Cost SPC* I propose shows that the sector's response of inflation to costs is influenced not only by its own nominal rigidities but also by those of its suppliers. Sectors are affected by both common and idiosyncratic shocks and face asymmetric nominal rigidities and production costs when setting prices and wages. For instance, sector 1 might face additional nominal rigidities arising from its primary supplier, sector 2. If sector 2 faces significant price stickiness, this will eventually pass through to sector 1 via the production network. Through the estimation of the *Full-cost SPC*, I observe a markedly higher response of sectoral inflation to firms' costs compared to the *Labour-cost SPC*. This difference arises from the inclusion of intermediate goods costs and embedded sectoral linkages. These findings hold particular significance considering the complexities in inflation dynamics over the last decade. They contribute to a more comprehensive understanding of the inflation process by capturing potential sectoral transmission of rigidities and shocks. Concerning the role of expectations and lagged inflation, the average parameters in both frameworks are very similar, with positive and significant values.

Another source of model misspecification can arise from the sectoral homogeneity assumption in the traditional Phillips Curve. When homogeneity is imposed - and inconsistent with the data - estimations yield potentially misleading and inconsistent results, such as high inflation inertia

[1] They implement the Seemingly Unrelated Regression Equations (SURE) correction to capture cross-sector interdependencies.

[2] The most common assumptions behind the New Keynesian Phillips Curve are that there is one representative sector, firms are monopolistically competitive and face price rigidities, their production function has labour as the only variable cost, there is perfect competition in labour markets, and firms form rational expectations.

and low significance of costs. By estimating sector-specific parameters through the SPCs, I find substantial heterogeneity in the strength of the slope and in the role of expectations across sectors. Allowing for heterogeneous coefficients challenges previous homogeneity assumptions, as shown in Byrne et al. (2013) and Imbs et al. (2011).

Panel analysis introduces also the problem of sectors being affected by unobserved common shocks. Without accounting for these common effects, the errors will be correlated with sector-specific variables. I will then use the Common Correlated Effects (CCE) estimator proposed by Chudik and Pesaran (2015). This method is instrumental in effectively reducing cross-sectional dependence, as I will show in my results. By controlling for CCEs, I eliminate the strong cross-sectional dependence.

Upon unmasking the sectoral heterogeneity, I delve into its potential sources, focusing on industry characteristics often overlooked in the existing frameworks. While the microfoundation of the SPC predicts sectoral heterogeneity in its parameters, it lacks a specific theoretical framework for explaining these differences. I will then investigate specific industry-characteristics that may be associated with the observed sectoral heterogeneity. Notably, my research reveals a positive and significant association between the degree of market concentration and the sensitivity of current inflation to expected future inflation. This finding aligns with Leith and Malley (2007), which also noted a positive correlation between market concentration and price stickiness. Their argument suggests that higher concentration, indicating less competition, results in stickier price-setting behaviour and a stronger tendency to respond in a forward-looking manner.

This paper's findings bear relevance to current policy discussions on the impact of inflation expectations on current inflation and our understanding of the sources of sectoral heterogeneity. According to IMF (2022), more backward-looking inflation — i.e. lower relevance of future expected inflation — requires a more pronounced and faster monetary policy response to mitigate the risks of further rising inflation. The inclusion of sectoral linkages into the estimation of the SPC facilitates a better understanding of the complex dynamics of supply and demand shocks experienced in the last decade. This sheds light on the risk of overlooking the inflation process when focusing on labour as the only source of cost variation. Additionally, weak identification of the Phillips Curve parameters poses challenges for central banks in maintaining inflation on target. For instance, the strength of the slope determines the necessary adjustments in nominal interest rates to meet the inflation target. Finally, as explained in Carvalho (2006), monetary policy effects are larger and more persistent when accounting for the sectoral heterogeneity, accentuating the importance of sector-level Phillips Curve estimations.

Related Literature. This paper connects to various areas of economic research, spanning inflation dynamics, Phillips Curve estimation, the use of non-rational expectations, and heterogeneity in macroeconomics. The initial success of Phillips Curve estimation relied on the utilisation of aggregate data, rational expectations assumptions, and proxies like labour cost or output gap to capture firms' cost pressure, as evidenced in Gali and Gertler (1999), Sbordone (2002), Rudd and Whelan (2006). However, subsequent studies have raised doubt about the robustness of data choices, estimation methods, and model specifications.

For example, papers like Coibion and Gorodnichenko (2015), Del Negro, Giannoni, et al. (2015), and Del Negro, Lenza, et al. (2020) found a disconnection between inflation and real activity when using aggregate data, challenging the validity of the Phillips Curve. Recent studies suggested using disaggregate data for the estimation of the Phillips Curve. In studies conducted by McLeay and Tenreyro (2019) and Hazell et al. (2022), regional data is employed, revealing a positive and significant Phillips Curve slope. McLeay and Tenreyro (2019) explains that a positive slope using disaggregate data — i.e. either regional or sectoral — is consistent with a theoretically positive aggregate Phillips Curve slope. However, the empirically observable positive-sloped Phillips Curve cannot be obtained using aggregate data due to the endogenous response of monetary policy. In this study, I use sectoral data and find a positive slope, consistent with the results obtained from regional data. I also confirm that the slope is close to zero and insignificant when using aggregated data, aligned with findings discussed in Mavroeidis et al. (2014). They provide a comprehensive review of the challenges associated with weak identification and instability in Phillips Curve estimation with aggregate data, conclude that it is susceptible to a severe weak instruments problem, and recommend the use of micro or sectoral data.

While prior studies in the literature (Leith and Malley (2007), Imbs et al. (2011) and Byrne et al. (2013)) employed sectoral data for Phillips Curve estimation, they relied on indirect measures of expectations — i.e. actual inflation, or rational expectations — probably due to unavailability of direct measures of firms' expectations. The importance of using direct measures of expectations was firstly stated by Roberts (1995), finding the correctly signed (positive) and statistically significant Phillips Curve slope when using survey data. Their estimates are statistically insignificant when actual future inflation is used as a proxy for inflation expectations. Moreover, Adam and Padula (2011) and Coibion and Gorodnichenko (2015) also emphasised the importance of using direct measures of expectations, arguing that even household data can serve as a more accurate proxy for firms' expectations than using instrumental variables or rational expectations assumptions.

Coibion and Gorodnichenko (2015) and Coibion, Gorodnichenko, and Kamdar (2018) support the use of subjective expectations in estimating the Phillips Curve by showing considerable departures from full-information rational expectations among firms in New Zealand. Similarly, Boneva et al. (2020) reject the assumption of rationality in the UK using the same survey data that I use in this study. Other recent evidence of the use of direct measures of expectations within the UK context is presented in Meeks and Monti (2023), which estimates aggregate Phillips Curves using survey data from households and firms. To my knowledge, this paper is the first study to estimate the Phillips Curve using sectoral data in conjunction with survey-based firms' expectations.

The relevance of expectations was originally stressed by Friedman (1968) and more recently reaffirmed by Werning (2022) and Hazell et al. (2022). The former explores the effect of expectations on inflation through theoretical approaches, highlighting a near one-for-one pass-through from inflation expectations to current inflation, especially when assuming price stickiness à la Calvo. This insight contrasts with the conventional view that inflation management hinges solely on the Phillips Curve slope. Moreover, Hazell et al. (2022) underscores the importance of long-run inflation expectations for achieving stable inflation, also challenging the traditional perspective. In the context of the UK economy, a recent speech by Mann (2022) sheds light on the central role of inflation expectations in explaining the recent inflation process. My findings confirm the relevance of expectations in explaining the recent inflation process. Sectors in the UK are mostly forward looking.

An additional layer proposed in the literature to enhance the Phillips Curve identification is the incorporation of intermediate goods costs and production networks. For instance, Rubbo (2023) investigated an economy with multiple sectors and input-output linkages, demonstrating that the Phillips Curve slope decreases as intermediate input shares rise. Meanwhile, Höynck (2020) delved into the role of changes in the structure of production networks, contributing to the flattening of the Phillips Curve over time. Additionally, Afrouzi and Bhattarai (2023) highlighted how production linkages amplify the persistence of inflation concerning monetary and sectoral shocks, enhancing the pass-through of sectoral shocks to aggregate inflation. My results from estimating SPCs with intermediate goods alongside labour reveals a larger inflation response to costs when including sectoral linkages.

Outline. The rest of the paper is structured as follows. Section 2 explains the economics of price-setting behaviour and the microfoundation of the SPC, considering frameworks where costs are mainly explained by the labour factor and when intermediate goods costs are also factored in. Section 3 outlines the empirical methodology and addresses how measurement and identification issues are dealt with. Section 4 describes the data used for the estimations. Section 5 presents the results obtained from the empirical estimation. In Section 6, additional industry characteristics associated with the SPC parameters are examined. Section 7 provides the conclusion.

2 The Economics of Price-Setting Behaviour and Sectoral Heterogeneity

In this section, I will discuss two frameworks for studying sectoral inflation dynamics. First, I will introduce the *Labour-Cost SPC*, 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 the omission of sectoral interactions within the theoretical setting. They approximate sectoral linkages empirically using econometric techniques to capture the cross-sectoral interdependencies. Thus, in the second part I introduce the *Full-Cost SPC* using elements from Rubbo (2023) which explicitly models the production network.

Using input-output tables, I use micro-level intermediate input shares to capture sectoral linkages, providing novel empirical evidence on how these interconnections influence the inflation process. More details on this second framework are provided in the second subsection.

2.1 Labour-Cost SPC

The *Labour-Cost SPC* is analogous to the aggregate New Keynesian Phillips Curve (NKPC), but instead of being nationwide, it provides sector-specific parameters.[3] Within this SPC framework, there is a continuum of firms, indexed by i within each sector k, each producing a distinct variety of good k with identical technology but varying labour intensity. Monopolistic competition among these firms prevails, where each supplier understands that its sales rely on its offered price relative to the sector-level price. Detailed derivation is provided in Appendix A.

$$\hat{\pi}_{kt} = \frac{\omega_k}{\phi_k}\,\hat{\pi}_{k\,t-1} + \frac{\beta\alpha_k}{\phi_k}\,E_t\,\hat{\pi}_{k\,t+4} + \frac{(1-\omega_k)(1-\alpha_k)(1-\beta\alpha_k)}{\phi_k}\,h_{kt}\,\hat{s}_{kt} + \varepsilon^{\pi}_{kt} \tag{1}$$

The expression in Equation 1 describes inflation dynamics within each sector, $\hat{\pi}_{kt}$, as a function of past inflation, $\hat{\pi}_{k\,t-1}$; expected future inflation, $E_t\hat{\pi}_{k\,t+4}$; and real marginal costs, $\hat{s}_{kt}$. The variables represented by hatted and lowercase letters are log-linearised deviations from the steady state. Here, the underlying structural parameters encompass the degree of backward-looking behaviour ω_k, the degree of price stickiness α_k, and the discount factor β. The error term ε^{π}_{kt}, is a cost-push shock.

The factor h_{kt} is a labour adjustment which depends on the elasticity of substitution across varieties, η, and the labour share $(1-a_{kt})$.[4]

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

The relationship in Equation 1 can also be expressed in reduced-form:

$$\hat{\pi}_{kt} = \gamma^b_k\,\hat{\pi}_{k\,t-1} + \gamma^f_k\,E_t\,\hat{\pi}_{k\,t+4} + \gamma^s_k\,h_{kt}\,\hat{s}_{kt} + \varepsilon^{\pi}_{kt} \tag{2}$$

where

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

Note that γ^b_k, γ^f_k and γ^s_k are functions of the underlying structural parameters.

The IJP framework rests upon several key assumptions, such as optimal price setting by monopolistically competitive firms. Price updating à la Calvo (1983), where the degree of price stickiness,

[3] This expression is obtained by IJP by combining insights from Gali, Gertler, and David Lopez-Salido (2001), Sbordone (2002), and Woodford (2003), but extending the analysis to encompass multiple sectors.

[4] The parameter η is included in the demand function, as described in Appendix A.

denoted as α_k, is allowed to vary across sectors.[5] 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, firms form expectations about future costs. They then optimally set their prices at P^*_{kt} as a mark-up over their marginal costs. Therefore, the sectoral price level in period t is calculated as:

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

Among the firms that are able to adjust prices within a specific period, only a portion represented by $1-\omega_k$ follows optimal pricing strategies, setting prices based on expectations of future marginal costs. Conversely, a fraction ω_k uses a simple rule of thumb: they set prices based on past inflation data $\hat{\pi}_{k,t-1}$. By introducing this concept, we arrive at the hybrid SPC shown in Equations 1 and 2.

In this context, the production function features labour L_{kt} as the only factor, complemented by sector-specific technology Z_{kt}, represented as:

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

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

Additionally, the model incorporates a constant frictionless markup, and assumes perfect competition in labour markets, where labour is homogeneous and freely mobile across industries. Real marginal cost is defined as $\hat{s}_{kt} = \hat{w}_{kt} - \hat{p}_{kt}$, where nominal labour costs $\hat{w}$ are deflated by prices.

A notable limitation of this framework is the absence of sectoral interactions within the theoretical setting. I will then introduce the *Full-Cost SPC* where I explicitly account for sectoral linkages.

2.2 *Full-Cost SPC*: The Labour and Intermediate Goods Cost SPC

By explicitly modeling sectoral linkages, as stated in Rubbo (2023), price rigidities are claimed to compound at each step along the production chain. I integrate elements from Rubbo's paper to derive the *Full-Cost SPC*, where the reduced-form is equivalent to the *Labour-Cost SPC*. However, the underlying parameters now incorporate the sectoral linkages.

Notably, several key assumptions in this framework differ from the one in the previous subsection. The production function now involves both labour L_{kt} and intermediate goods as inputs, with firms utilising intermediate goods X_{kjt} from all industries N while retaining sector-specific technology.

$$Y_{kt} = Z_{kt} \, F_k \left(L_{kt}, [X_{kjt}]_{j=1}^{N} \right)$$

This framework captures sectoral linkages through micro-level intermediate input shares and incorporates the concept that nominal rigidities might emerge from other sectors' stickiness. Firms

[5] One advantage of Calvo's time-dependent framework, as opposed to state-dependent models, is its explicit closed-form equation describing the relationship between aggregate inflation and output.

within this model optimise their input combination to minimise costs, considering industry-level marginal costs as:

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

where W_t represents nominal labour cost and P_{jt} is the price of the intermediate good supplied by sector j.

The main expressions I use from Rubbo are as follows:[6] [7]

$$\hat{\boldsymbol{\pi}}_t = A(\hat{\mathbf{mc}}_t - \hat{\mathbf{p}}_{t-1}) + \boldsymbol{\beta}(I - A)\boldsymbol{E_t} \, \hat{\boldsymbol{\pi}}_{t+4} \tag{3}$$

Equation 3 represents the sectoral inflation rate process, jointly explained by sector-level marginal costs $\hat{\mathbf{mc}}_t$, net of same sector lagged prices $\hat{\mathbf{p}}_{t-1}$, and sector-level inflation expectations. Bold letters indicate vectors, implying that the variable applies to all sectors, leaving the subindex k unnecessary. Capital letters represent matrices, and the parameter A corresponds to the diagonal of sector-level price stickiness.

For illustrative purposes, considering two sectors, matrix A is as follows: $\begin{pmatrix} \tilde{\alpha}_1 & 0 \\ 0 & \tilde{\alpha}_2 \end{pmatrix}$ where $\tilde{\alpha}_1$ is the degree of price stickiness in sector 1 and $\tilde{\alpha}_2$ is the degree of price stickiness in sector 2.[8] In reality, matrix A will be of size $k \times j$.

$$\hat{\mathbf{mc}}_t = (1 - \mathbf{a}) \, \hat{\mathbf{w}}_t + \Lambda \, \hat{\mathbf{p}}_{jt} - log\mathbf{Z}_t \tag{4}$$

Equation 4 represents the evolution of marginal costs for any sector. It is explained by the sector-level labour cost $\hat{\mathbf{w}}_t$, which is weighted by the share of labour; the contemporaneous prices in the other sectors from which sector k buys intermediate inputs, $\hat{\mathbf{p}}_{jt}$, weighted by the matrix of shares of intermediate goods, Λ; and the logarithm of productivity.

As an illustration, matrix Λ with two sectors is as follows: $\begin{pmatrix} \lambda_{11} & \lambda_{12} \\ \lambda_{21} & \lambda_{22} \end{pmatrix}$ where λ_{11} is the share of intermediate goods that sector 1 buys to a firm in the same sector and λ_{12} is the share of intermediate goods that sector 1 buys to a firm in sector 2. Indeed, matrix Λ will be of size $k \times j$.

By combining Equation 3 and Equation 4 and after working out the algebra, I obtain the expression shown in Equation 5. In Appendix B I show the derivation of the system with 2 sectors for illustrative purposes.

$$\hat{\boldsymbol{\pi}}_t = (I - \Lambda \, \tilde{A})^{-1} \boldsymbol{\beta}(1 - \tilde{A}) \, \boldsymbol{E_t} \hat{\boldsymbol{\pi}}_{t+4} + (I - \Lambda \, \tilde{A})^{-1} \tilde{A} \; \hat{\mathbf{s}}_t^F \tag{5}$$

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

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

[7] These linearised equations correspond to Equations 14 and 15 in Rubbo's paper, with the notation adjusted to match the format used in this paper.

[8] Following the original paper, the tilde, $\tilde{\alpha}$, refers to α being adjusted by the discount factor, β.

are λ_{kj}, and β is the discount factor.

$$\hat{\mathbf{s}}_t^F \equiv (1 - \mathbf{a}_t)\, \hat{\mathbf{w}}_t + \sum_j \lambda_{kjt}\, \hat{\mathbf{p}}_{jt} - (1 - \lambda_{kkt})\hat{\mathbf{p}}_{t-1} \tag{6}$$

Expression 6 defines the full cost measure $\hat{\mathbf{s}}_t^F$ as explained by nominal wages weighted by the labour share for each sector, supplier prices weighted by the intermediate goods share bought by sector k from sector j, and respective sector past prices.

Intuitively, suppose sector 1 is very flexible in their price strategy (non-sticky) and willing to update prices every quarter. Now, suppose that this sector buys goods only from a very rigid sector (say, sector 2) which only updates prices annually. Then the costs of sector 1 will probably look rigid as well, and that may reflect as rigid prices in sector 1. A flexible industry could be thought of as an industry not tied to annual contracts. Conversely, a sticky industry could be due to using annual contracts or other type of price indexation.

By further reducing the expression in Equation 5, I obtain the *Full-Cost SPC*, which is equivalent to the *Labour-Cost SPC* but accounting for the sectoral linkages:

$$\hat{\boldsymbol{\pi}}_t = \boldsymbol{\gamma^f}\, \mathbf{E}_t\, \hat{\boldsymbol{\pi}}_{t+4} + \boldsymbol{\gamma^s}\, \hat{\mathbf{s}}_t^F + \boldsymbol{\varepsilon}_t^{\pi} \tag{7}$$

Despite the similarity between the two SPCs, the underlying structural parameters of the *Full-Cost SPC* encompass sectoral linkages, integrating the transmission of nominal rigidities and different productivity shocks. Sectoral inflation within a specific sector is influenced by both wages and intermediate goods prices. Let's compare the sets of reduced-form parameters from the two SPCs. One interesting difference that emerges is that, in the *Labour-Cost SPC*, pricing behaviour in a sector responds to expected inflation and costs based on their own degree of price stickiness. However, in the *Full-Cost SPC*, the inflation response is influenced not only by the nominal rigidities within the sector itself but also by its suppliers' rigidities, contingent upon the sector's purchases from its suppliers. Even in the absence of nominal rigidities, sectors may be differentially exposed to wage and productivity fluctuations. In the *Labour-Cost SPC*, sector k's pricing response to changes in costs arises only from wages. In contrast, in the *Full-Cost SPC*, the pricing behaviour could be indirectly responding to changes in costs in other sectors via suppliers' prices. Both aspects combined, 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.

By using input-output tables data, the estimation of this framework allows me to capture intermediate goods costs and sectoral linkages, offering novel empirical insights into how these interconnections influence inflation dynamics.

2.3 Open Economy Features

The SPC frameworks presented in the previous sections do not consider the role of foreign factors such as the import prices, the price of oil, and the degree of openness. Abbas et al. (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 et al. (2005) derived an aggregate-level 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 an open economy SPC framework. Therefore, I will only add these features empirically to the provided theoretical frameworks. I show in Section 5 that adding oil inflation and real import prices as CCEs helps reduce the cross-sectional dependence.

3 Sectoral Phillips Curve: An Empirical Investigation

In this section, I provide a brief overview of the key identification challenges that have been discussed in the literature concerning Phillips Curve estimation, along with the strategies I employ to address them. These approaches include the utilisation of survey and sector-based data with direct measures of expectations, supplier prices, and salary costs. Additionally, I incorporate input-output tables to account for production networks and employ heterogeneous dynamic panel data models with Common Correlated Effects (CCE) estimator to account for unobserved common factors. I will also explain the tradeoffs of using marginal cost and the output gap as proxies for the forcing variable. For a more comprehensive review of all challenges faced in Phillips Curve estimation, please refer to Mavroeidis et al. (2014) and Abbas et al. (2016).

3.1 Survey-Based Expectations

Most studies proxy expectations with instrumental variables (IV) or imposing rational-expectations (RE) assumptions mainly due to the lack of available data on firms' expectations.[9] However, these methods have faced criticism, particularly regarding the issue of weak instruments. A proposed solution is to use survey-based expectations, as suggested by studies like Nason and G. W. Smith

[9] Gali and Gertler (1999), Leith and Malley (2007), Maćkowiak et al. (2009), and IJP are some examples.

(2005), Byrne et al. (2013), and Coibion, Gorodnichenko, and Kumar (2018). The latter states: *"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"*.

Subjective 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), as explained in Adam and Padula (2011). The LIE condition entails that agents are unable to predict revisions in their own or other agents' forecasts.[10]

One interesting aspect of the survey data used in this study is that firms are being asked about inflation in their sector. This is an advantage as one would expect firms to pay more attention and be better informed about prices in their sector compared to aggregate economic conditions. Relatedly, Andrade et al. (2022) 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 Sectoral Data

The disconnection between inflation and output gap may be due to the dynamic response of monetary policy to inflationary pressures, as elaborated in McLeay and Tenreyro (2019). The empirical disconnect between inflation and output gap results from the successful and optimally set monetary policy. The central bank raises interest rates when output is above potential, thereby lowering inflation. They explain that observing a positive slope at the disaggregate level — i.e. either regional or sectoral — is consistent with a theoretically positive-sloped Phillips Curve at the aggregate level. However, the positive slope cannot be empirically observed using aggregate data due to the endogenous monetary policy response.

By using sectoral data, I find a positive response of inflation to marginal costs, thereby confirming that hypothesis. At the sector level, the monetary policy cannot offset the demand variation which helps identify the slope. I also confirm that the slope is close to zero and insignificant when using aggregated data, aligned with findings discussed in Mavroeidis et al. (2014).

3.3 Heterogeneous Dynamic Panel Estimation

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 R. Smith (1995). Furthermore, Byrne et al. (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.

[10] Coibion and Gorodnichenko (2012) fail to detect deviations from LIE using survey-based expectations. Also, see Coibion, Gorodnichenko, and Kamdar (2018) for the derivation of the Phillips Curve with survey-based expectations.

$$\pi_{kt} = \gamma^f \, E_{kt}\pi_{k\,t+4} + \gamma^b \, \pi_{k\,t-1} + \gamma^s \, h_{kt} \, \hat{s}_{kt} + \varepsilon_{kt} \tag{9}$$

By estimating Equation 9, and if any of the coefficients are not homogeneous across sectors — $\gamma_k^f \neq \gamma^f$, $\gamma_k^b \neq \gamma^b$ 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.

$$\varepsilon_{kt} = \left[u_{kt} + (\gamma_k^f - \gamma^f) \, E_{kt}\{\pi_{k\,t+4}\} + (\gamma_k^b - \gamma^b) \, \pi_{k\,t-1} + (\gamma_k^s - \gamma^s) \, h_{kt} \, \hat{s}_{kt}\right]$$

Therefore, I will estimate dynamic panel model with heterogeneous sector-specific coefficients. The empirical importance of this approach has been previously shown by IJP and Byrne et al. (2013). They found lower persistence of inflation and significantly larger coefficients on real marginal costs compared to aggregate level estimations.

3.4 Addressing Cross-Sectoral Interdependencies:

Factors such as input-output production linkages and integrated factor markets can lead to cross-sectoral interdependencies. Previous studies that estimated SPCs tried to address cross-sector interdependencies through econometric techniques, without explicitly modelling the sectoral linkages.[11] 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. They also use CCEs to account for unobserved common factors and reduce the cross-sectional dependence.[12] Proposed by Pesaran (2006), this estimator introduces a correction technique to account for unobserved common factors, potentially correlated with sector-specific regressors.

I complement both CCEs as means of capturing unobserved common factors and input-output tables to capture observed sectoral linkages. By doing this, I can further alleviate the risk of cross-sectional dependence and capture the effect of intermediate goods shares and input prices through the supply chain.

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

Given the dynamic panel structure of the analysis, I implement the Dynamic Panel Mean Group Estimation along with the Common Correlated Effects (CCE) introduced by Chudik and Pesaran (2015). The CCE estimator, initially proposed by Pesaran (2006) and further developed by Chudik

[11] Imbs et al. (2011) and Byrne et al. (2013)

[12] I provide a more detailed explanation of CCE in Section 3.5.

and Pesaran (2015), is designed to address the challenge of Cross-Sectional Dependence (CSD) and enhance the estimation efficiency.[13]

In the study of sectoral inflation dynamics, potential unobserved common shocks might be mistakenly introduced into the model residuals, thereby reducing estimation efficiency. To address these concerns, I incorporate CCEs into the estimation framework, aiming to mitigate these risks and reduce CSD. Despite Rubbo's model incorporating intermediate goods and its embedded production network, facilitating the inclusion of some sectoral linkages through input-output tables, empirical results reveal remaining CSD even after accounting for the production network.

To provide further insight: certain UK economy-affecting shocks, such as Brexit and Covid, might have impacted several sectors differently and simultaneously. These events may not be entirely captured by the input-output table. These omitted factors are not only overlooked variables that could theoretically be included in the model; they represent an unknown, fluctuating set of determinants that are correlated with inflation and the regressors. Consequently, CCEs are integrated into the estimation of the *Full-Cost SPC*.

The inclusion of CCEs is achieved by considering time-varying covariates, which are instrumental in capturing sectoral linkages, unobserved factors, and common shocks that may affect sectors heterogeneously. These common elements are complemented by sector-specific "factor loadings" aimed to capture the differential impact across sectors. This approach effectively reduces data dimensionality and prevents overfitting by concentrating on the most influential factors affecting the variables of interest.[14]

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

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

In this representation, we observe variables such as y_{kt}, x_{kt}, and the common factors f_{It}, while the factor loadings g_{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[15] potentially leads to (i) Omitted variable bias if $g_{x,k} \neq 0$ 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 $g_{u,k} \neq 0$.

[13] They developed 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.

[14] See Eberhardt and Presbitero (2015) for an empirical application of these methods

[15] This is explained in detail in Ditzen (2021), based on Everaert and De Groote (2016).

Then, in the case of the *Labour-Cost SPC*, I augment Equation 2 as follows:

$$\hat{\pi}_{kt} = \alpha_k + \gamma_k^b\, \hat{\pi}_{k\,t-1} + \gamma_k^f\, E_{kt}\, \hat{\pi}_{k\,t+4} + \gamma_k^s\, h_{kt}\, \hat{s}_{kt} + u_{kt} \tag{10}$$

$$u_{kt} = g_k\, f_t + \varepsilon_{kt}^{\pi} \tag{11}$$

where Equation 10 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. 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, including just one is sufficient.[16] Additionally, in line with empirical evidence mentioned in the previous section, I incorporate real import prices and oil price inflation.

Next, I provide an illustrative specification framework for estimating Equation 10, which effectively mitigates strong cross-sectional dependence (CSD) by utilising the following variables for z_t: average expectations (lags zero to three), average labour costs (lags zero to two), and oil inflation (lags zero to two). For detailed results, please refer to the regression outputs in Table 3.

$$\begin{aligned}\pi_{kt} = {} & \alpha_k + \gamma_k^b\, \pi_{k\,t-1} + \gamma_k^f\, E_{kt}\, \pi_{k\,t+1} + \gamma_k^s\, h_{kt}\, \hat{s}_{kt} \\ & + \sum_{t=0}^{3} g_{1\,k}\, \overline{E_{kt}\, \pi_{k\,t+1}} + \sum_{t=0}^{2} g_{2\,k}\, \overline{\hat{s}_{kt}} + \sum_{t=0}^{2} g_{3\,k}\, \pi_t^{oil} + \varepsilon_{kt}^{\pi}\end{aligned} \tag{12}$$

3.6 Other Potential Identification Concerns

3.6.1 Shifting Trend Inflation

It is common in the Phillips Curve literature 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) use time fixed effects to control for shifting trend inflation.

I propose using CCEs as an enhanced approach compared to time fixed effects to control for potential shifting trend inflation. While CCEs encompass time-components, these are estimated with heterogeneous loadings associated with each sector, thereby capturing sector-specific trends.

[16] See details in Correlation Table 7.

3.6.2 Time Series Properties

Temporal aggregation presents another common challenge in this literature. Actual and expected inflation data refer to annual changes, while the frequency is quarterly. To address potential correlation over time, I use lagged variables[17] to instrument the regressors.

Another concern commonly raised is the potential nonstationarity of the inflation series. In Table 6 I conduct panel unit root tests following Pesaran (2007). The results reject the panel unit root test hypothesis, indicating that a statistically significant proportion of the sectors are stationary.

Additionally, inflation expectations and actual inflation are simultaneously determined. By conducting a first-stage regression, the resulting fitted value mitigates the endogeneity issue. I show in Table 8 the potential endogenous variables regressed on their lags. For expectations, all coefficients exhibit the expected sign and are highly significant, reflecting the time overlapping effect. The labour cost series is converted from an annual to a quarterly measure. This is reflected in the short-dated correlation, with only one lag being 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.

3.7 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 SPC.

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

[17] As emphasised in Mavroeidis et al. (2014), lags can be used as instruments for robust inference in the presence of unit roots.

'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 SPC by Woodford (2003) contains both relative prices and aggregate output gap whereas the sectoral inflation equation which uses the real marginal cost (instead of the output gap) does not require relative prices.[18] Sector-level nominal marginal costs are calculated as the average of the costs across firms of sector k. Therefore, I 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 completed by firms operating in the UK.[19] 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

Survey	**Sectors covered**	**Ave. Number of firms /reports[1]**	**Representation of sector[2]**
Industrial Trends Survey (ITS)	Manufacturing	336	2.71%
Distributive Trades Survey (DTS)	Retail, Wholesaling, Motor Trades	97	2.54%
Services Sector Survey (SSS)	Consumer, Business, Prof. Services	128	1.98%
Financial Services Survey (FSS)	Banking, Insurance, Investment	71	1.92%
All		632	

[1] Number of firm's reports per quarter: 2009-2020 mean 650 (max:813, min:451); 2021-2022 mean 388 (max:464, min:314)
[2] 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.[20] The CBI collects this information through supplementary questions managed jointly with the Bank of England (BoE). The CBI-BoE dataset

[18]See Woodford (2003) section B.27 and Appendix B.7
[19]Industrial Trends Survey (ITS), Distributive Trades Survey (DTS), Financial Services Survey (FSS), and the Services Sector Survey (SSS)
[20]This work focuses on data starting in 2009 given that very few data points were collected in 2008

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.

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 et al. (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) whereas for DTS, FSS and SSS are -5% to 5%.[21] [22] 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 which had the highest bucket at 5%.[23]

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 those expectations reports that are very far from the other firms' reports in the same sector.[24] 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

[21] 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%.

[22] 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%.

[23] Bank of England/Ipsos Inflation Attitudes Survey

[24] 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.

45 quarters.

4.1.2 Stylised Facts from CBI Survey Data

The CBI data shows evidence of substantial sectoral heterogeneity in inflation expectations. See Figures 21 through 24 in Appendix D. This highlights the importance of adopting a heterogeneous approach with sector-specific parameters in the estimation of the Phillips Curve.

Table 2: Average number of firms in each sector and quarter

Sector	2009-2014	2015-2020	2021-2022	Sector	2009-2014	2015-2020	2021-2022
Manufacturing Firms				**Services Firms**			
Fabricated Metal	52	46	20	Financial Services	30	35	13
Machinery and Equipment	61	38	9	Act. related to Fin. Svces	20	16	3
Rubber and Plastic	30	27	12	Legal and Accounting	16	13	3
Electrical Equipment	21	24	12	Insurance and Pension	19	12	4
Computer and Electronic	23	19	5	Land Transport	13	10	2
Non-Metallic Mineral	19	16	7	Accommodation	11	7	2
Food Products	19	14	5	Real Estate	6	6	3
Basic Metals	17	13	7	Postal and Courier	6	5	1
Chemicals	15	12	5	Architect. & Engineering	8	4	2
Paper and Paper	15	11	4	Advertising & Mkt Research	7	4	0
Textiles	13	11	3	Management Consulting	5	5	2
Motor Vehicles	11	13	5	Employment Activities	6	4	2
Other Manufacturing	12	9	2	Sporting Activities	5	4	2
Wood	10	8	2	Computer Programming	4	4	1
Furniture	8	8	2	Restaurants and Food	3	5	2
Other Vehicles	8	6	2	Recreational and Cultural	4	3	1
Printing and Media	7	7	2	Private Security	2	4	3
Wearing Apparel	7	6	1	Water Transport	3	3	1
Beverages	5	8	1	Travel Agents	3	5	0
Footwear and Luggage	5	5	2	Cleaning	4	2	1
Pharmaceutical	4	4	3	Renting and Leasing	2	4	2
Other Mining	5	3	1	Travel Agency	2	3	2
				Medical and Optical	2	2	1
Distributive Firms							
Retail (Non-Vehicles)	55	39	21				
Wholesale (Non-Vehicles)	38	35	15				
Wholesale, Retail Vehicles	9	7	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 Official Inflation vs. Survey-based perceived Inflation

There are at least two sources of data that I can utilise for inflation: the actual inflation rates reported by the Office for National Statistics (ONS) and the survey-based reports on perceived sectoral inflation provided by firms. Each of these sources has its own set of challenges. In this section, I will explain the difficulties associated with each source and why I choose to utilise the CBI survey-based reports for SPC estimation.

The key challenge 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) by SIC code for industrial sectors. For non-industrial sectors, the Consumers Price Indices (CPI) and Services Producer Prices Indices (SPPI) could be used.[25] [26]

Regarding the survey-based reports, 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. However, I show in Figure 1 that the survey-based perceived sectoral inflation is a good proxy for the official actual inflation rates. The average of CBI perceived inflation reports follows quite closely the average of official 2-digit SIC inflation rates.

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:

$$Totalcost_k = Intermediatecosts_k + CompensationtoEmployees_k$$

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

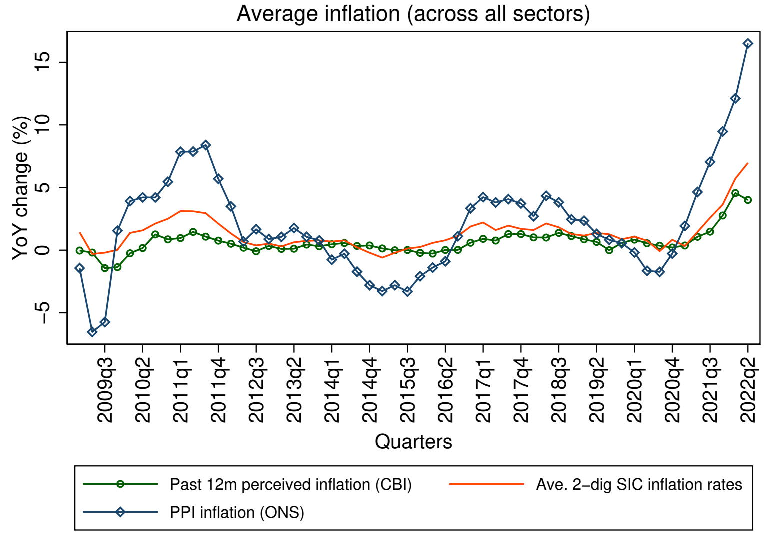
$$ICshare_{kj} = \frac{IC_{kj}}{Totalcost_k}$$

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.

[25] 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.

[26] The mapping of 4-digit SIC sectors and PPI, CPI, SPPI data is detailed in Table 12.

Figure 1: 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.

4.4 Measures of cost

4.4.1 Labour Cost

I explored two measures for sectoral labour costs: the log detrended real wage, constructed using survey-based changes in salary costs, and a measure of unit labour cost (ULC) provided by the ONS.[27] The log detrended real wage, denoted as $\hat{s}_{kt}$ and shown in Figure 2, is calculated using the nominal wage series constructed from the survey-based "change in wage/salary cost per person employed". Subsequently, I compute the log deviations from the steady state.[28] To obtain a real measure, I deflate it by prices, also constructed based on the survey-based inflation data. This is represented as $\hat{s}_{kt} = s_{kt} - \overline{s}_k$ and $\hat{p}_{kt} = p_{kt} - \overline{p}_k$.

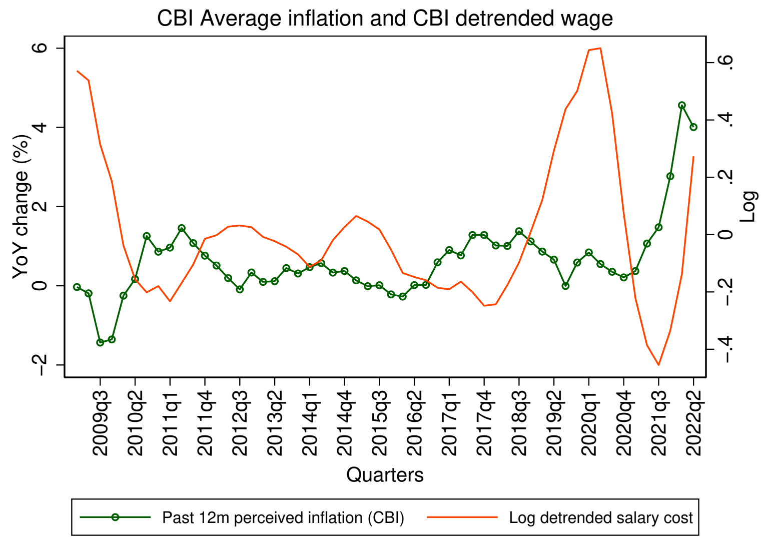
4.4.2 Full Costs

In order to construct the measure of "Full costs" — defined in Equation 6 — that I use for the estimation of the *Full-Cost SPC*, I require specific data elements: the labour share for each sector, the intermediate goods share bought by sector k from sector j, and sector j's intermediate goods' prices. I have explained in Section 4.3 how I obtain the first two from the input-output table, LS_k and $ICshare_{kj}$, respectively.

[27] Details on how I construct the ULC measure can be found in Appendix D.

[28] For empirical purposes, the steady state is approximated using the sample mean over time for each sector.

Figure 2: 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.

The process of calculating intermediate goods' prices involves several steps. First, I compute quarterly sectoral prices by dividing the perceived sectoral inflation reported by CBI over the past 12 months by four, represented as $\pi^{q}_{kt} \equiv \frac{\pi^{y}_{kt}}{4}$. By indexing the price series with the first quarter data point as 100 and applying quarterly changes throughout the series, I generate a price level series for each sector on a quarterly basis. Lastly, I calculate the natural logarithm of this series and detrend it by subtracting the sample mean price for each sector, resulting in $\hat{p}_{kt}$.

4.4.3 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.[29] I show the series for each industry from 2009 to 2021 in Figure 28 in the Appendix, 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_i represent turnover (net sales) of an i-th entity operating in a given industry (i=1,2,...n), then the market share (ms_i) of the i-th entity operating on a given market can be defined as: $ms_i = \frac{q_i}{\sum_{i=1}^{n} q_i}$.

I then define the HHI for a given sector k as follows: $HHI_k = \sum_{i=1}^{n} (ms_i)^2$ (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.

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

4.5 Other Relevant Aspects About the Data

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

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

In this section I show the regression estimation of the *Labour-Cost SPC* and the *Full-Cost SPC*. Each framework is estimated for 52 sectors. To calculate the expectations variable, I use the sector-weighted average of firms' reports, weighted by the number of employees.

For the *Labour-Cost SPC*, I estimate the reduced-form parameters using Equation 2:

$$\hat{\pi}_{kt} = \gamma_k^b\, \hat{\pi}_{k\,t-1} + \gamma_k^f\, E_t\, \hat{\pi}_{k\,t+4} + \gamma_k^s\, h_{kt}\, \hat{s}_{kt} + \varepsilon_{kt}^{\pi}$$

where $\hat{s}_{kt} = \hat{w}_{kt} - \hat{p}_{kt}$, representing $\hat{w}_{kt}$ the log deviation of wage from the sectoral sample mean. For estimation purposes, I adopt IJP's approach of computing h_{kt} using observed labour shares, and a value for η corresponding to a level of markups calibrated at 10% which gives $\eta = 11$.

For the *Full-Cost SPC*, and referring to the derived Equation 7, I estimate the following specification:

$$\hat{\pi}_{kt} = \gamma_k^f\, E_t\, \hat{\pi}_{k\,t+4} + \gamma_k^s\, \hat{s}_{kt}^F + \varepsilon_{kt}^{\pi}$$

The hybrid version of the *Full-Cost SPC* is as follows:

$$\hat{\pi}_{kt} = \gamma_k^b\, \hat{\pi}_{k\,t-1} + \gamma_k^f\, E_t\, \hat{\pi}_{k\,t+4} + \gamma_k^s\, \hat{s}_{kt}^F + \varepsilon_{kt}^{\pi} \tag{13}$$

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 et al. (2005) through econometric techniques to estimate unobserved expectations and by Meeks and Monti (2023) using households expectations. In the UK context, Byrne et al. (2013) represents the only available evidence of SPC estimation, also relying on econometric methods to proxy unobserved expectations.

Incorporating some of the variables used in the aggregate Phillips Curve proposed by Batini et al. (2005) — such as oil price inflation and real import prices — I found that they are not statistically significant as sector-specific parameters when added to the SPC. However, adding oil inflation as a common factor was helpful in eliminating cross-sectional dependence in both the *Labour-* and *Full-Cost SPC* frameworks.

5.2 Estimation of the Sectoral Phillips Curve

I present the regression results for the *Labour-Cost SPC* in Table 3 and for the *Full-Cost SPC* in Table 4. In both cases, the three columns indicate different specifications: Column 1 shows the estimation of a pooled model assuming homogeneous coefficients for all sectors, while Column 2 shows Mean Group (MG) estimation with heterogeneous coefficients. Column 3 represents the integration of all features: Mean Group estimation, heterogeneous coefficients, and CCEs, labelled the "full model". All models incorporate sector-level fixed effects, and Model 3 is augmented with common factors to control for CCEs.

For estimation, I use the Stata command xtdcce2 developed by Ditzen (2021). This command is particularly convenient as it facilitates the estimation of dynamic panel data models with CCEs and supports instrumental variable estimation.

Comparing the three model specifications reveals that the full model consistently yields the lowest Root Mean Squared Errors (RMSE) in both frameworks.[30] This suggests that allowing for heterogeneous coefficients across sectors and accounting for CCEs leads to substantially lower average residual magnitudes. Additionally, considering production networks in the *Full-Cost SPC* results in a lower RMSE compared to the *Labour-Cost SPC*.

In the full model for both the *Labour* and *Full-Cost SPC*, the average coefficient for the role of expectations is approximately 0.6, while for lagged inflation, it's around 0.2. These estimates align with economic theory, which predicts that γ^f should be larger than γ^b, indicating that firms predominantly set prices in a more forward- than backward- looking way. While not directly comparable, similar parameter values have been obtained in other studies estimating Phillips Curves for the UK and the US.

In the UK, Meeks and Monti (2023) found $\gamma^b : 0.2$ and $\gamma^f : 0.8^{***}$; Byrne et al. (2013) obtained

[30] 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.

$\gamma^b : 0.1^{***}$ and $\gamma^f : 0.9^{***}$; while Batini et al. (2005) reported $\gamma^b : 0.3^{***}$ and $\gamma^f : 0.7^{***}$.[31] None of these studies use direct measures of firms' expectations. Moreover, Boneva et al. (2020) estimated firm-level pricing equations using the same survey that I use but assessing own-prices — instead of sectoral prices — obtained $\gamma^f : 0.2 - 0.3$ (γ^b is not explicitly reported). Some recent evidence using US data: Meeks and Monti (2023) found $\gamma^b : 0.1$ $\gamma^f : 1.6^{***}$ and McLeay and Tenreyro (2019) reported $\gamma^b : 0.1^{***}$ $\gamma^f : 0.22$.

Table 3: *Labour-Cost SPC*

	Pooled (1)	MG (2)	Full model (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)
Heterogeneous/Homogeneous Coeff.	Homogeneous	Heterogeneous	Heterogeneous.
FE (k)/CCE	FE(k)	FE(k)	FE(k) + 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 "Full model" uses a CCEMG estimator, 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.

The comparison of the slopes between the *Labour-* and the *Full-Cost SPC* frameworks reveals their distinct underlying parameters. The *Labour-Cost SPC* shows a slope around 0.1, indicating the inflation response to labour costs. In contrast, the *Full-Cost SPC* exhibits a slope around 0.9, representing a much higher inflation response to the *Full Cost* measure involving both labour and intermediate goods. In Table 9 in the Appendix I show that the slope is not significant when focusing on aggregate data, whether using a measure of the output gap or labour costs.

Overall, these outcomes suggest that considering heterogeneous coefficients and controlling for CCEs through cross-sectional averages enhances the outcomes in both frameworks. Additionally, it highlights the greater impact of the slope in explaining sectoral inflation dynamics when the cost

[31] The stars represent the significance level, as reported in the original papers, *** p<0.01, ** p<0.05, * p<0.1.

function includes intermediate goods, thereby the sectoral linkages being explicitly accounted for.

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

Table 4: *Full-Cost SPC*

	Pooled (1)	MG (2)	Full model (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)
Full cost (Labour and Int. goods)	0.32***	0.86***	0.89***
	(0.10)	(0.17)	(0.24)
Heterogeneous/Homogeneous Coeff.	Homogeneous	Heterogeneous	Heterogeneous.
FE (k)/CCE	FE(k)	FE(k)	FE(k) + 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 "Full model" uses CCEMG estimator, 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.

5.3 Unmasking Sectoral Heterogeneity in Price Setting Behaviour

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 Section 6 I will focus on potential sources — i.e. industry-characteristics and other common factors — that might explain the asymmetries.

Sector-specific parameters are obtained using the full model from both frameworks. In Figures 3 through 8 I show the histogram distribution of the estimated parameters. In Appendix C, I present the parameters from the *Labour-* and the *Full-Cost SPC* frameworks for each of the sectors, as well as the average parameters across sector within each group.[32]

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

Figure 3: *Labour-Cost SPC* γ_s

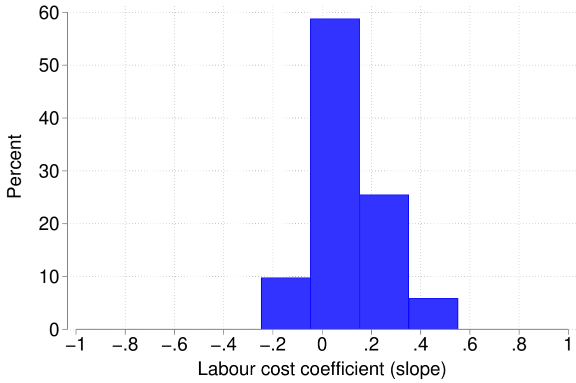


Figure 4: *Full-Cost SPC* γ_s

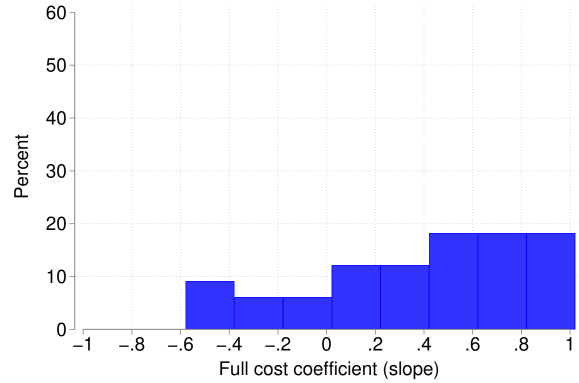


Figure 5: *Labour-Cost SPC* γ_f

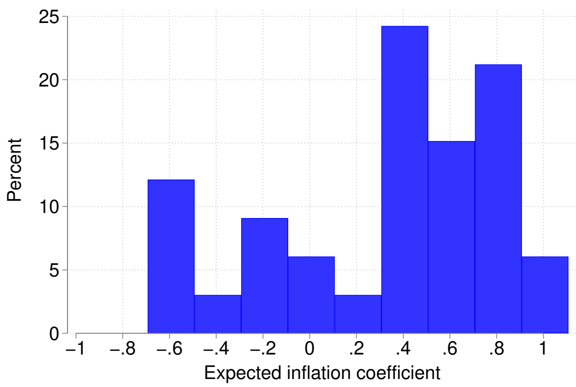


Figure 6: *Full-Cost SPC* γ_f

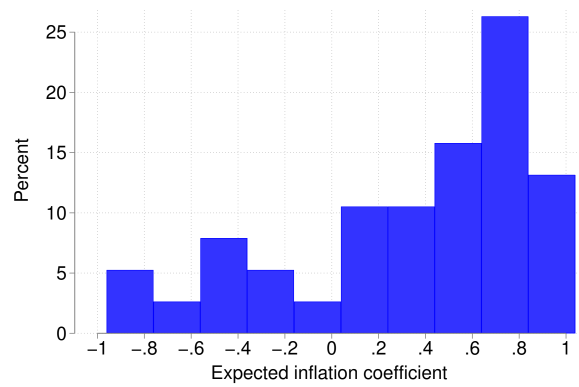


Figure 7: *Labour-Cost SPC* γ_b

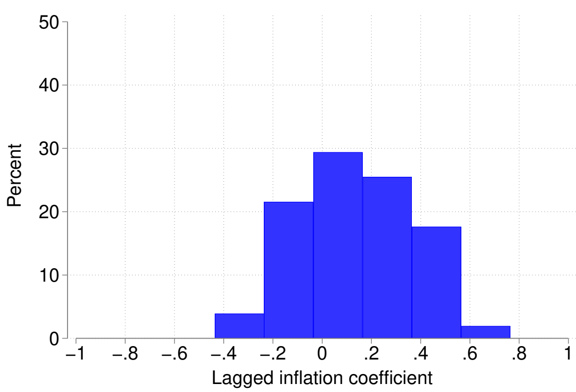
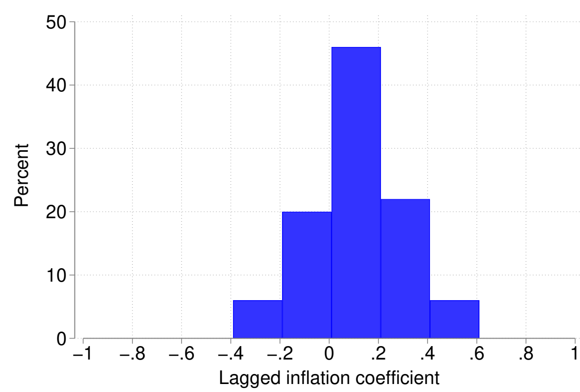


Figure 8: *Full-Cost SPC* γ_b



The slopes γ_s obtained from the *Labour-Cost SPC* are mostly centered between values of 0 and 0.4 while the slopes obtained from the *Full-Cost SPC* are much larger and spread away. See Figures 3 and 4. These results are particularly relevant to the widely discussed point that labour is considered the main source of cost variation in the *Labour-Cost SPC*, while intermediate goods costs are also included in *Full-Cost SPC*. This indicates that embedding the production networks yield a much larger responsiveness of inflation to costs.

Additionally, based on Figure 5, we can see that while there is not a significant difference in the distribution of estimated parameters for the role of expected future inflation between frameworks. However, the figures in Appendix C underscore the differences in the parameters across sectors (rather than across frameworks).

In Figure 7, we can observe that the estimated parameters related to lagged inflation are mostly located between -0.5 and 0.5 in results from both frameworks. I will show in in Appendix C that 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, 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.

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

6 Determinants of Sectoral Heterogeneity in Price Setting Behaviour

The microfoundations of the SPCs described in Section 2 emphasise differences in parameters without providing structural explanations. While both the *Labour* and *Full-Cost SPC* frameworks reveal variations in price stickiness among industries, they lack a structural rationale. This is further emphasised in Section 5, where I presented evidence of substantial heterogeneity in sector-specific parameters. Now, the next objective is to investigate potential factors contributing to these asymmetries.

In the first subsection I will discuss some additional industry-specific characteristics not considered in the theoretical frameworks studied above, drawn from existing research. In the second subsection, I will show the results from the empirical analysis.

6.1 Industry Characteristics and Sectoral Heterogeneity

While I am not aware of studies that explicitly explain industry characteristics potentially driving the SPC structural parameters, some papers have focused on their relationship with price stickiness α. This parameter, sometimes proxied through the frequency of price changes, is behind all structural parameters in the *Labour*- and *Full-Cost SPC* frameworks. The remaining parameters that influence the γ values include β [33] in both frameworks, ϕ in the *Labour-Cost SPC* (ultimately

[33] Representing the discount factor, which is typically assumed to be close to 1 and will not be the focus of this study.

influenced by α, β, and ω), and the input shares in the *Full-Cost SPC*.

I will then explain the provided relationship between α and industry-characteristics. It's worth to note that it is commonly assumed that the backward-looking (γ_b or ω) and forward-looking γ_f behaviour move in opposite directions, as my evidence shows as well.

The NKPC states 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.

6.1.1 Potential Sources of Sectoral Heterogeneity

In the following subsections, I will review industry-specific characteristics studied in the existing literature. Peter J. 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 Peter J 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.

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 concentration 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.

The findings described above collectively contribute to our understanding of why different sectors exhibit varying levels of price stickiness, providing valuable insights into cross-sector heterogeneity within the SPC. These determinants will be tested empirically in the next section.

6.2 Estimated Parameters Weighted by their Standard Error

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. It's important to note that the estimated sector-specific parameters exhibit various levels of estimation precision.[34] To ensure comparability, I will initially adjust the estimates based on their estimation precision. I will do so by applying weights to the parameters based on their standard errors. This approach is similar to weighted least squares (WLS).[35] Since

[34] This variability may be due to their estimation as a panel, without consideration of potential sector-specific characteristics or shocks that may affect certain sectors.

[35] 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).

the standard errors are derived from the OLS estimation of the SPCs, 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.

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

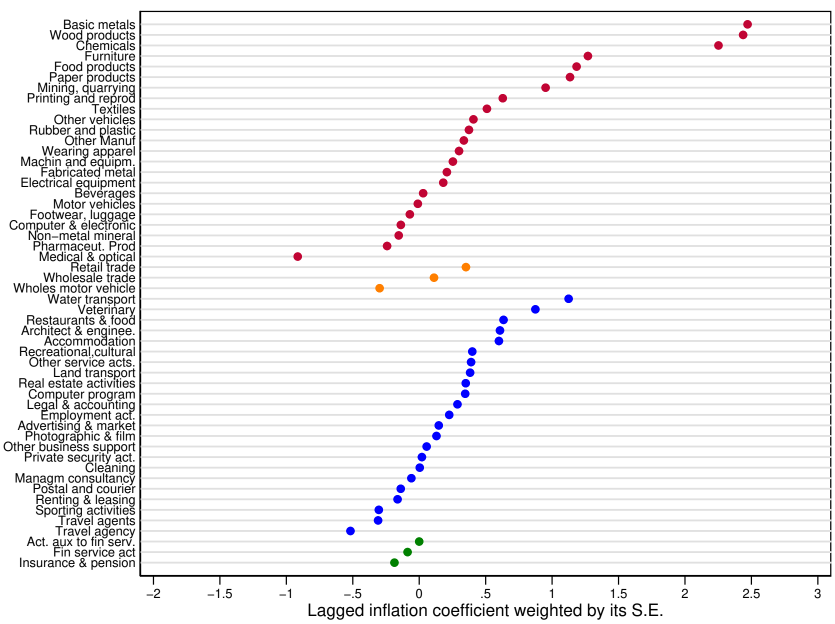
where p represents the SPC parameters (f for forward-looking, b for backward-looking, and s for slope).

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

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

I show in Figures 9, 10, and 11 the weighted parameters by sector from the *Labour-Cost SPC*, and in Appendix C I show the estimated parameters from the *Full-Cost SPC*.

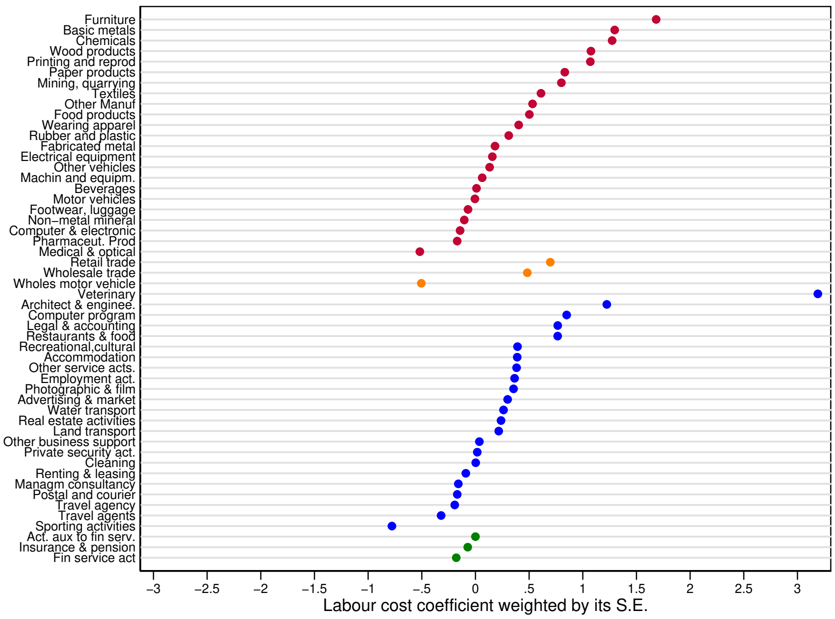
Figure 9: Weighted parameter on lagged inflation (*Labour-Cost SPC*)



Note: The coefficients presented in the figure have been weighted based on their respective S.E. from the *Labour-Cost SPC*. 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.

Figure 10: Weighted parameter on labour cost (*Labour-Cost SPC*)



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

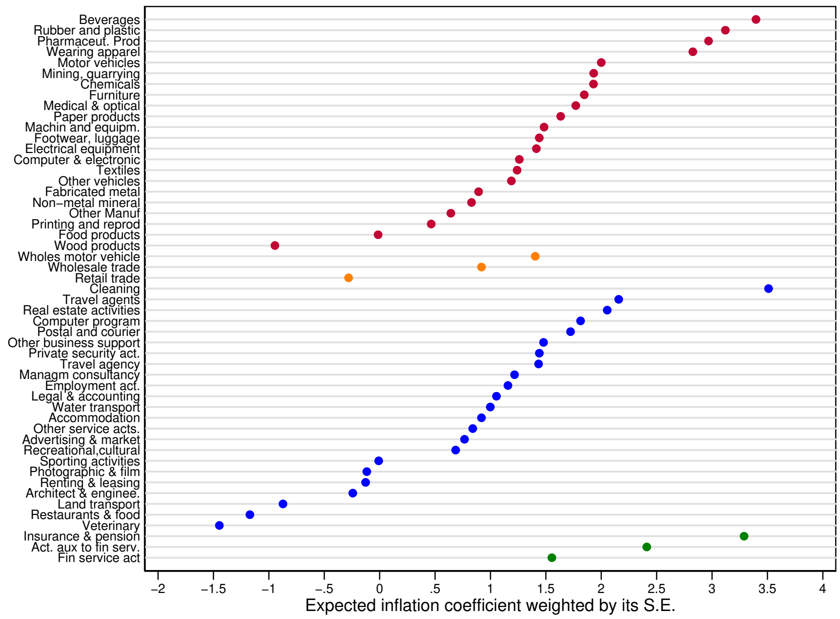
The weighted regression used is expressed as follows:

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

6.3 Regression Estimation Results

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

Figure 11: Weighted parameter on expected inflation (*Labour-Cost SPC*)



Note: The coefficients presented in the figure have been weighted based on their respective S.E. from the *Labour-Cost SPC*. 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.

Table 5: Regressions estimations (*Labour-Cost SPC*)

	γ_f (1)	γ_b (2)	γ_s (3)	γ_f (4)	γ_b (5)	γ_s (6)
		MC: CR5			*MC: HHI*	
Market concentration (MC)	69.44**	-16.73	23.63	1.48*	-0.61	0.05
	(29.82)	(13.04)	(19.77)	(0.85)	(0.42)	(0.38)
MC x Services Dummy	-15.12	-7.80	49.62	-1.14	-0.05	0.67
	(78.56)	(22.06)	(46.79)	(2.35)	(0.54)	(1.48)
Imports over supply	-0.16	0.57*	0.20	0.04	0.60*	0.10
	(0.53)	(0.33)	(0.13)	(0.51)	(0.32)	(0.11)
Energy over costs	-8.25	7.90***	6.33	-7.16	7.69***	5.70
	(7.15)	(2.57)	(6.08)	(7.01)	(2.60)	(5.53)
Petrol over costs	-13.38***	2.50	-1.12	-12.53**	2.48	0.45
	(4.51)	(1.72)	(3.86)	(4.67)	(1.49)	(3.61)
ULC variability	0.41	0.59	-1.67	0.75	0.51	-0.70
	(2.15)	(0.64)	(1.01)	(1.68)	(0.60)	(0.78)
Observations	51	51	51	51	51	51
R-squared	0.34	0.60	0.22	0.30	0.61	0.08

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 SPC estimated parameters.

The results in Table 5 reveal a positive relationship between the role of expectations and two standard Market Concentration measures: the Five Firm Concentration Ratio (CR5) and the HHI. I particularly focus here on the estimates obtained from the *Labour-Cost SPC* as its reduced-form parameters enable straightforward comparisons with own-industry characteristics. In contrast, the *Full-Cost SPC* involves interactions with other sectors. I present its results in Table 10.

The positive association between the role of expectations and Market Concentration indicates that firms operating in less competitive sectors — higher degree of concentration — tend to update prices less frequently, indicating higher price stickiness. This can be attributed to the low demand elasticity in highly-concentrated sectors. Few competitors mean lower demand elasticity, while in competitive sectors, setting prices slightly below competitors can result in reduced or no sales. Hence, firms in less concentrated sectors are more likely to follow competitors' prices, giving less weight to their own expectations. This effect is slightly smaller in services firms compared to manufacturing firms, evident through a dummy variable for services sectors, as these — manufacturing and services — constitute the largest groups in the studied panel.

In highly concentrated sectors with significant price stickiness, firms often raise prices beyond the optimal level when updating them, aiming to offset potential future losses during periods of unchanged prices. This underlines the increased importance of expectations for firms facing significant price rigidities.

Regarding the backward-looking behaviour — i.e. price adjustment based on past inflation — the results indicate that firms tend to adjust prices more in a backward-looking manner when facing a larger share of imports and energy costs. Sectors highly exposed to imports, petrol, and energy costs possibly may likely adhere to longer contracts or some form of price indexation, resulting in greater price persistence. Notably, the slope parameter does not exhibit any statistically significant association with the selected industry-characteristics.

These findings shed light on the need for further research into the potential sources of heterogeneity in the structural parameters of the Phillips Curve.

7 Conclusions

In this paper, I overcome several challenges typically encountered in Phillips Curve estimations, leveraging a unique, confidential survey dataset. By estimating Sectoral Phillips Curves across 52 sectors in the UK, combining sectoral data with direct measures of firms' expectations, supplier prices and salary costs, I mitigate against the challenges faced when using aggregate data and weak proxies to estimate the Phillips Curve. Through these approaches, I establish that the (positively sloped) Phillips Curve has not disappeared, as it has been claimed in other papers using more aggregated data. I find a positive response of inflation to expected inflation and marginal costs. My findings also reveal that including the intermediate goods into the measure of costs yields a larger slope, highlighting the overlooked yet crucial role of sectoral linkages in explaining the inflation response to costs.

This highlights the drawbacks of overlooking inflation dynamics when relying on aggregate data, indirect measures of expectations, or exclusively focusing on labour as the primary source of cost variation. Moreover, the challenges related to the weak identification of Phillips Curve parameters pose direct implications for central banks, as the strength of the slope determines the necessary adjustments in nominal interest rates to meet the inflation target.

Unveiling that sectors in the UK predominantly exhibit forward-looking behaviour, my study underscores the critical role of using direct measurement of firms' expectations in mitigating the identification issues associated with indirect measures. This result carries significant implications for policymakers as more forward-looking price-stetting behaviour mitigates the risk of price persistence.

Employing panel time series methods with sector-specific coefficients unmasks large sectoral heterogeneity in the Sectoral Phillips Curve parameters. Investigating the potential sources of this asymmetry, I find that market concentration is one of the factors driving the sensitivity of inflation to expected future inflation. Sectors facing higher competition closely monitoring their competitors' prices, potentially reducing the weight placed on their own expectations. These outcomes not only offer valuable insights for future research, aiding in addressing gaps in microfoundations for better-informed policy decisions and macroeconomic modelling.

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Appendix A SPC derivation by IJP

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

$$Y_{ikt} = Y_{kt}\left(\frac{P_{ikt}}{P_{kt}}\right)^{-\eta} \tag{14}$$

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:

$$Y_{kt} = \left[\int_0^1 Y_{ikt}^{\frac{\eta-1}{\eta}}\, di\right]^{\frac{\eta}{\eta-1}} \tag{15}$$

$$Y_{ikt} = Z_{kt}\, f(h_{ikt}) \tag{16}$$

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. For the theoretical derivation, IJP assume that costs in steady state are as follows: $S_{ik\,t,t+j} = S_k = \eta/(\eta-1)$.

$$\max_{P_{ikt}{}^{*}} E_t \sum_{j=0}^{\infty} (\alpha_k\beta)^j \; [Y_{ik\,t,t+j}\, P^*_{ikt} - \Psi\left(Y_{ik\,t,t+j}\right)] \tag{17}$$

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

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

$$\hat{p}^*_{ikt} = (1-\alpha_k\beta)\sum_{j=0}^{\infty} (\alpha_k\beta)^j E_t\left[\hat{s}_{ik\,t,t+j} + \hat{p}_{ik\,t,t+j}\right] \tag{19}$$

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:

$$\hat{p}_{kt} = \alpha_k \, \hat{p}_{k\,t-1} + (1 - \alpha_k) \, \hat{p}^*_{kt} \tag{20}$$

$$\hat{p}^*_{kt} = \omega_k \, \hat{p}^b_{kt} + (1 - \omega_k) \, \hat{p}^f_{kt} \tag{21}$$

$$\hat{p}^b_{kt} = \hat{p}^*_{k\,t-1} + \hat{\pi}_{k\,t-1} \tag{22}$$

and p^f_{kt} refers to prices set by forward-looking firms according to Equation 19.

$$\hat{\pi}_{kt} = \frac{\omega_k}{\phi_k} \, \hat{\pi}_{k\,t-1} + \frac{\beta\alpha_k}{\phi_k} \, E_t \hat{\pi}_{k\,t+1} + \frac{(1-\omega_k)(1-\alpha_k)(1-\beta\alpha_k)}{\phi_k} \, h_k \, \hat{s}_{kt} \tag{23}$$

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

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:

$$\hat{\pi}_{kt} = \gamma^b_k \, \hat{\pi}_{k\,t-1} + \gamma^f_k \, E_t \hat{\pi}_{k\,t+1} + \gamma^s_k \, \hat{s}_{kt} + \varepsilon^\pi_{kt} \tag{24}$$

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

I will first present Equation 3 and Equation 4 in matrix form for two sectors for illustrative purposes. Hatted letters are omitted for simplicity, but all variables are expressed as log-linearised deviations from the steady state.

$$\begin{pmatrix} \hat{\pi}_{1t} \\ \hat{\pi}_{2t} \end{pmatrix} = \begin{pmatrix} \tilde{\alpha}_1 & 0 \\ 0 & \tilde{\alpha}_2 \end{pmatrix} \begin{pmatrix} mc_{1t} - \hat{p}_{1\,t-1} \\ mc_{2t} - \hat{p}_{2\,t-1} \end{pmatrix} + \beta \begin{pmatrix} 1 - \tilde{\alpha}_1 & 0 \\ 0 & 1 - \tilde{\alpha}_2 \end{pmatrix} \begin{pmatrix} E_t \hat{\pi}_{1\,t+1} \\ E_t \hat{\pi}_{2\,t+1} \end{pmatrix} \tag{25}$$

$$\begin{pmatrix} mc_{1t} \\ mc_{2t} \end{pmatrix} = \begin{pmatrix} (1-a_1)\hat{w}_{1t} + \lambda_{11t} \, \hat{p}_{1t} + \lambda_{12t} \, \hat{p}_{2t} \\ (1-a_2)\hat{w}_{2t} + \lambda_{21t} \, \hat{p}_{1t} + \lambda_{22t} \, \hat{p}_{2t} \end{pmatrix} - \begin{pmatrix} logZ_{1,t} \\ logZ_{2,t} \end{pmatrix} \tag{26}$$

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 25 and 26, and ignore the productivity term just for brevity. This omission won't affect the results.

$$\begin{pmatrix}\hat{\pi}_{1t}\\ \hat{\pi}_{2t}\end{pmatrix} = \begin{pmatrix}\tilde{\alpha}_1 & 0\\ 0 & \tilde{\alpha}_2\end{pmatrix}\begin{pmatrix}(1-a_1)\hat{w}_{1t} + \lambda_{11t}\,\hat{p}_{1t} + \lambda_{12t}\,\hat{p}_{2t} - \hat{p}_{1\,t-1}\\ (1-a_2)\hat{w}_{2t} + \lambda_{21t}\,\hat{p}_{1t} + \lambda_{22t}\,\hat{p}_{2t} - \hat{p}_{2\,t-1}\end{pmatrix} + \beta\begin{pmatrix}1-\tilde{\alpha}_1 & 0\\ 0 & 1-\tilde{\alpha}_2\end{pmatrix}\begin{pmatrix}E_t\hat{\pi}_{1\,t+1}\\ E_t\hat{\pi}_{2\,t+1}\end{pmatrix}$$

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

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

Further combining terms to get expressions for the inflation rates:

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

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

This 2-sector matrix illustration shows that inflation in sector 1 depends on a more complete cost measure, which I will call "Full cost 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 the full cost measure, $\mathbf{\hat{s}}_t^F$, and inflation expectations:

$$\hat{\boldsymbol{\pi}}_t = (I - \Lambda\,\tilde{A})^{-1}\boldsymbol{\beta}(1-\tilde{A})\,\boldsymbol{E_t}\hat{\boldsymbol{\pi}}_{t+4} + (I - \Lambda\,\tilde{A})^{-1}\tilde{A}\;\hat{\mathbf{s}}_t^F \tag{27}$$

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

Lags	CBI inflation	*(p)*	Labour cost	*(p)*	Expected inflation	*(p)*	Full cost	*(p)*
Specification with constant								
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)*	Full 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	Full 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					
Full 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

Dependent Variable:	*Expectations* (1)	*Expectations* (2)	*Labour Cost* (3)	*Labour Cost* (4)	*Full Cost* (5)	*Full Cost* (6)
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	t & k	t & k	t & k	t & k	t & k	t & k
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.

Table 9: Aggregate (nationwide) PC regression

	OLS (1)	OLS (2)	OLS - IV (3)	OLS - IV (4)
	Dependent variable: CBI sectoral inflation			
Expected inflation	0.65***	0.66***	0.84***	0.93***
	(0.08)	(0.10)	(0.18)	(0.35)
Lagged inflation (t-1)	0.58***	0.59***	0.43***	0.40***
(t-2)	-0.16	-0.16		
(t-3)	0.06	0.06		
Labour cost	-0.01		0.01	
	(0.03)		(0.03)	
BoE output gap		-0.01		-0.06
		(0.04)		(0.07)
Real oil inflation			-0.00	-0.00
			(0.00)	(0.00)
Intercept	-0.22**	-0.25*	-0.35***	-0.50
	(0.08)	(0.14)	(0.10)	(0.32)
Observations	51	51	51	51
R-squared	0.92	0.92	0.91	0.91
R-squared Adj	0.912	0.912	0.904	0.901

Note: Time-series estimation results. Current inflation, expected inflation, and labour costs are calculated as weighted average across sectors based on number of employees. IV is used in models 3 and 4, where Costs/Output Gap and expectations are instrumented out with: lags (1, 2, 3) of expectations and Costs/Output Gap. *** p<0.01, ** p<0.05, * p<0.1.

Table 10: Regressions estimations (*Full-Cost SPC*)

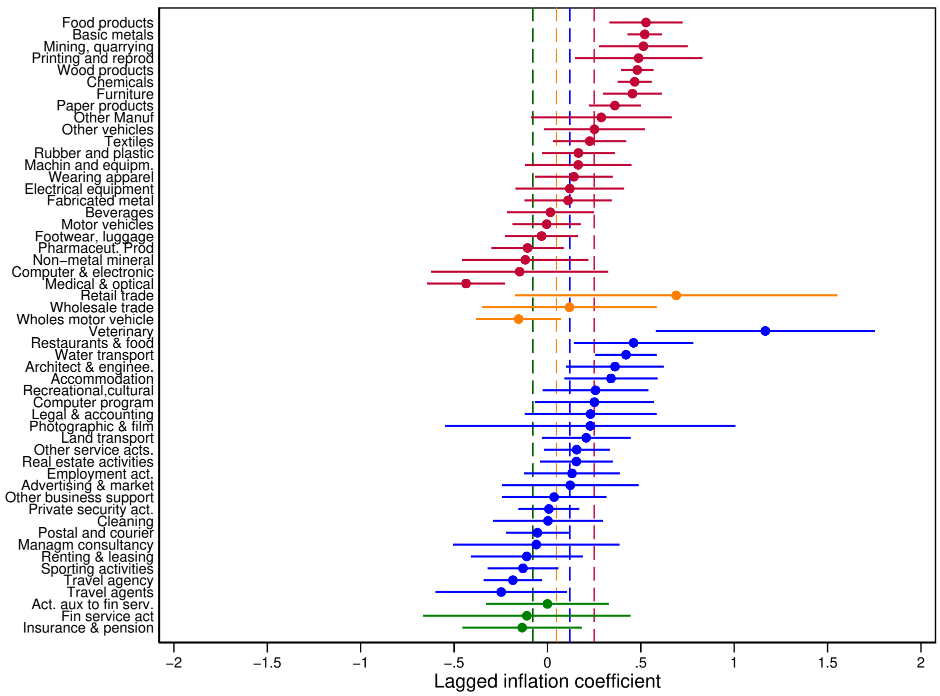
	γ_f (1)	γ_b (2)	γ_s (3)	γ_f (4)	γ_b (5)	γ_s (6)
		MC: CR5			*MC: HHI*	
Market concentration (MC)	13.81	27.89**	-13.90	-1.74	-0.26	0.13
	(43.70)	(13.63)	(13.73)	(1.50)	(0.39)	(0.26)
MC x Services Dummy	137.71	92.31**	1.72	4.61	0.64	4.45
	(107.88)	(41.67)	(27.86)	(3.73)	(0.58)	(3.08)
Imports over supply	1.43	0.21	-0.04	1.85	-0.08	0.19
	(1.02)	(0.13)	(0.20)	(1.12)	(0.20)	(0.12)
Energy over costs	17.93*	7.34**	8.85***	15.76*	8.73***	8.74***
	(10.48)	(2.84)	(3.11)	(8.95)	(3.11)	(2.88)
Petrol over costs	-13.06	-2.14	0.41	-9.56	0.17	-1.04
	(7.99)	(1.89)	(1.29)	(6.68)	(1.28)	(1.74)
ULC variability	-2.44	-0.62	-0.29	-1.31	-0.42	-0.38
	(2.17)	(0.62)	(0.55)	(1.71)	(0.55)	(0.69)
Observations	51	51	51	51	51	51
R-squared	0.30	0.56	0.29	0.30	0.29	0.42

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 SPC estimated parameters.

Figure 13 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 16 with parameters obtained from the *Full-Cost SPC*.

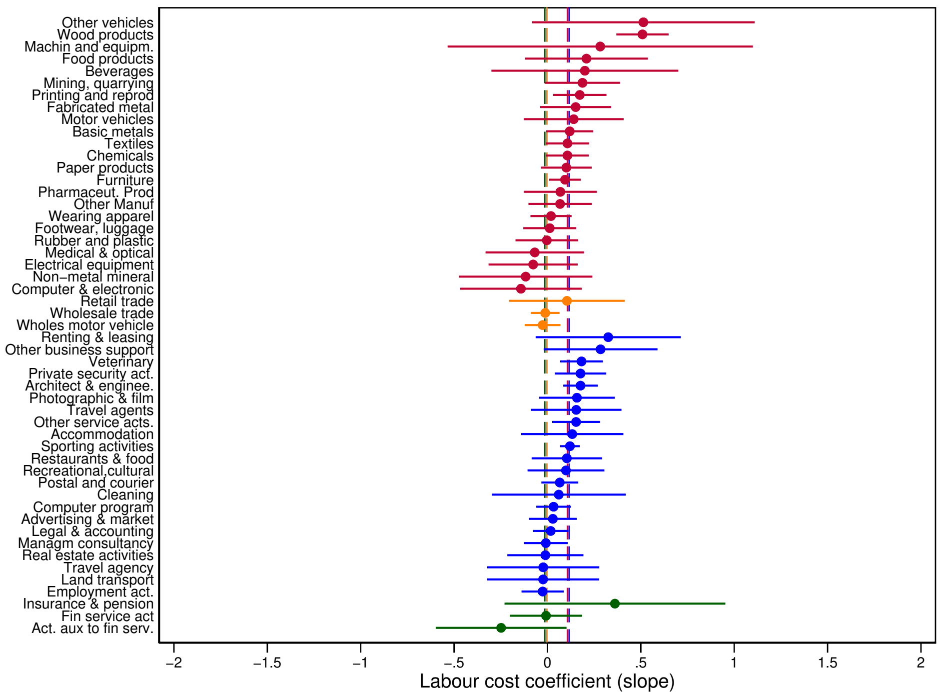
Finally, based on Figure 14, we can see that while there is not a significant difference in the average estimate between Manufacturing and Services firms, both at around 0.9, there are large differences within the groups. Certain Manufacturing sectors, such as Mining, Computer and Rubber have sector-specific 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.

Figure 12: Role of lagged inflation by sector (*Labour-Cost SPC*)



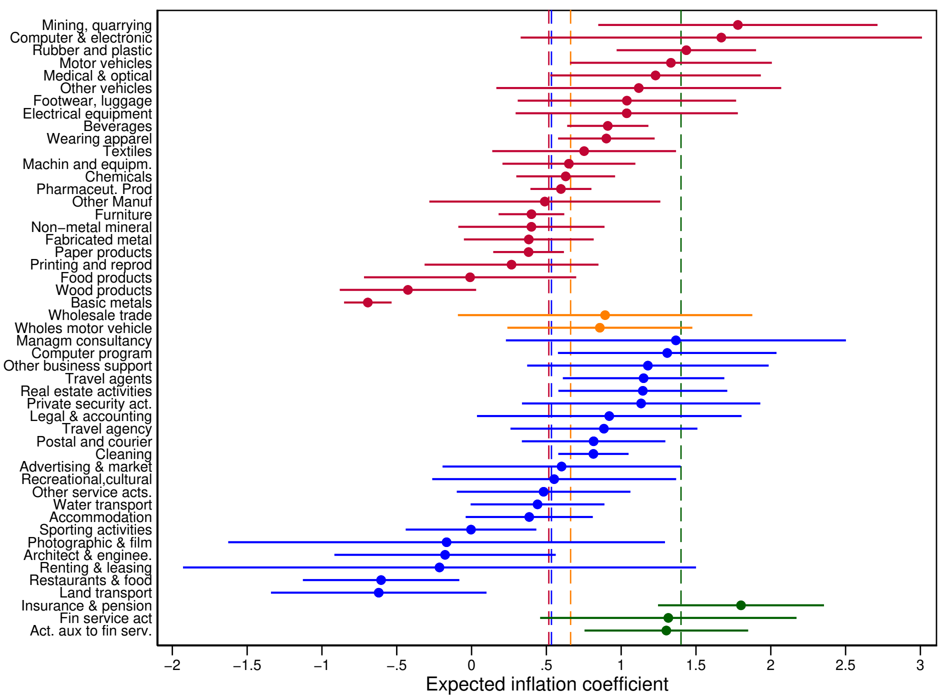
Note: Sector-specific parameters related to lagged inflation from Model 3 (Table 3, through dynamic panels with CCE). These coefficients are net from common factor effects. Intervals are calculated as the mean +/- s.e. The labels indicate the mean estimated coefficient for each sector. The dashed vertical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

Figure 13: Slope by sector (*Labour-Cost SPC*)



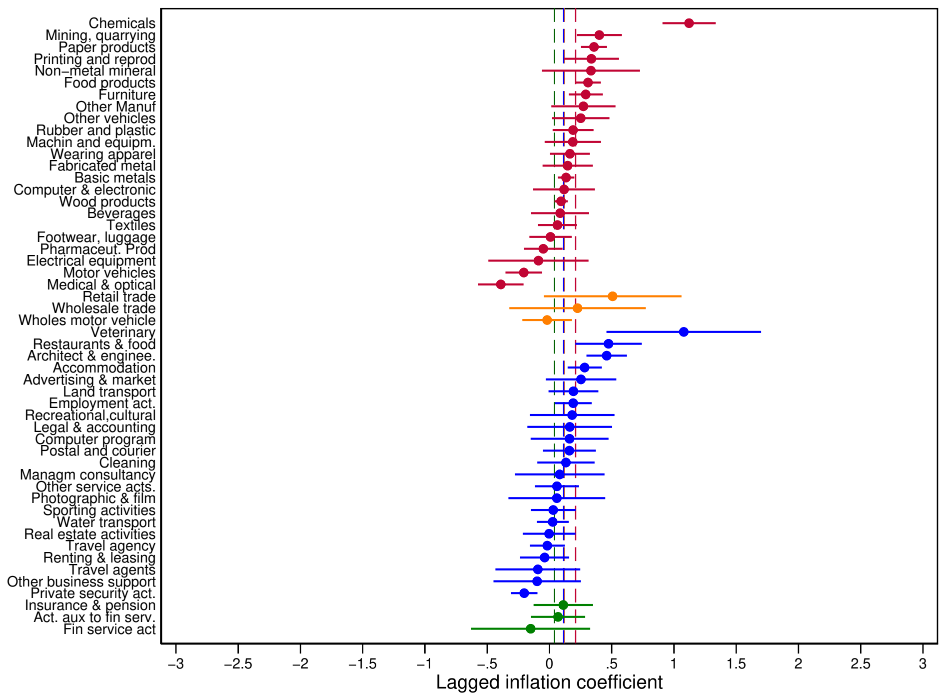
Note: Sector-specific parameters related to labour costs from Model 3 (Table 3, through dynamic panels with CCE). These coefficients are net from common factor effects. Intervals are calculated as the mean +/- s.e.. The labels indicate the mean estimated coefficient for each sector. The dashed vertical lines highlight the weighted mean coefficient across each of the groups (weighted by the s.e.). 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.

Figure 14: Role of expectations by sector (*Labour-Cost SPC*)



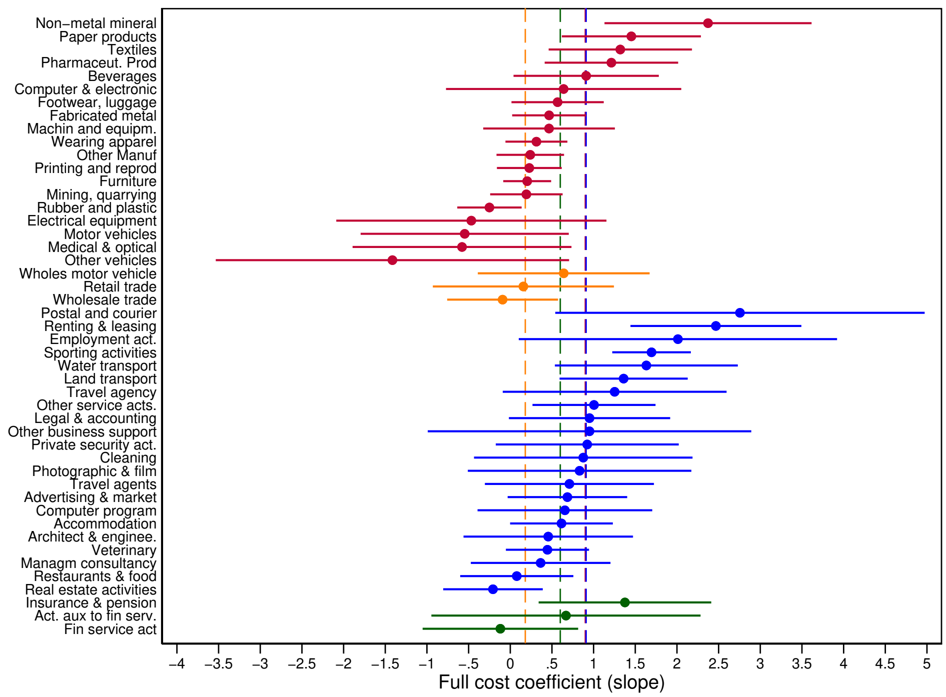
Note: Sector-specific parameters related to inflation expectations from Model 3 (Table 3, through dynamic panels with CCE). These coefficients are net from common factor effects. Intervals are calculated as the mean +/- s.e. The labels indicate the mean estimated coefficient for each sector. The dashed vertical lines highlight the weighted mean coefficient across each of the groups (weighted by the s.e.). 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.

Figure 15: Role of lagged inflation by sector (*Full-Cost SPC*)



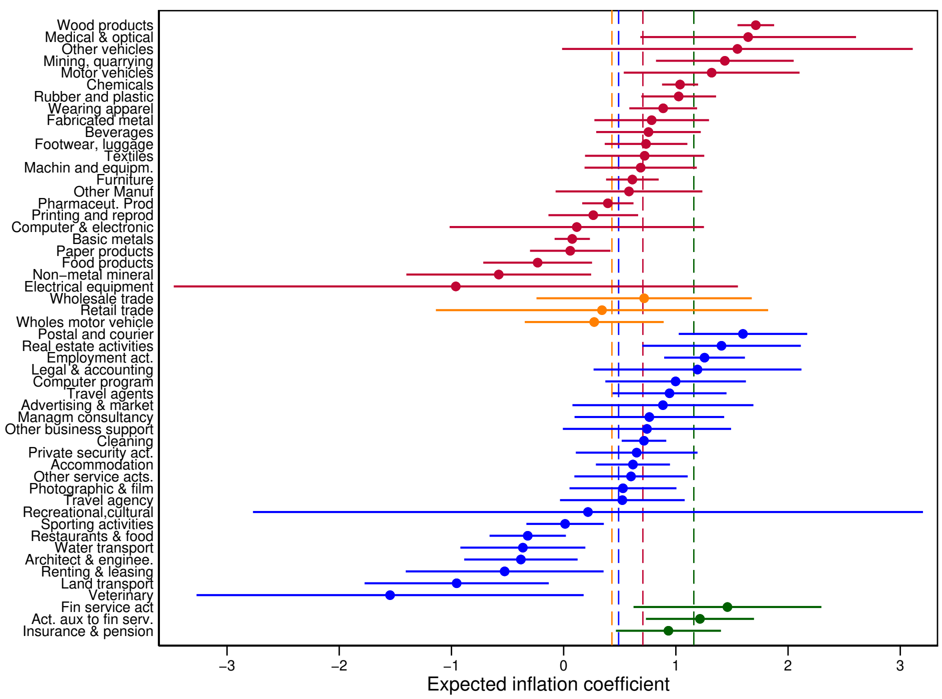
Note: Sector-specific parameters related to lagged inflation from Model 3 (Table 4, through dynamic panels with CCE). These coefficients are net from common factor effects. Intervals are calculated as the mean +/- s.e. The labels indicate the mean estimated coefficient for each sector. The dashed vertical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

Figure 16: Slope by sector (*Full-Cost SPC*)



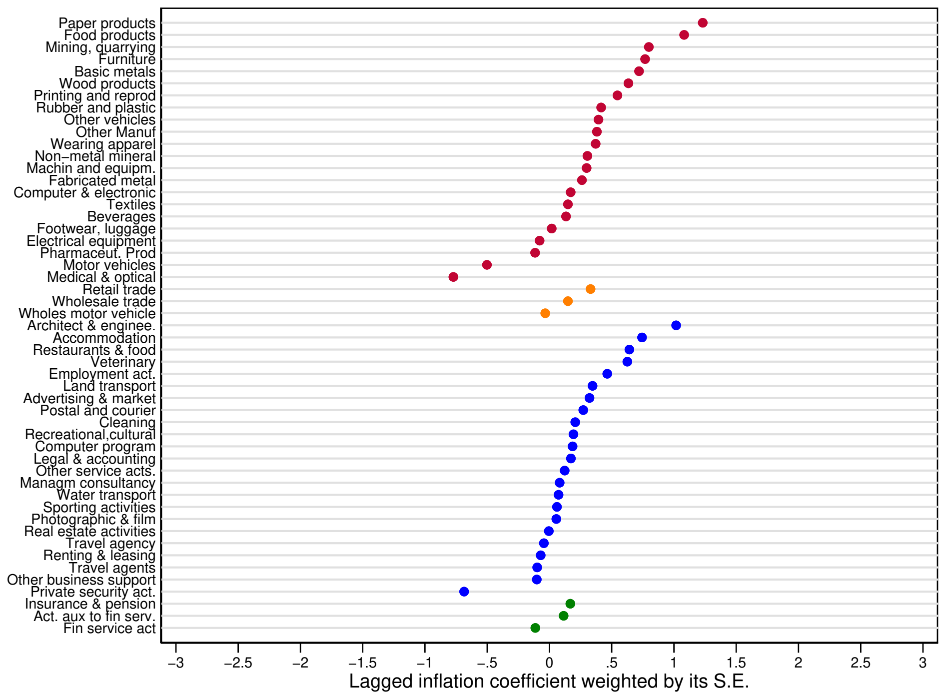
Note: Sector-specific parameters related to the full cost measure from Model 3 (Table 4, through dynamic panels with CCE). These coefficients are net from common factor effects. Intervals are calculated as the mean +/- s.e. The labels indicate the mean estimated coefficient for each sector. The dashed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

Figure 17: Role of expectations by sector (*Full-Cost SPC*)



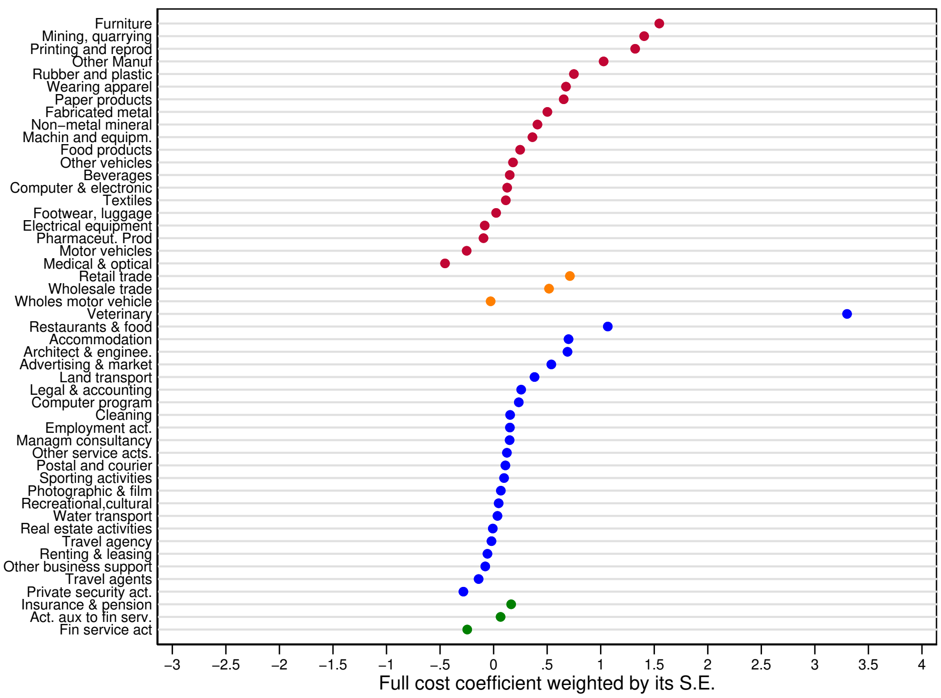
Note: Sector-specific parameters related to inflation expectations from Model 3 (Table 4, through dynamic panels with CCE). These coefficients are net from common factor effects. Intervals are calculated as the mean +/- s.e. The labels indicate the mean estimated coefficient for each sector. The dashed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

Figure 18: Weighted coefficient on lagged inflation (*Full-Cost SPC*)



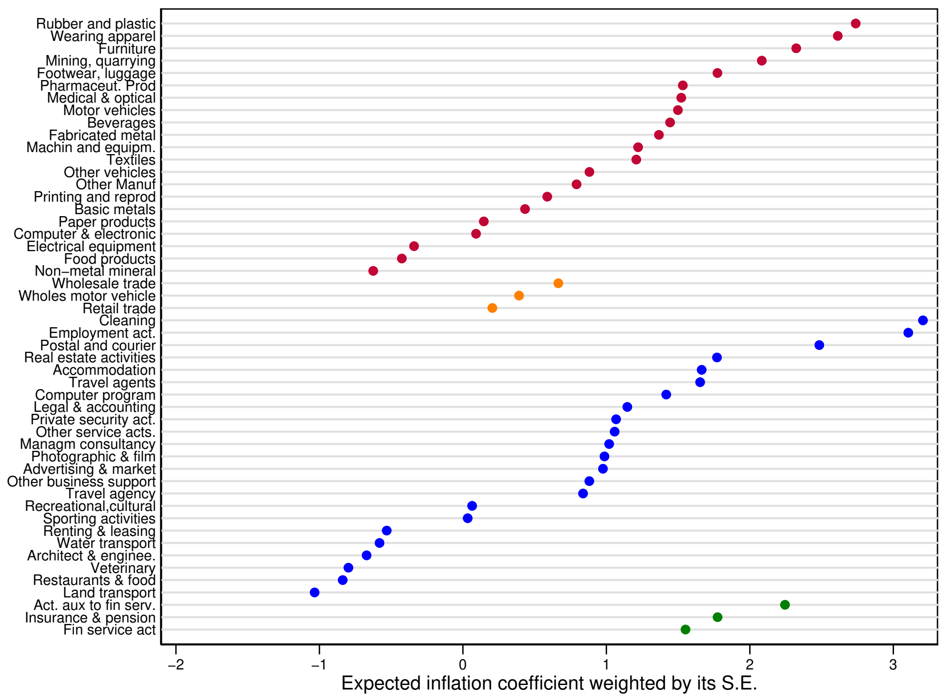
Note: The coefficients presented in the figure have been weighted based on their respective S.E. from the *Full-Cost SPC*. The Chemicals industry was excluded due to the estimated parameters falling outside the range of -3 to 3, adding them would distort the axis scales. This adjustment was made to ensure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

Figure 19: Weighted coefficient on Full cost (*Full-Cost SPC*)



Note: The coefficients presented in the figure have been weighted based on their respective S.E. from the *Full-Cost SPC*. 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 20: Weighted coefficient on expected inflation (*Full-Cost SPC*)



Note: The coefficients presented in the figure have been weighted based on their respective S.E. from the *Full-Cost SPC*. 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 11 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 11: 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 12: 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 CBI survey data

In the following figures I show expectations of sectoral inflation as an average of expectations cross firms for each 2-digit SIC. Figures 21 and 22 show that 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 23 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.

Figures 23 and 24 also indicate substantial sectoral heterogeneity. Services sectors 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.

Figure 21

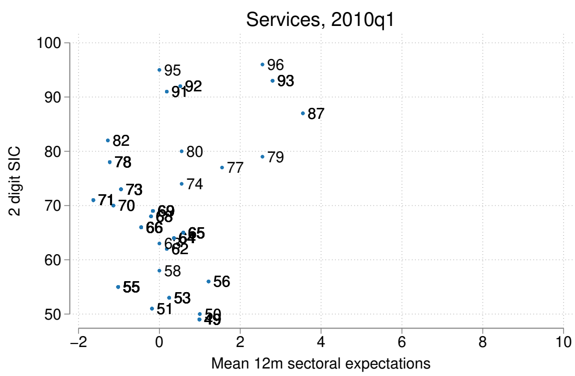


Figure 22

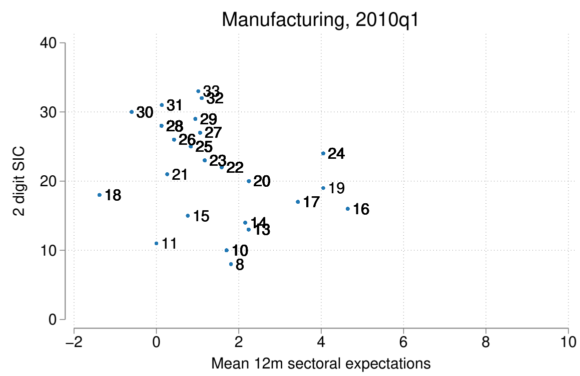


Figure 23

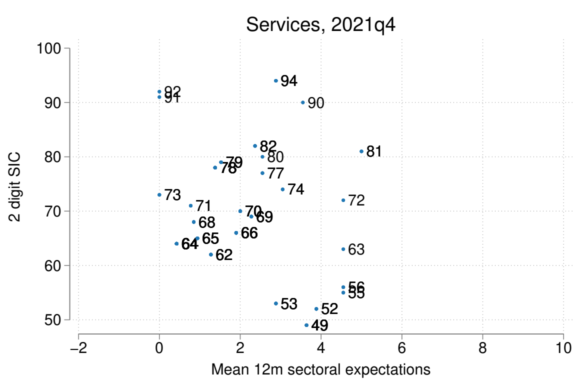
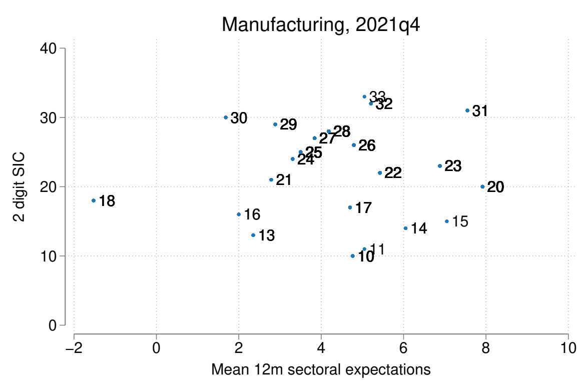


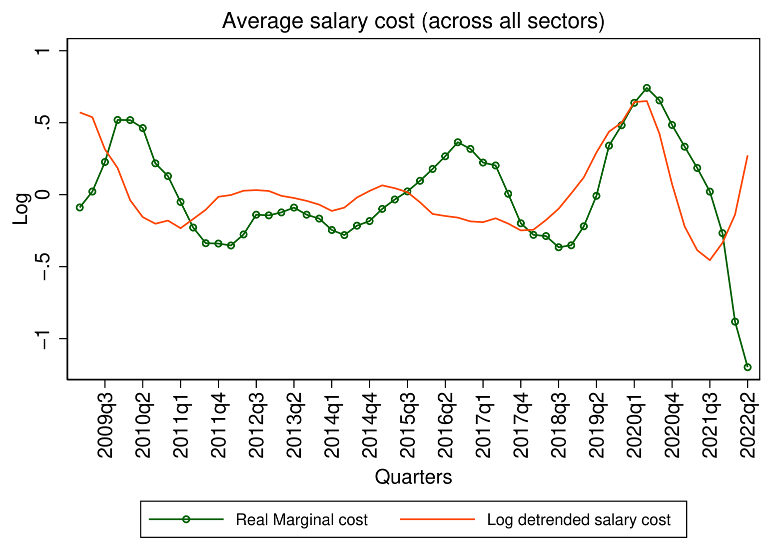
Figure 24



D.4 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 25: 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 CBI survey-based "wage/salary cost per person employed".

D.5 Output gap

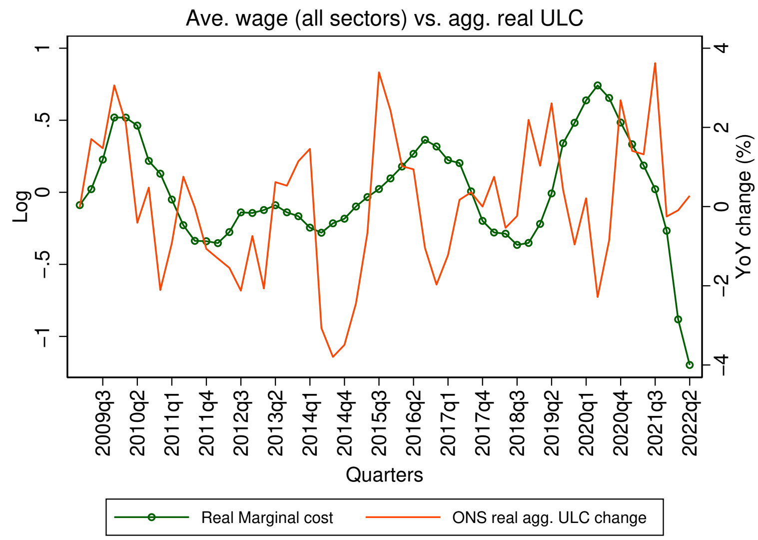
The other measure I used as proxy for the slack measure for SPC estimation is the UK output gap calculated and provided by the Bank of England. See the time series in Figure 27. This measure was not statistically significant when used as a slack measure in the SPC estimation.

D.6 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

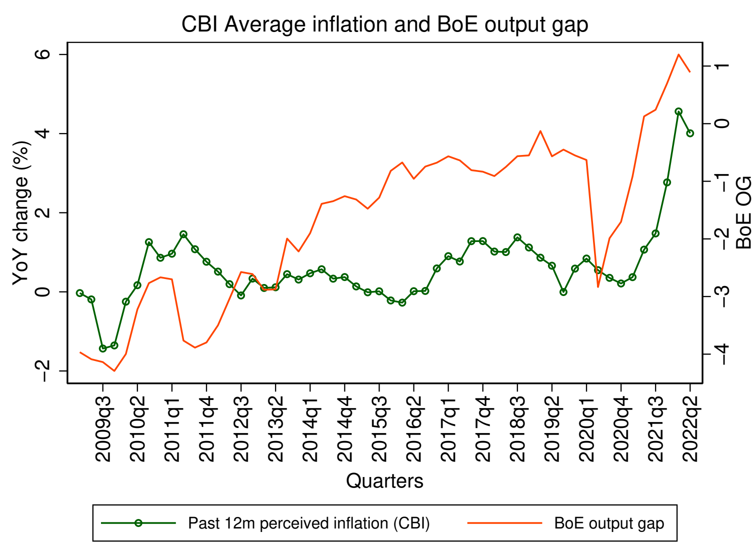
An alternative measure for the labour share used in the estimations, as suggested by BJN:

Figure 26: 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 27: 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.

ln[((HAEA*A)/ABML)*100], where A = (E + SE)/E. E is given by BCAJ[36], the number of

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

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[37], where IKBI is total imports (current prices), and IKBL is total imports (constant prices).

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

Figure 28: 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.