

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 industries in the UK by estimating Sectoral Phillips Curves (SPCs) — which measure the sectoral inflation responsiveness to industry-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 industry-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 industries.

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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 industry-level 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 industry-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

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

²The 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 industry-level 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 industry-level 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 this regard, noting that 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.

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

where

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

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. 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. 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_{kt}^{π} , 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:

$$\hat{\pi}_{kt} = \gamma_k^b \hat{\pi}_{k,t-1} + \gamma_k^f E_t \hat{\pi}_{k,t+4} + \gamma_k^s h_{kt} \hat{s}_{kt} + \varepsilon_{kt}^{\pi} \quad (2)$$

Note that γ_k^b , γ_k^f and γ_k^s 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,

³This 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.

⁴The 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:

$$P_{kt} = \alpha_k P_{kt-1} + (1 - \alpha_k) P_{kt}^*$$

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 $\hat{\pi}_{kt-1}$. 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:

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

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.

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 compounded at each step along the production chain. I integrate elements from Rubbo's model 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 differ from the *Labour-Cost SPC* framework. 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.

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

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

⁵One advantage of Calvo's time-dependent framework, as opposed to state-dependent models, is its mathematical simplicity, allowing to obtain an explicit closed-form equation describing price setting.

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 are:^{6 7}

$$\hat{\pi}_t = \tilde{A}(\hat{\mathbf{m}}\mathbf{c}_t - \hat{\mathbf{p}}_{t-1}) + \beta(I - \tilde{A})\mathbf{E}_t \hat{\pi}_{t+4} \quad (3)$$

Equation 3 represents the sectoral inflation rate process, jointly explained by sector-level marginal costs $\hat{\mathbf{m}}\mathbf{c}_t$, 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 \tilde{A} corresponds to the diagonal of sector-level price stickiness.

For illustrative purposes, considering two sectors, matrix \tilde{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 \tilde{A} will be of size $k \times j$.

$$\hat{\mathbf{m}}\mathbf{c}_t = (1 - \mathbf{a}) \hat{\mathbf{w}}_t + \Lambda \hat{\mathbf{p}}_{jt} - \log \mathbf{Z}_t \quad (4)$$

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 firms in the same sector and λ_{12} is the share of intermediate goods that sector 1 buys to firms 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.

$$\hat{\pi}_t = (I - \Lambda \tilde{A})^{-1} \beta (1 - \tilde{A}) \mathbf{E}_t \hat{\pi}_{t+4} + (I - \Lambda \tilde{A})^{-1} \tilde{A} \hat{\mathbf{s}}_t^F \quad (5)$$

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

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

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

⁸Following the original paper, the tilde in $\tilde{\alpha}$ (and \tilde{A}) refers to α (and A) being adjusted by the discount factor, β .

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

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

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:

$$\hat{\pi}_t = \gamma^f \mathbf{E}_t \hat{\pi}_{t+4} + \gamma^s \hat{\mathbf{s}}_t^F + \varepsilon_t^\pi \quad (7)$$

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. That is, changes in employment, real import prices and oil prices are pivotal in explaining UK inflation. Below is the expression they derived, slightly modified to match the notation in this work.

$$\pi_t = \gamma^f E_t\{\pi_{t+1}\} + \gamma^b \pi_{t-1} + \gamma^s s_t + \alpha_1 z_{p,t} + \alpha_2 (p_t^W - p_t) + \alpha_3 s_{L,t} + \alpha_4 p_{m,t} + \alpha_5 \Delta n_t + \varepsilon_t^\pi \quad (8)$$

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 industry-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

⁹Gali 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 industry. This is an advantage as one would expect firms to pay more attention and be better informed about prices in their industry 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 Industry-level 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 industry-level data, I find a positive response of inflation to marginal costs, thereby confirming that hypothesis. At the industry 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.

¹⁰Coibion 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.

$$\pi_{kt} = \gamma^f E_{kt} \pi_{kt+4} + \gamma^b \pi_{kt-1} + \gamma^s h_{kt} \hat{s}_{kt} + \varepsilon_{kt} \quad (9)$$

By estimating Equation 9, and if any of the coefficients are not homogeneous across industries — $\gamma_k^f \neq \gamma^f$, $\gamma_k^b \neq \gamma^b$ or $\gamma_k^s \neq \gamma^s$ — then the errors ε_{kt} will be correlated with the explanatory variables — as indicated in Equation 10—, and the estimated coefficients will be biased.

$$\varepsilon_{kt} = \left[u_{kt} + (\gamma_k^f - \gamma^f) E_{kt} \{\pi_{kt+4}\} + (\gamma_k^b - \gamma^b) \pi_{kt-1} + (\gamma_k^s - \gamma^s) h_{kt} \hat{s}_{kt} \right] \quad (10)$$

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 (Imbs et al. 2011; Byrne et al. 2013). 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 industry-level 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.¹¹ Proposed by Pesaran (2006), this estimator introduces a correction technique to account for unobserved common factors, potentially correlated with industry-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

¹¹I 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.¹²

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 shocks affecting the UK economy, such as Brexit and Covid, might have impacted various industries differently and simultaneously. These events may not be entirely captured by the input-output table. The omitted factors not only represent overlooked variables that could theoretically be included in the model but also constitute 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 industries heterogeneously. These common elements are complemented by industry-specific “factor loadings” aimed to capture the differential impact across industries. This approach effectively reduces data dimensionality and prevents overfitting by concentrating on the most influential factors affecting the variables of interest.¹³

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 potentially leads to (i) Omitted variable bias if $g_{x,k} \neq 0$ indicating that industries are exposed to the same common factor or shock, and ordinary least squares becoming inconsistent; (ii) Residuals can be correlated across industries if $g_{u,k} \neq 0$.¹⁴

¹²They 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.

¹³See Eberhardt and Presbitero (2015) for an empirical application of these methods.

¹⁴This is explained in detail in Ditzén (2021), based on Everaert and De Groote (2016).

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

$$\hat{\pi}_{kt} = \alpha_k + \gamma_k^b \hat{\pi}_{k,t-1} + \gamma_k^f E_{kt} \hat{\pi}_{k,t+4} + \gamma_k^s h_{kt} \hat{s}_{kt} + u_{kt} \quad (11)$$

$$u_{kt} = g_k f_t + \varepsilon_{kt}^\pi \quad (12)$$

where Equation 11 includes industry fixed-effects, α_k , and a set of unobserved common factors f_t with industry-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 the methodology described in the literature (Chudik and Pesaran 2015), I compute cross-sectional averages z_t to approximate the time-varying covariates. The initial set of cross-sectional averages is computed on the model's explanatory variables: inflation, expected inflation, and a cost measure. Due to the high correlation between the first two variables, including only one is sufficient.¹⁵ Additionally, in line with empirical evidence mentioned in the previous section, I incorporate oil price inflation. I also attempted to include real import prices, but they yielded insignificant results, likely due to their high correlation with oil price inflation.

Next, I provide an illustrative specification framework for estimating Equation 11, 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 4.

$$\begin{aligned} \pi_{kt} = & \alpha_k + \gamma_k^b \pi_{k,t-1} + \gamma_k^f E_{kt} \pi_{k,t+1} + \gamma_k^s h_{kt} \hat{s}_{kt} \\ & + \sum_{t=0}^3 g_{1k} \overline{E_{kt} \pi_{k,t+1}} + \sum_{t=0}^2 g_{2k} \overline{\hat{s}_{kt}} + \sum_{t=0}^2 g_{3k} \pi_t^{oil} + \varepsilon_{kt}^\pi \end{aligned} \quad (13)$$

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 industry, thereby capturing industry-specific trends.

¹⁵See details in Correlation Table 8.

3.6.2 Time Series Properties

Temporal aggregation presents another common challenge in this literature. Perceived and expected sectoral inflation data refer to annual changes, while the frequency is quarterly. To address potential correlation over time, I use lagged variables¹⁶ to instrument the regressors.

Another concern commonly raised is the potential nonstationarity of the inflation series. In Table 9 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 perceived past inflation are simultaneously determined. To mitigate endogeneity, I conduct a first-stage regression, using the resulting fitted values. Table 10 displays the potential endogenous variables regressed on their lags. Notably, all coefficients for expectations exhibit the expected sign and are highly significant, reflecting a time overlapping effect. The conversion of the labour cost series from an annual to a quarterly measure is reflected in the short-dated correlation, with only one lag being statistically significant. Furthermore, it is noteworthy that the lags of expectations have practically no predictive power on labour costs, and vice versa.

Finally, I include industry 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

¹⁶As emphasised in Mavroeidis et al. (2014), lags can be used as instruments for robust inference in the presence of unit roots.

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

Moreover, the expression with real marginal cost more directly generalises to models such as the multisector one studied here. The expression obtained for the SPC by Woodford (2003) contains both relative prices and aggregate output gap whereas the industry-level inflation equation which uses the real marginal cost (instead of the output gap) does not require relative prices.¹⁷ Industry-level nominal marginal costs are calculated as the average of the costs across firms of industry 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 CBI suite of business surveys comprises four surveys completed by firms operating in the UK: Industrial Trends Survey (ITS), Distributive Trades Survey (DTS), Financial Services Survey (FSS), and Services Sector Survey (SSS). A detailed description of the CBI surveys and the representation of CBI firms in terms of the UK economy can be found in Lee et al. (2020). These surveys gather information from thousands of firms on various aspects including inflation expectations, salary costs, output, investment, capacity, and inventories at the firm level, both retrospectively and prospectively.

These surveys stand out for several reasons. Firstly, they provide quantitative data, distinguishing them from many other surveys that rely mainly on qualitative information. This quantitative measure enhances our ability to understand and analyse firms’ expectations. Secondly, the surveys target the same firms on a quarterly-basis, although participation is voluntary, leading to an unbalanced panel for firm-level analysis. Thirdly, these surveys have been conducted since 2009, offering a substantial time series compared to other UK surveys like the Decision Maker Panel¹⁸. They also cover significant shocks affecting the UK economy, such as Brexit and Covid.

The CBI dataset primarily comprises manufacturing firms, with retail and distributive firms being the second most prevalent group. In terms of firm size, the dataset oversamples small, medium and large firms.¹⁹ While the absolute number of firms in the CBI dataset does not precisely mirror the distribution across the four sectors, there is an under-representation of manufacturing and

¹⁷See Woodford (2003) section B.27 and Appendix B.7.

¹⁸The Decision Maker Panel was set up in August 2016 by the Bank of England, Stanford University, and the University of Nottingham. The question about “Expected inflation” started in 2017 and refers to the firm’s expected average price in the year ahead.

¹⁹Based on the following classification: micro 0-9 employees, small 10-49 employees, medium 50-249 employees and large 250 or more employees.

mining firms, and an over-representation of financial service firms.

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	

Notes: This table describes the four CBI surveys, the main sectors covered in each of them, and provides some summary statistics.

¹ Number of firms' 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 dataset is an excellent source of data regarding firms' inflation expectations, given its panel structure which allows to track firms over a significant period of time. It provides quarterly reports of perceived past changes in sectoral prices 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.

The collection of responses is conducted quarterly. The survey round questionnaires for the ITS, DTS and SSS are conducted simultaneously. For instance, the quarter 1 round occurs around the end of March each year, with concurrent results published around mid-April. For the FSS, the quarter 1 round takes place around the end of February, and results are published around the end of March.

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 industries and capturing broader cross-sectional effects.

²⁰This work focuses on data starting in 2009 given that very few data points were collected in 2008.

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 about their perceived past changes in sectoral prices and expected changes in future sectoral prices 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 broad range captured by this dataset 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 of price movements, the full dataset from 2009q2 to 2022q3 contains 36,299 observations. Also, I identified as outliers and winsorised those reports that are very far from the other firms’ reports in the same industry.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 industries classified at the 2-digit SIC level. However, for my analysis, I focus on 52 industries for which I have a time series spanning more than 45 quarters.

4.1.2 Stylised Facts from CBI Survey Data

The analysis of inflation expectations derived from CBI data reveals significant heterogeneity across industries and their responses through the high-inflation period by the end of 2021. See Figures 18 through 21 in Appendix D.

At the outset of 2010, expected sectoral inflation for services firms were predominantly centered between -2% and 4%, with industries 79, 87, 93, and 96 displaying the highest expected inflation rates (see Figure 18). However, a notable shift has occurred in recent times. By the end of 2021, as shown in Figure 20, the entire distribution of services expectations has skewed towards higher expected inflation rates, being located by then between 0% to 6%. Interestingly, the industries with

²¹Specifically, 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%.

²²The 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%.

²³Bank of England/Ipsos Inflation Attitudes Survey.

²⁴Winsorising 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 + 6*IQR.

the highest expected sectoral inflation rates in this period were 55, 56, 63, 72, and 81, a departure from the trends observed in 2010.

Figures 19 and 21 further underscore the significant sectoral heterogeneity. Notably, services sectors have exhibited a lower response to the series of shocks experienced by the UK over the past decade, including Brexit, the Covid pandemic, and the Ukraine war, which have resulted in fluctuating inflation rates. In contrast, manufacturing firms have exhibited more pronounced reactions to these events.

TABLE 2: AVERAGE NUMBER OF FIRMS IN EACH INDUSTRY AND QUARTER FROM THE SURVEY

Industry	2009- 2014	2015- 2020	2021- 2022	Industry	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				

Notes: This table displays the average number of reports (i.e. participating firms) in each quarter by industry for three different periods: 2009-2014, 2015-2020, and 2021-2022.

This evidence underscores the complex dynamics of inflation expectations across diverse industries, highlighting the necessity of employing a heterogeneous approach that incorporates industry-specific parameters in estimating the Phillips Curve. Such an approach is essential for a compre-

hensive understanding of inflationary pressures.

4.2 Official Inflation vs. Survey-based Perceived Inflation

There are two primary sources of data that I can utilise for inflation: official inflation rates reported by the Office for National Statistics (ONS) and survey-based sectoral inflation perceptions provided by firms. Each source presents its own 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.

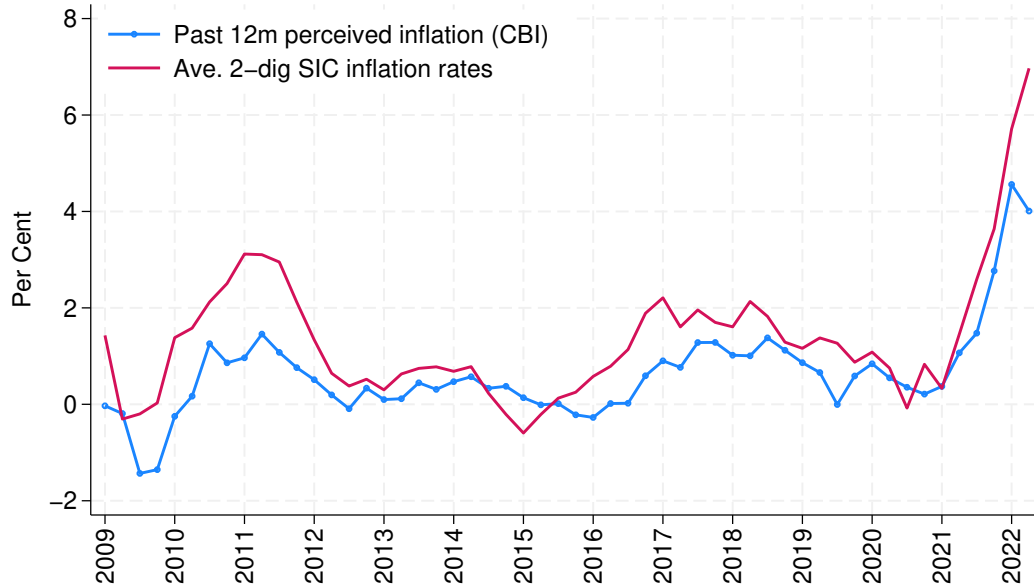
One challenge with using ONS inflation data is the lack of granularity at the 4-digit SIC level observed in the CBI reports. The ONS provides disaggregated Producers Price Indices (PPI) by SIC code for industrial sectors, while Consumers Price Indices (CPI) and Services Producer Prices Indices (SPPI) are available for non-industrial sectors. However, mapping 4-digit SIC sectors to PPI, CPI, and SPPI data can be imperfect and subject to assumptions. Table 13 outlines one suggested mapping method and associated considerations.²⁵

In contrast, the CBI collects firms’ expected and past perceived “changes in the general level of output prices in the UK markets that your firm competes in”, without specifying industry. This lack of specification raises the challenge of precisely identifying the exact “markets” with which each firm competes. Firms are asked to indicate their business activity covered by their reports and refer to the SIC listed at the end of the questionnaire. I aggregate firms’ inflation expectations and perceived past price changes using their self-reported 4-digit SIC to construct 2-digit SIC data for sector-level Phillips Curve analysis.

However, using the reported 4-digit SIC code may still introduce bias as firms’ interpretations of markets could vary based on factors like sales locations, input sourcing, or labour recruitment. To mitigate this concern, I show in Table 3 and Figure 1 that survey-based sectoral inflation perceptions closely align with official inflation rates at the 2-digit SIC level.

²⁵For the PPI, I utilise the output price index, representing the prices of goods sold by UK manufacturers within the UK market, 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.

FIGURE 1: MEASURES OF SECTORAL INFLATION



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

TABLE 3: SUMMARY STATISTICS

	<i>2009-2020</i>		<i>2021-2022q2</i>	
CBI Survey data	Mean	SD	Mean	SD
Perceived sectoral inflation, past 12m	0.7	3.2	2.5	5.6
Expected sectoral inflation, next 12m	0.9	2.6	2.5	4.2
Reported own-wage cost growth, past 12m	2.0	2.4	2.6	3.0
Aggregate inflation rates (ONS)	Mean	SD	Mean	SD
CPI headline inflation, y-o-y	2.1	1.3	4.4	3.1
CPI service inflation, y-o-y	2.9	0.8	3.0	1.2
CPI inflation, fuels, y-o-y	1.0	10.8	20.4	13.4
Services PPI inflation, y-o-y	1.0	0.9	3.3	1.6
PPI inflation (output), y-o-y	1.3	3.3	8.6	5.3

Notes: This table displays the mean and Standard Deviation (SD) of CBI survey data and ONS inflation series for the period 2009q1-2020q4 and the period 2021q1-2022q2.

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 industry j and LS_k refers to the annual Labour costs share in industry k .

4.4 Measures of Cost

In the Phillips Curve literature, the measure of real economic activity is typically proxied by either the output gap or some measure of real marginal costs. As discussed in Section 3.7, variations in production costs are considered the most theoretically sound representation of the slack measure. For the sake of robustness, I have used both marginal cost and the output gap in the estimation of the Phillips Curve. Notably, statistically significant results were obtained when employing the CBI measure of labour cost. Below, I will provide a detailed explanation of the data sources and methodological approach used for each of these measures.

4.4.1 Labour Cost

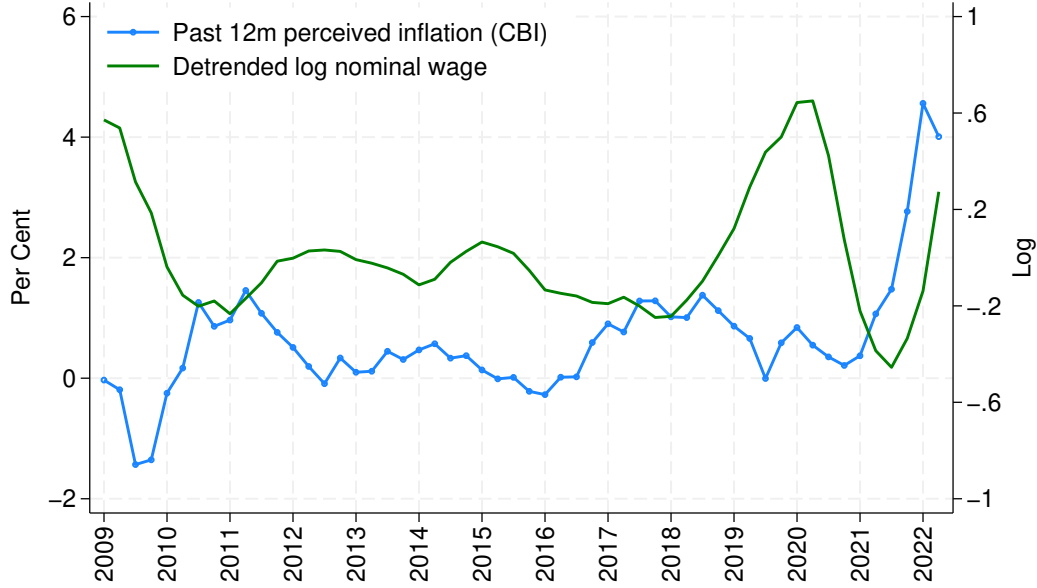
I explored two measures for industry-level labour costs: the detrended log real wage, constructed using survey-based changes in salary costs, and a measure of unit labour cost (ULC) provided by the ONS.²⁶ To compute the detrended log real wage, denoted as \hat{s}_{kt} and shown in Figure 2, I first compute the nominal wage series as levels from the survey-based “change in wage/salary cost per person employed”. Secondly, I compute the log deviations from the steady state.²⁷ Thirdly, to obtain a real measure, I deflate the log of wage by prices, also constructed based on the survey-based sectoral inflation data.²⁸ Detrended log nominal wage is represented as $\hat{w}_{kt} = w_{kt} - \bar{w}_k$ and detrended log price is represented as $\hat{p}_{kt} = p_{kt} - \bar{p}_k$. Lastly, detrended log real wage $\hat{s}_{kt} = \hat{w}_{kt} - \hat{p}_{kt}$.

²⁶Details on how I construct the ULC measure can be found in Appendix D.

²⁷For empirical purposes, the steady state is approximated by the Hodrick-Prescott (HP) filter trend over time for each industry.

²⁸See a time series plot of the average real marginal cost in Figure 22 in the Appendix.

FIGURE 2: CBI AVE. INFLATION AND AVE. DETRENDED LOG WAGE (ACROSS ALL INDUSTRIES)



Notes: This figure displays the average perceived sectoral inflation using CBI data and the detrended log nominal wage. The former is calculated as the average across all industries. The latter is calculated as the deviation of log nominal wage from the industry-level Hodrick-Prescott (HP) filter trend using the self-reported change in each firm’s “wage/salary cost per person employed”, obtained from the CBI. Inflation is plotted on the left y-axis in percentage annual rates, while wage is plotted on the right y-axis in log terms.

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 industry, the intermediate goods share bought by industry k from industry j , and industry 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.

The process of calculating intermediate goods’ prices involves several steps. First, I compute quarterly sectoral prices by dividing the perceived sectoral inflation from the CBI over the past 12 months by four, represented as $\pi_{kt}^q \equiv \frac{\pi_{kt}^y}{4}$. 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 industry on a quarterly basis. Lastly, I calculate the natural logarithm of this series and detrend it by subtracting the HP filter trend price for each industry, 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 25 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 ($i=1,2,\dots,n$), 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 industry k as follows: $HHI_k = \sum_{i=1}^n (ms_i)^2$ (summing up all firms i in each industry). $HHI < 0.1$ suggests an unconcentrated industry, $0.1 < HHI < 0.2$ moderately concentrated and $HHI > 0.2$ highly concentrated.

4.4.4 Market Concentration: Five Firm Concentration Ratio

Given that the FAME BvD does not provide turnover data for the entire population of firms in each industry, I also construct the five-firm concentration ratio (CR5) and test the robustness of the results. The CR5 is another measure of market concentration that focuses specifically on the combined market share of the five largest firms in the market. It is calculated by summing the market shares of the five largest firms for each industry, as follows:

$$CR5_k = ms_{k,1} + ms_{k,2} + ms_{k,3} + ms_{k,4} + ms_{k,5}$$

Using both measures of market concentration, the most concentrated industries are consistently led by Postal and Courier, Wearing apparel, Paper products, Mining, and the Pharmaceutical industry, as shown in Table 14.

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 collected 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.

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

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 present the regression estimation results for both the *Labour-Cost SPC* and the *Full-Cost SPC* frameworks for 52 industries. To aggregate the firm-level data into industry-level data, I calculate the industry-weighted average of firms' reports, with weights based on 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:

$$\hat{\pi}_{kt} = \gamma_k^b \hat{\pi}_{k,t-1} + \gamma_k^f E_t \hat{\pi}_{k,t+4} + \gamma_k^s \hat{s}_{kt}^F + \varepsilon_{kt}^\pi \quad (14)$$

5.1 Previous Research on Phillips Curve Estimation in the UK

Previous studies on Phillips Curve estimation at the sector level in the UK have provided valuable insights and significant results, although they do not employ direct measures of inflation expectations. For instance, Byrne et al. (2013) study fifteen UK sectors spanning from 1971 to 2006, revealing a high degree of forward-lookingness in UK industries, alongside a significant but low response of inflation to marginal costs. Similarly, Aquilante et al. (2024) analyse industry-level data for the period 2000-2014, focusing on the impact of the share of imported intermediate inputs on the response of the sectoral inflation to the sectoral output gap. Their findings indicate that industries with higher proportions of imported inputs from emerging market economies exhibit a lower inflation response, i.e., a flatter Phillips curve.

The validity of the aggregate Phillips Curve in UK data has been confirmed by Batini et al. (2005) through econometric techniques to estimate inflation expectations and by Meeks and Monti

(2019) using households expectations.

Exploring some of the open-economy features proposed by Batini et al. (2005) in the context of the estimation of the UK Phillips Curve, as discussed in Section 2.3, I investigated the relevance of foreign factors. However, the inclusion of oil price inflation and real import prices as regressors in the SPC did not yield statistically significant results. Nevertheless, incorporating 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 4 and for the *Full-Cost SPC* in Table 5. 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 industry-level fixed effects, and Model 3 is augmented with common factors to control for CCEs.

TABLE 4: *Labour-Cost SPC*

	Pooled [1]	MG [2]	Full model [3]
<i>Dependent variable: CBI sectoral inflation</i>			
Expected sectoral inflation	1.02*** (0.21)	0.80*** (0.08)	0.63*** (0.11)
Lagged sectoral inflation	0.35*** (0.10)	0.23*** (0.04)	0.17*** (0.04)
Labour cost	0.06** (0.02)	0.07* (0.04)	0.13*** (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

Notes: This table presents the OLS panel time-series estimation results using the IV method. The averages of industry-specific parameters are reported. Expectations are calculated as weighted averages among all firms in each industry. 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.

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 industries 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 (2019) found $\gamma^b : 0.2$ and $\gamma^f : 0.8^{***}$; Byrne et al. (2013) obtained $\gamma^b : 0.1^{***}$ 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 $\gamma^b : 0.1^{***}$ $\gamma^f : 0.22$.

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 6 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 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.

5.3 Unmasking Sectoral Heterogeneity in Price Setting Behaviour

While the average parameters obtained in the previous section shed light on average industry behaviour, it's important to highlight the broad heterogeneity that exists across industries beneath

³⁰The 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.

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

TABLE 5: *Full-Cost SPC*

	Pooled [1]	MG [2]	Full model [3]
<i>Dependent variable: CBI sectoral inflation</i>			
Expected sectoral inflation	0.87*** (0.20)	0.57*** (0.07)	0.56*** (0.10)
Lagged sectoral inflation	0.32*** (0.08)	0.23*** (0.04)	0.16*** (0.04)
Full cost (Labour and Int. goods)	0.32*** (0.10)	0.86*** (0.17)	0.89*** (0.24)
Heterogeneous/Homogeneous Coeff. FE (k)/CCE	Homogeneous FE(k)	Heterogeneous FE(k)	Heterogeneous. 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

Notes: This table presents the OLS panel time-series estimation results using the IV method. The averages of industry-specific parameters are reported. Expectations are calculated as weighted averages among all firms in each industry. 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). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

these averages. In this section, I will delve into the results further, presenting industry-specific parameters. Next section will focus on potential sources, such as industry-characteristics and other common factors, that may explain these asymmetries.

Industry-specific parameters are obtained from the Full model in both frameworks (shown in column [3] in the corresponding regression outputs). Figures 3, 4 and 5 display the histogram distribution of the estimated parameters. Below, I provide the specific parameters from the *Labour-Cost* frameworks for each industry, along with the average parameters within each group. In Appendix C I provide the specific parameters from the *Full-Cost SPC* framework for each industry.³²

5.3.1 Slope

The slopes γ_s obtained from the *Labour-Cost SPC* typically range between 0 and 0.4, while those from the *Full-Cost SPC* are, on average, much larger and spread away, as shown in Figure 3. This contrast underscores the significant impact of including intermediate goods costs in the pricing decisions within the latter framework. This finding suggests that embedding the production networks into the pricing decisions yields a much larger responsiveness of inflation to costs for the majority of industries.

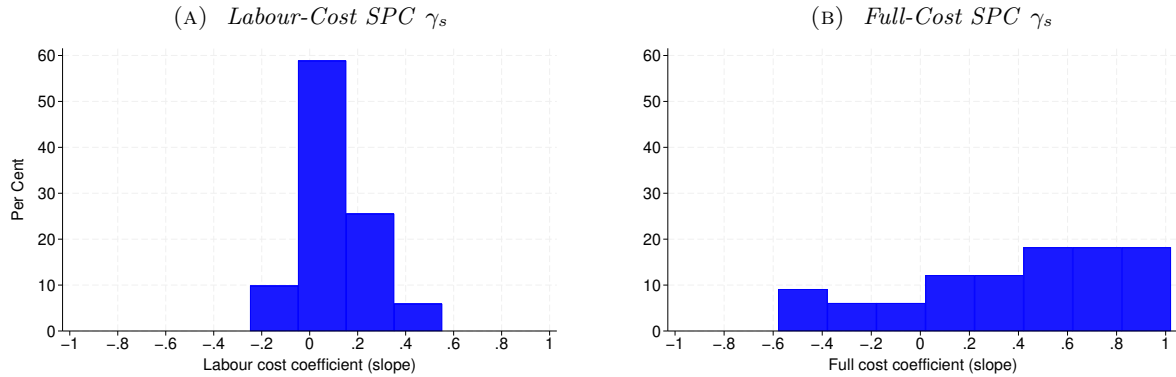
³²With groups I refer to: Manufacturing, Distributive/Retail, Services, Financial Services.

TABLE 6: AGGREGATE (NATIONWIDE) PHILLIPS CURVE REGRESSION

	OLS [1]	OLS [2]	OLS - IV [3]	OLS - IV [4]
<i>Dependent variable: CBI sectoral inflation</i>				
Expected inflation	0.65*** (0.08)	0.66*** (0.10)	0.84*** (0.18)	0.93*** (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 (0.03)		0.01 (0.03)	
BoE output gap		-0.01 (0.04)		-0.06 (0.07)
Real oil inflation			-0.00 (0.00)	-0.00 (0.00)
Intercept	-0.22** (0.08)	-0.25* (0.14)	-0.35*** (0.10)	-0.50 (0.32)
Observations	51	51	51	51
R-squared	0.92	0.92	0.91	0.91
R-squared Adj	0.91	0.91	0.90	0.90

Notes: Time-series estimation results. Current inflation, expected inflation, and labour costs are calculated as weighted average across industries 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

FIGURE 3: INDUSTRY-SPECIFIC PARAMETERS: SLOPE



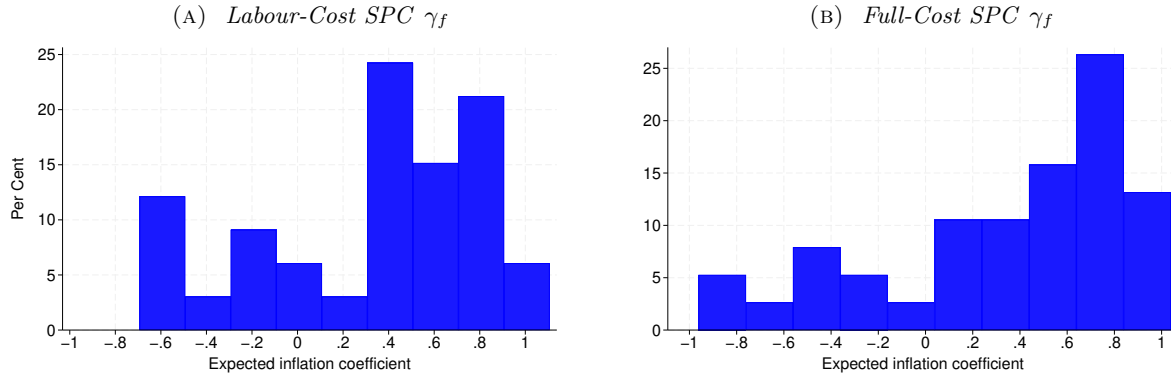
Upon examining whether differences in parameters can be explained by their broad group nature — e.g. manufacturing versus services industries — I find no discernible differences. The average parameter for manufacturing is similar to that of services, at around 0.1. While retail and financial services industries exhibit, on average, the lowest and almost null inflation response to costs (refer to Figure 9), the smaller sample size in these groups requires caution in drawing conclusions. Nonetheless, considerable variation within groups suggests that other industry-characteristics may

be driving these differences. Parameters obtained from the *Full-Cost SPC* (see Figure 11 in the Appendix) show similar patterns, emphasising underscoring substantial variation within groups when accounting for costs beyond labour inputs.

5.3.2 Forward-lookingness

While Figure 4 indicates no significant difference in the distribution of estimated parameters for expected future inflation between frameworks, there are substantial differences across industries (see Figure 10). Notably, certain manufacturing industries such as basic metals and wood products exhibit similar low levels of forward-looking behaviour as firms in land transport and restaurants industries, suggesting that industry-specific characteristics may play a pivotal role. On average, the role of expectations in pricing decisions appears consistent between manufacturing and services firms, at around 0.5. However, significant asymmetries exist within each group. Financial services, albeit represented by only three industries, indicate the largest role on expectations in pricing decisions.

FIGURE 4: INDUSTRY-SPECIFIC PARAMETERS: EXPECTED INFLATION

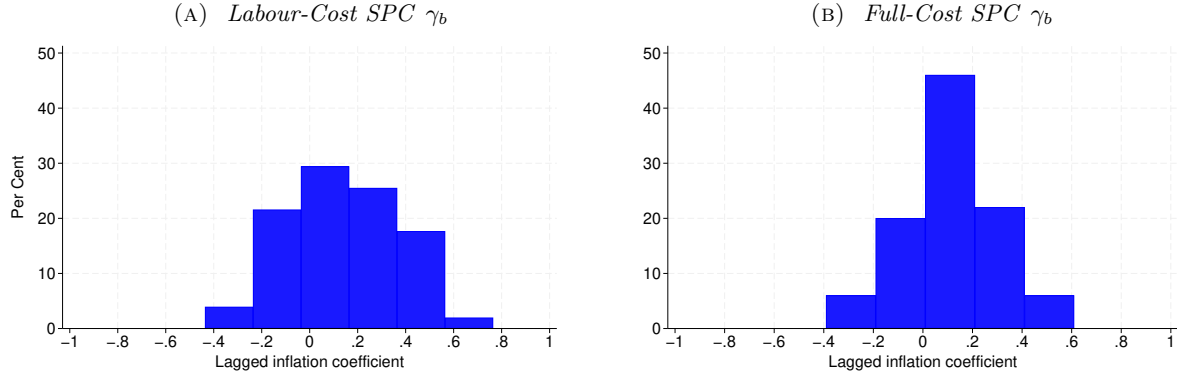


5.3.3 Backward-lookingness

In Figure 5, the estimated parameters associated with lagged sectoral inflation predominantly fall within the range of -0.5 to 0.5 across both frameworks. However, as detailed in Figure 8, certain estimates may lack statistical or economic significance, suggesting potential oversight of industry-specific characteristics by the model. Upon comparing coefficients across industry groups, the average parameters display minimal disparity: for instance, the average among Manufacturing is 0.25, while among Services is 0.12. Nevertheless, a broader heterogeneity persists within each group, with notable differences observed. Manufacturing industries such as Food Products and Basic metals exhibit greater persistence, whereas others, such as Medical and Optical, display less.

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

FIGURE 5: INDUSTRY-SPECIFIC PARAMETERS: LAGGED INFLATION



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 industry-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

I am not aware of studies that explicitly explain industry characteristics potentially driving the estimated SPC reduced-form nor structural parameters. Some papers have focused on the relationship between price stickiness α_k and industry characteristics, but this parameter is computed from data on the frequency of price changes rather than derived from the SPC. Computing the implied α_k from the estimated SPC requires some assumptions and employing specific techniques, given that α_k influences all reduced-form parameters. However, this aspect is not the main focus of this study. At this stage, I will assess the estimated reduced-form industry-specific parameters, γ_k^f , γ_k^b , and γ_k^s .

A primary focus in the literature has been the degree of market concentration. Consistent with Leith and Malley (2007), I find a positive and significant association between market concentration and the sensitivity of current inflation to expected future inflation. This aligns with their findings, suggesting that higher market concentration, indicative of reduced competition, leads to stickier price-setting behaviour and a stronger tendency to respond in a forward-looking manner.

Additionally, I will explore other factors that have gathered attention in the literature, such as external competition, inflation variability, and cost structure.

Let us first recapitulate the underlying framework explained above. The traditional SPC – referred to as the Labour-Cost SPC in Section 2 – is a microfounded relationship that can be expressed in terms of reduced-form parameters: the degree of forward-lookingness γ_k^b , the degree of backward-lookingness γ_k^f , and the SPC slope γ_k^s , as represented in Equation 2,

These reduced-form parameters depend on some underlying structural parameters, as shown in Equation 1. The coefficient γ_k^b comprises ω_k and ϕ_k , the latter ultimately influenced by α_k , representing price stickiness; β , the discount factor; and ω_k , the rule of thumb.³³ The coefficient γ_k^f comprises β , α_k , and ϕ_k . The slope γ_k^s comprises all underlying structural parameters.

The traditional New Keynesian Phillips Curve (NKPC) states that in industry k , greater price stickiness leads to firms being less able to adjust prices in each period t . Consequently, they assign more weight to expected future markups, resulting in a higher value of γ^f . This positive relationship between γ^f and price stickiness emerges because firms, faced with greater price stickiness, are compelled to maintain prices for longer periods.

This rationale aligns with the argument presented by Werning (2022), who suggests that firms initially set prices above their ideal level, but as time progresses, prices tend to fall below the desired level. Therefore, when firms expect higher inflation, they adjust prices further above the currently ideal price. Consequently, industries 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.

It's worth noting that the interpretation of γ^f and γ^b is somewhat connected, as it is commonly assumed that backward-looking behaviour (γ_b) and forward-looking behaviour (γ_f) move in opposite directions, consistent with the evidence presented in my research.

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: the structure and degree of market competition, inflation variability, the frequency and magnitude of cost and demand shocks and the statistical methods used to collect price data. I will complement these factors with others studied in the literature.

6.1.2 Market Concentration

The influence of market structure on firms' pricing decisions has gathered substantial interest in research. Various studies approach this question from different angles, some examining the impact of pricing complementarities, while others focus on the speed of adjustment to a shock. For

³³The parameter ω_k is introduced in the IJP derivation to capture sectoral inflation persistence.

instance, Kato et al. (2021) analyse US producer price data for manufacturing firms spanning from 1976 to 2005. They find a negative correlation between sectoral inflation persistence and market concentration. Their results suggest that as market concentration increases, there is a reduction in pricing complementarity among monopolistically competitive firms, leading to lower γ^b and, consequently, higher γ^f .

Estimating NKPC structural parameters for US industries over the period 1958 to 1996 Leith and Malley (2007) find a positive correlation between market concentration (using the 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. Also using US data, Bils and Peter J Klenow (2004) examine the frequency of price changes for 350 categories of goods and services for the period 1995-1997 and find an inverse relationship between the concentration ratio and the frequency of price changes, suggesting that more competition leads to more frequent price adjustments. 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.

Focusing on nine Euro area countries, L. Alvarez and Hernando (2007) show evidence that firms in most competitive markets give them a greater capacity to react to shocks and make, in practice, for greater flexibility in their prices.

All the above-mentioned papers find evidence consistent with a positive relationship between the degree of forward-looking behaviour and market concentration. However, I will now present a paper that shows opposing findings. Domberger (1979) finds 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 in the UK, 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.

6.1.3 External Competition

In addition to domestic competition being positively associated with the frequency of price changes, L. J. Alvarez et al. (2005) investigate the effect of external competition in price setting behaviour of Spanish firms over the period 1991-1999. They find that the degree of import penetration,

which proxies external competition, is significant and positively associated to the frequency of price changes.

6.1.4 Inflation Variability

Dhyne et al. (2006) studied price changes in the Euro Area from 1996 to 2001 and show that sectors with higher inflation variability tend to have significantly higher price change frequencies. This suggests that firms may adjust prices more frequently when facing greater volatility in inflation to stay closer to their optimal prices.

6.1.5 Cost Structure

Studies by Vermeulen et al. (2007) and L. Alvarez and Hernando (2007) investigated the influence of cost structure on price change frequencies, focusing on data from select countries in the Euro Area during the early 2000s.³⁴ Their findings revealed that firms operating in labour-intensive sectors tend to adjust prices less frequently. The underlying logic stems from the principles of monopolistic competition, where firms set prices as a mark-up over marginal costs. Consequently, the volatility of input prices plays a crucial role in determining the frequency of price adjustments. When input costs exhibit higher volatility, such as energy prices, firms are compelled to adjust prices more frequently. Conversely, sectors characterised by more stable input costs, such as wages, tend to experience less frequent price changes. Therefore, firms with a larger proportion of energy and intermediate inputs in their total costs exhibit a positive correlation with the frequency of price changes.

The findings described above collectively contribute to our understanding of why different industries exhibit varying levels of forward- and backward-lookingness, 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

I will now 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 industry-specific parameters exhibit various levels of estimation precision.³⁵ 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).³⁶ Since the standard

³⁴The time period covered varies across countries, subject to availability.

³⁵This variability may be due to their estimation as a panel, without consideration of potential industry-specific characteristics or shocks that may affect certain industries.

³⁶For 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).

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.

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

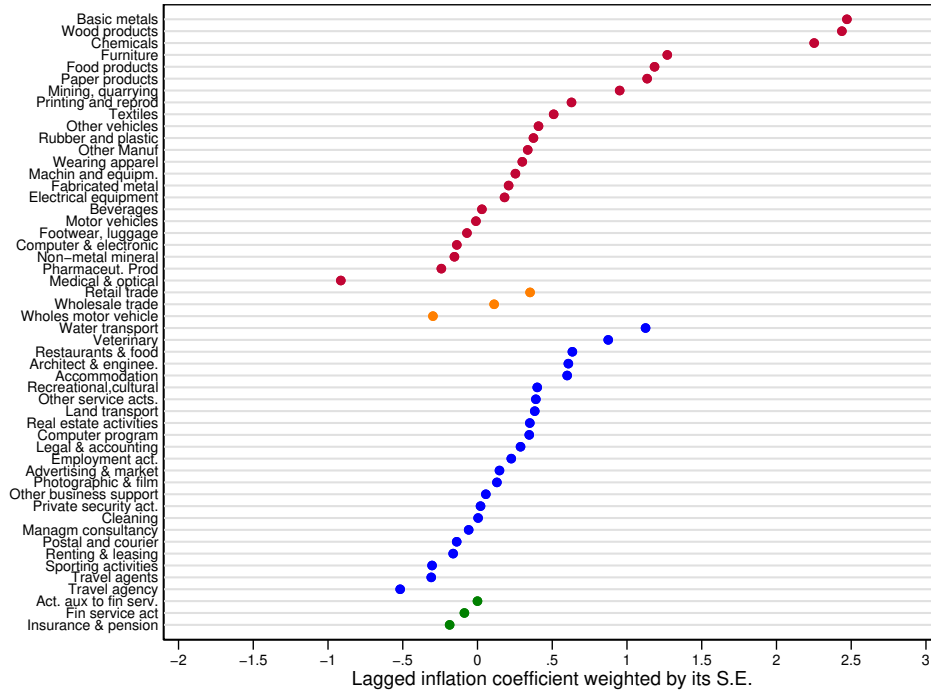
where p represents the SPC parameters (f for forward-looking, b for backward-looking, and s for slope).

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

$$\tilde{X}_k^j = X_k^j * \bar{w}_k^p$$

I show in Figures 6, 7, and 14 the weighted parameters by industry from the *Labour-Cost SPC*, and in Appendix C I show the estimated parameters from the *Full-Cost SPC*.

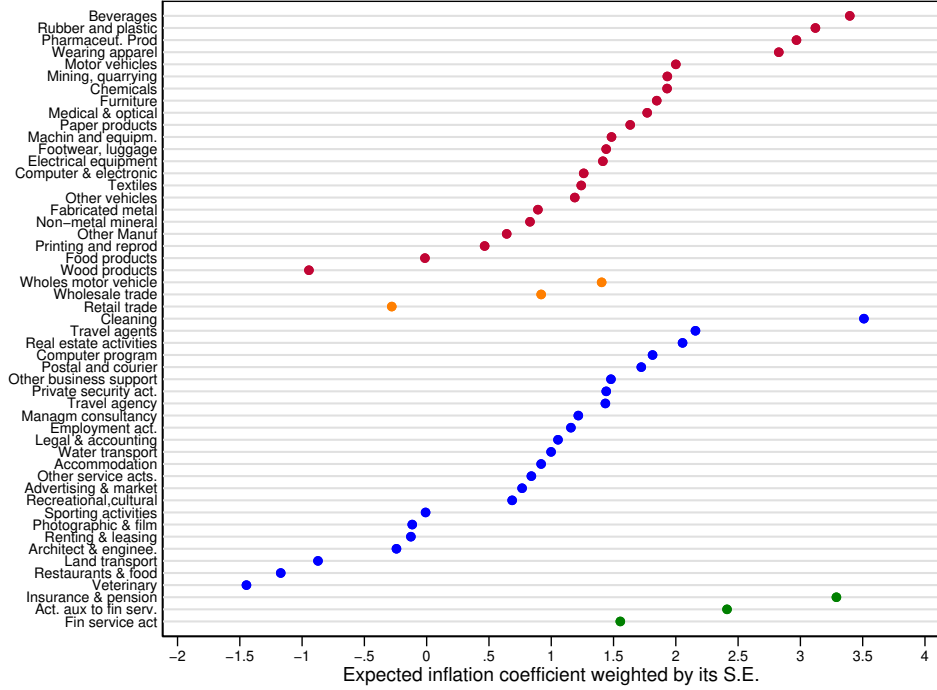
FIGURE 6: WEIGHTED PARAMETER ON LAGGED INFLATION (*Labour-Cost SPC*)



Notes: The parameters displayed in the figure have been weighted based on their inverted S.E. from the *Labour-Cost SPC*. Red colour: Manufacturing; Orange: Retail; Blue: Services; and Green: Financial Services.

I will then 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 industries.

FIGURE 7: WEIGHTED PARAMETER ON EXPECTED INFLATION (*Labour-Cost SPC*)



Notes: The parameters displayed in the figure have been weighted based on their inverted 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.

The weighted regression used is expressed as follows:

$$\tilde{\gamma}_k^p = \beta_0 \tilde{X}_k^0 + \beta_1 \tilde{X}_k^1 + \dots + \tilde{u}_k \quad (15)$$

6.3 Regression Estimation Results

The following regressions in Table 7 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.

TABLE 7: REGRESSIONS ESTIMATIONS (*Labour-Cost SPC*)

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

Notes: This table presents the OLS panel estimation as reflected in Equation 15. The dependent variables consist of the estimated parameters from the Labour-Cost SPC obtained for each industry. The observations refer to the number of industries. Both the dependent and independent variables are weighted by the inverse of the S.E. from the corresponding SPC estimated 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. The table is divided into two symmetric sets of regressors with the only difference being in the MC: columns 1-3 use CR5 for MC whereas columns 4-6 use HHI for MC. Inputs used in these regressions are shown in Table 14. S.E. in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The results presented in Table 7 indicate a positive and significant correlation between the role of expectations and two standard market concentration measures: the Five Firm Concentration Ratio (CR5) and the HHI. This finding supports the evidence discussed in Section 6.1. This phenomenon can be attributed to the low demand elasticity in highly-concentrated markets. With fewer competitors, firms face less competitive pressure to adjust prices, giving more weight to their own expectations. In contrast, in more competitive industries, individual firms have little market power. Setting prices slightly below competitors can result in reduced or no sales, thereby firms are more likely to follow competitors' prices, giving less weight to their own expectations.

The effect of market concentration 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.

Regarding the backward-looking behaviour, or inflation persistence, the results suggest that

firms tend to base pricing decisions on past inflation when facing a larger share of imports. This finding contrasts with the conclusions drawn by L. J. Alvarez et al. (2005), suggesting the need for further investigation into the specific dynamics at play, likely related to the differences in studied countries and timeframe.

Similarly, the positive association observed between backward-looking behaviour and the share of energy and petrol costs contradicts previous evidence linking cost structures to price change frequencies. As discussed in Section 6.1, earlier studies on Euro Area countries in the early 2000s found that firms exposed to energy prices tended to adjust prices more frequently. One possible explanation for this discrepancy could be that firms exposed to energy prices in my studied sample may be tied to longer-term contracts or engage in price indexation, leading to greater price persistence. In connection with the cost structure, I also tested the potential association between the variability in unit labour costs (ULC) and the SPC parameters. The analysis yielded non-significant results. The reason may be related to the lack of distinct data points for individual industries for ULC. This lack of variability may account for the observed insignificance.

Notably, the slope parameter does not exhibit any statistically significant association with the selected industry-characteristics, suggesting that other factors may play a more prominent role in influencing the inflation response to costs.

These findings highlight the need for further research into the sources of heterogeneity in the structural parameters of the Phillips Curve, providing valuable insights into the complexities of pricing behaviour in different market environments

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 industries in the UK, combining industry-level 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 labour 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 industries 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-setting behaviour mitigates the risk of price persistence. It also highlights the importance of understanding firms' expectations formation in order to stabilise inflation through better expectations management.

Employing panel time series methods with industry-specific coefficients unmasks large sectoral heterogeneity in the Sectoral Phillips Curve parameters. The findings from my analysis revealed a positive correlation between the role of expectations and two measures of market concentration. This supports the evidence found in previous research, suggesting that industries with higher competition tend to follow competitors' prices more closely, reducing the weight placed on their own expectations.

Additionally, the results suggest that firms tend to base pricing decisions on past inflation when facing a larger share of imports, contrasting with previous research. Similarly, the positive association observed between backward-looking behaviour and the share of energy and petrol costs contradicts previous evidence linking cost structures to price change frequencies. However, it is important to note that properly disentangling these discrepancies is challenging, as existing evidence primarily focuses on Euro Area countries and spans different timeframes.

These findings underscore the need for further research into the sources of heterogeneity in the structural parameters of the Phillips Curve. Understanding the factors driving the high role of expectations in pricing decisions is particularly important for monetary policymakers. An increase

in expectations may amplify the inflation response, making it more challenging for central banks to maintain stable inflation. Therefore, shaping expectations management policy requires a deeper understanding of these dynamics.

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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

$$Y_{ikt} = Y_{kt} \left(\frac{P_{ikt}}{P_{kt}} \right)^{-\eta} \quad (16)$$

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:

$$Y_{kt} = \left[\int_0^1 Y_{ikt}^{\frac{\eta-1}{\eta}} di \right]^{\frac{\eta}{\eta-1}} \quad (17)$$

$$Y_{ikt} = Z_{kt} f(h_{ikt}) \quad (18)$$

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: $S_{ikt,t+j} = S_k = \eta/(\eta - 1)$.

$$\max_{P_{ikt}^*} E_t \sum_{j=0}^{\infty} (\alpha_k \beta)^j [Y_{ikt,t+j} P_{ikt}^* - \Psi(Y_{ikt,t+j})] \quad (19)$$

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

$$\sum_{j=0}^{\infty} (\alpha_k \beta)^j E_t [Y_{ikt,t+j} (P_{ikt}^* - \eta S_{ikt,t+j} P_{ikt,t+j})] = 0 \quad (20)$$

$$\hat{p}_{ikt}^* = (1 - \alpha_k \beta) \sum_{j=0}^{\infty} (\alpha_k \beta)^j E_t [\hat{s}_{ikt,t+j} + \hat{p}_{ikt,t+j}] \quad (21)$$

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:

$$\hat{p}_{kt} = \alpha_k \hat{p}_{kt-1} + (1 - \alpha_k) \hat{p}_{kt}^* \quad (22)$$

$$\hat{p}_{kt}^* = \omega_k \hat{p}_{kt}^b + (1 - \omega_k) \hat{p}_{kt}^f \quad (23)$$

$$\hat{p}_{kt}^b = \hat{p}_{kt-1}^* + \hat{\pi}_{kt-1} \quad (24)$$

and \hat{p}_{kt}^f refers to prices set by forward-looking firms according to Equation 21.

$$\hat{\pi}_{kt} = \frac{\omega_k}{\phi_k} \hat{\pi}_{kt-1} + \frac{\beta \alpha_k}{\phi_k} E_t \hat{\pi}_{kt+1} + \frac{(1 - \omega_k)(1 - \alpha_k)(1 - \beta \alpha_k)}{\phi_k} h_k \hat{s}_{kt} \quad (25)$$

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

Lastly, ε_{kt}^π 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:

$$\hat{\pi}_{kt} = \gamma_k^b \hat{\pi}_{kt-1} + \gamma_k^f E_t \hat{\pi}_{kt+1} + \gamma_k^s \hat{s}_{kt} + \varepsilon_{kt}^\pi \quad (26)$$

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.

$$\begin{pmatrix} \hat{\pi}_{1t} \\ \hat{\pi}_{2t} \end{pmatrix} = \begin{pmatrix} \tilde{\alpha}_1 & 0 \\ 0 & \tilde{\alpha}_2 \end{pmatrix} \begin{pmatrix} mc_{1t} - \hat{p}_{1t-1} \\ mc_{2t} - \hat{p}_{2t-1} \end{pmatrix} + \beta \begin{pmatrix} 1 - \tilde{\alpha}_1 & 0 \\ 0 & 1 - \tilde{\alpha}_2 \end{pmatrix} \begin{pmatrix} E_t \hat{\pi}_{1t+1} \\ E_t \hat{\pi}_{2t+1} \end{pmatrix} \quad (27)$$

$$\begin{pmatrix} mc_{1t} \\ mc_{2t} \end{pmatrix} = \begin{pmatrix} (1 - a_1) \hat{w}_{1t} + \lambda_{11t} \hat{p}_{1t} + \lambda_{12t} \hat{p}_{2t} \\ (1 - a_2) \hat{w}_{2t} + \lambda_{21t} \hat{p}_{1t} + \lambda_{22t} \hat{p}_{2t} \end{pmatrix} - \begin{pmatrix} \log Z_{1,t} \\ \log Z_{2,t} \end{pmatrix} \quad (28)$$

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 27 and 28, and ignore the productivity term just for brevity. This omission won't affect the results.

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

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.

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

Further combining terms to get expressions for the inflation rates:

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

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

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 $j : 1, 2, \dots, N$ 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, $\hat{\mathbf{s}}_t^F$, and

inflation expectations:

$$\hat{\pi}_t = (I - \Lambda \tilde{A})^{-1} \beta (1 - \tilde{A}) \mathbf{E}_t \hat{\pi}_{t+4} + (I - \Lambda \tilde{A})^{-1} \tilde{A} \hat{\mathbf{s}}_t^F \quad (29)$$

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 8: CORRELATION TABLE

	CBI Sec- toral Infla- tion	Expec- ted Infla- tion	Labour Cost	Full Cost	Oil Price Infla- tion	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

Notes: This table displays correlation levels for the main studied variables. “IG” represents Intermediate Goods. Refer to Section 4.4 for details on how I construct the “Labour Cost” and the “Full Cost”

TABLE 9: PANEL STATIONARITY TEST: PESARAN (2007) CIPS

Specification with constant								
Lags	CBI inflation	(<i>p</i>)	Labour cost	(<i>p</i>)	Expected inflation	(<i>p</i>)	Full cost	(<i>p</i>)
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	(<i>p</i>)	Labour cost	(<i>p</i>)	Expected inflation	(<i>p</i>)	Full cost	(<i>p</i>)
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

Notes: This table displays 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 use the Stata routine *multipurt* by Markus Eberhardt.

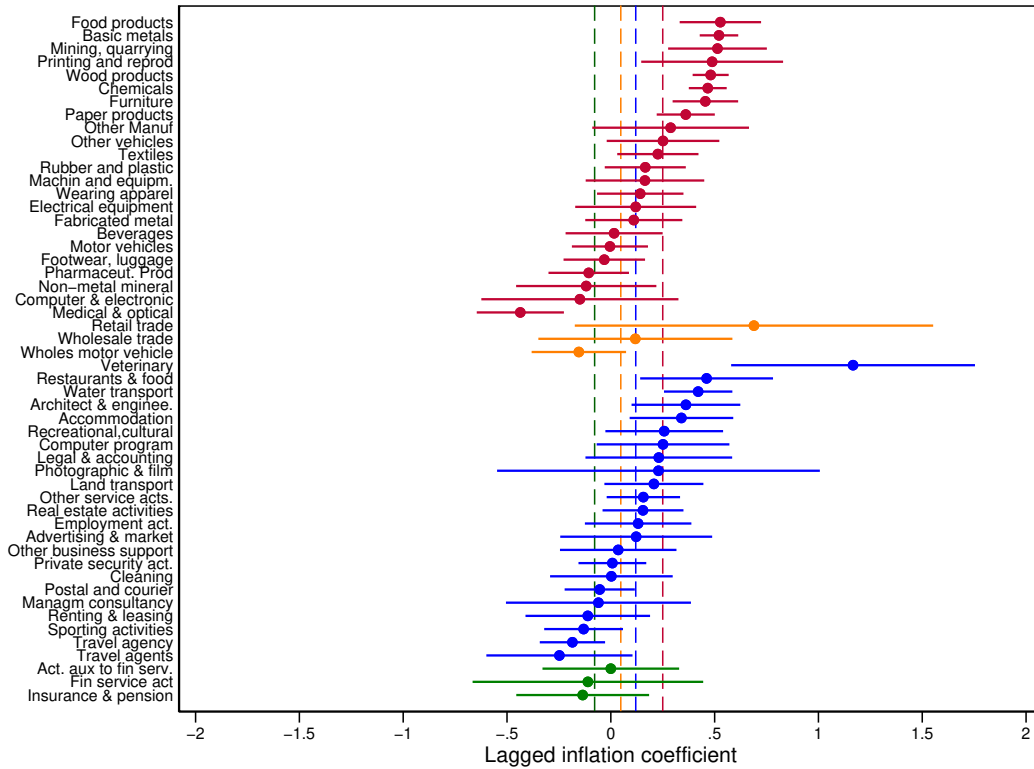
TABLE 10: RELEVANCE OF INSTRUMENTS

<i>Dependent Variable:</i>	<i>Expecta- tions</i>	<i>Expecta- tions</i>	<i>Labour Cost</i>	<i>Labour Cost</i>	<i>Full Cost</i>	<i>Full Cost</i>
	[1]	[2]	[3]	[4]	[5]	[6]
Expectations (1st lag)	0.23*** (0.03)	0.20*** (0.03)		0.01 (0.01)		-0.09*** (0.01)
Expectations (2nd lag)	0.13*** (0.03)	0.11*** (0.03)		-0.04*** (0.01)		0.01 (0.01)
Expectations (3rd lag)	0.07** (0.03)	0.11*** (0.03)		-0.02** (0.01)		-0.02** (0.01)
Cost (1st lag)		0.29** (0.12)	0.98*** (0.04)	0.97*** (0.04)	0.73*** (0.04)	0.81*** (0.05)
Cost (2nd lag)		-0.07 (0.15)	-0.00 (0.06)	-0.06 (0.06)	0.08* (0.05)	0.02 (0.05)
Cost (3rd lag)		0.28*** (0.10)	-0.22*** (0.04)	-0.15*** (0.03)	-0.09** (0.04)	-0.02 (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

Notes: OLS estimations. The letter “t” indicates time and the letter “k” indicates industry. Intercepts were included in the estimations but omitted in the table.

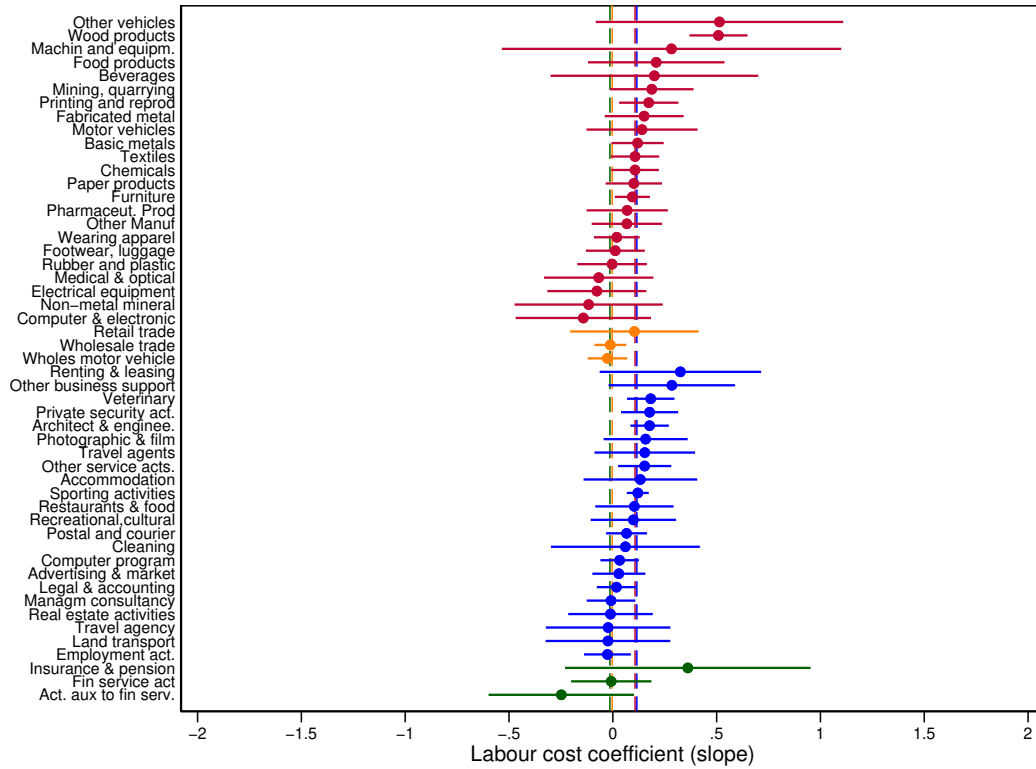
S.E. in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

FIGURE 8: ROLE OF LAGGED INFLATION BY INDUSTRY (*Labour-Cost SPC*)



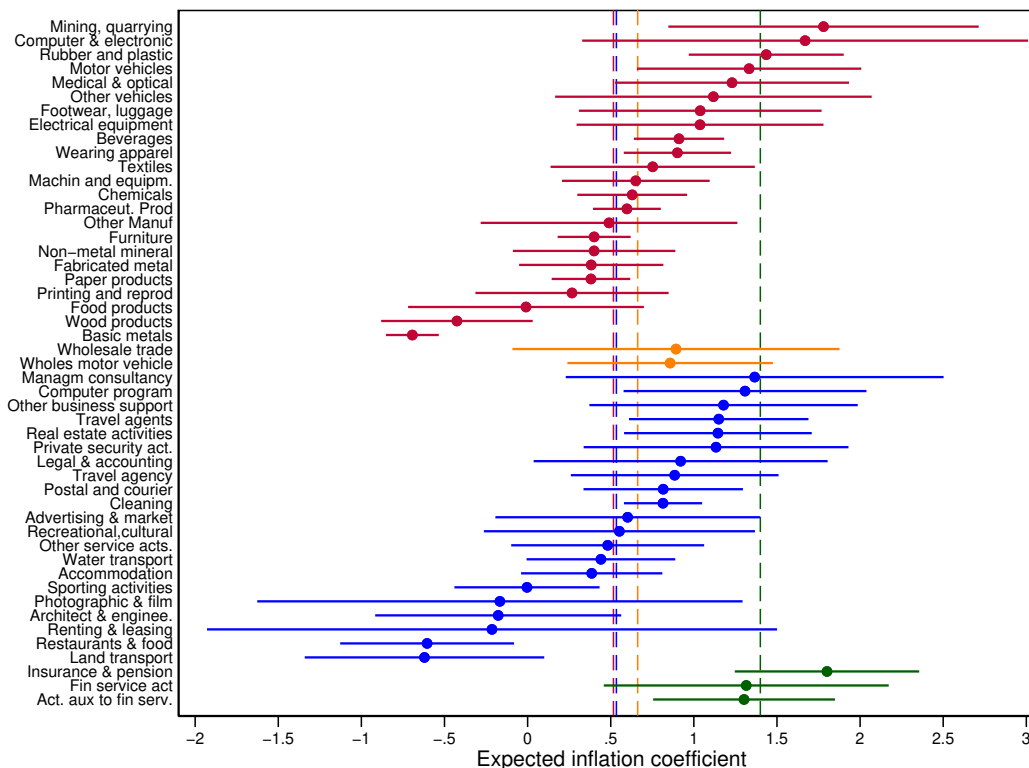
Notes: Industry-specific parameters related to lagged inflation from Model 3 (Table 4, through dynamic panels with CCE). These coefficients are net from common factor effects. Intervals are calculated as the mean \pm s.e. The labels indicate the mean estimated coefficient for each industry. The dashed 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 9: SLOPE BY INDUSTRY (*Labour-Cost SPC*)



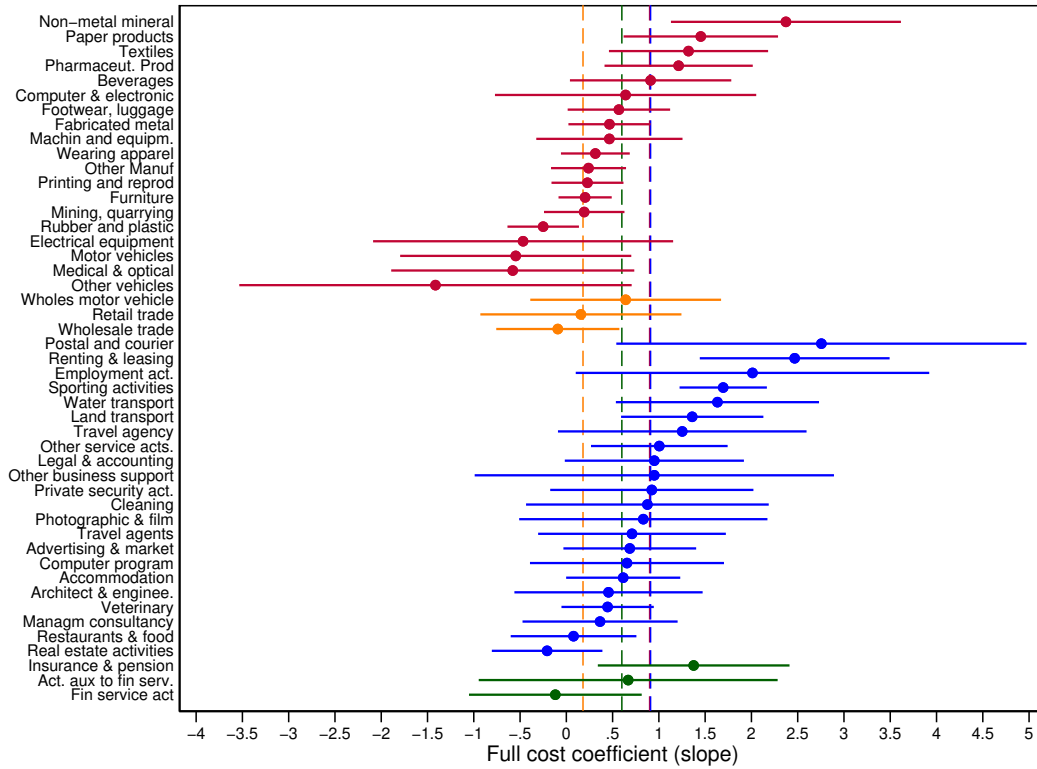
Notes: Industry-specific parameters related to labour costs from Model 3 (Table 4, through dynamic panels with CCE). These coefficients are net from common factor effects. Intervals are calculated as the mean \pm s.e.. The labels indicate the mean estimated coefficient for each industry. The dashed vertical 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 10: ROLE OF EXPECTATIONS BY INDUSTRY (*Labour-Cost SPC*)



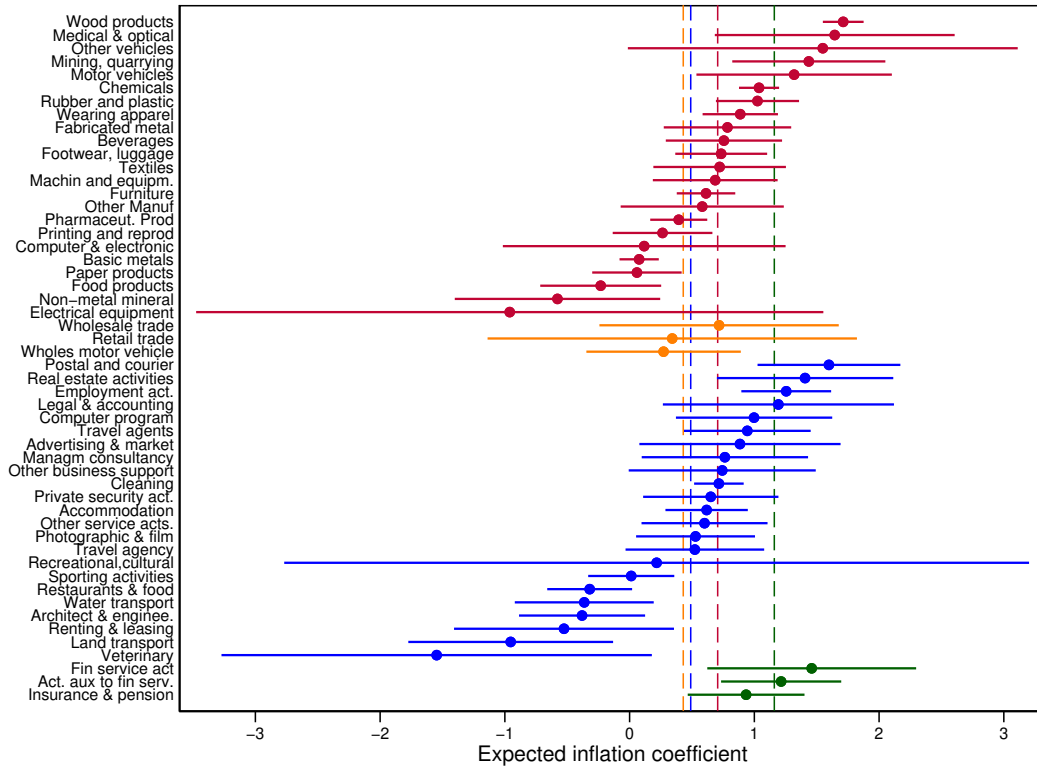
Notes: Industry-specific parameters related to inflation expectations from Model 3 (Table 4, through dynamic panels with CCE). These coefficients are net from common factor effects. Intervals are calculated as the mean \pm s.e. The labels indicate the mean estimated coefficient for each industry. The 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 11: SLOPE BY INDUSTRY (*Full-Cost SPC*)



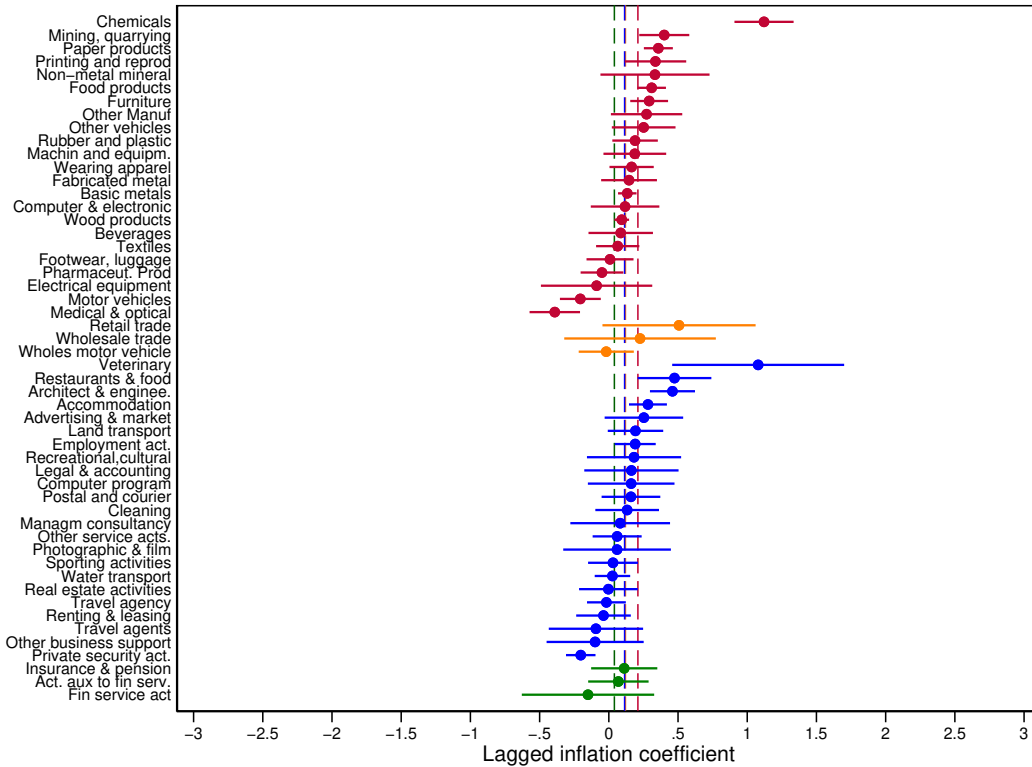
Notes: Industry-specific parameters related to the full cost measure from Model 3 (Table 5, through dynamic panels with CCE). These coefficients are net from common factor effects. Intervals are calculated as the mean \pm s.e. The labels indicate the mean estimated coefficient for each industry. The 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 12: ROLE OF EXPECTATIONS BY INDUSTRY (*Full-Cost SPC*)



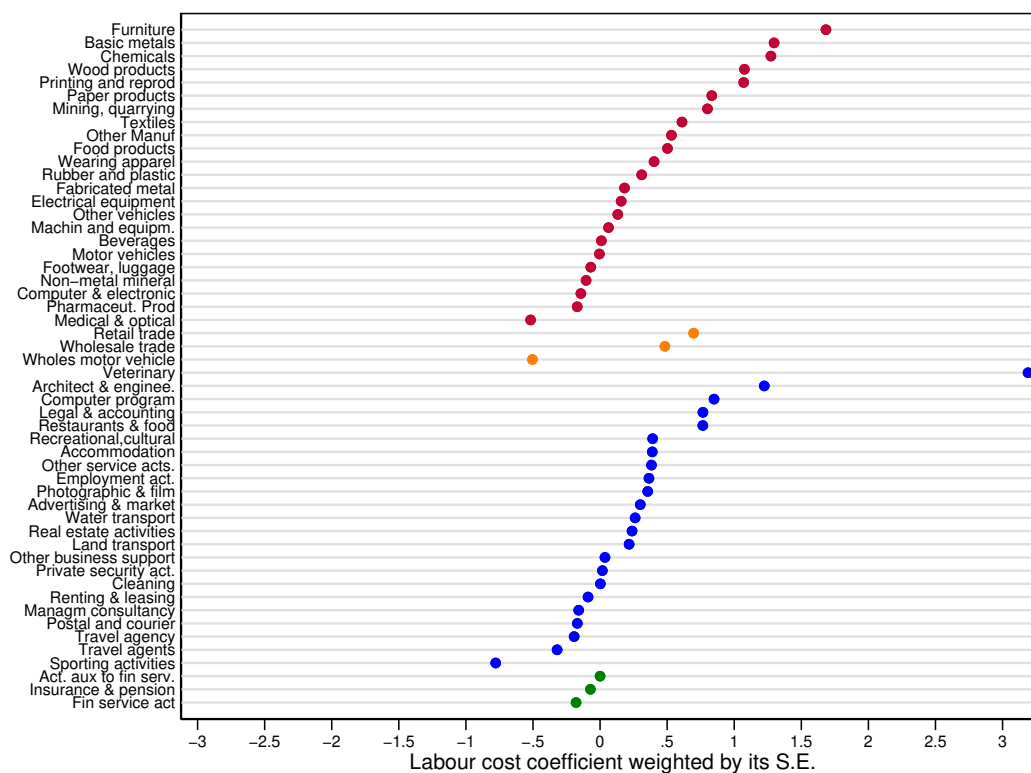
Notes: Industry-specific parameters related to inflation expectations from Model 3 (Table 5, through dynamic panels with CCE). These coefficients are net from common factor effects. Intervals are calculated as the mean \pm s.e. The labels indicate the mean estimated coefficient for each industry. The 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 13: ROLE OF LAGGED INFLATION BY INDUSTRY (*Full-Cost SPC*)



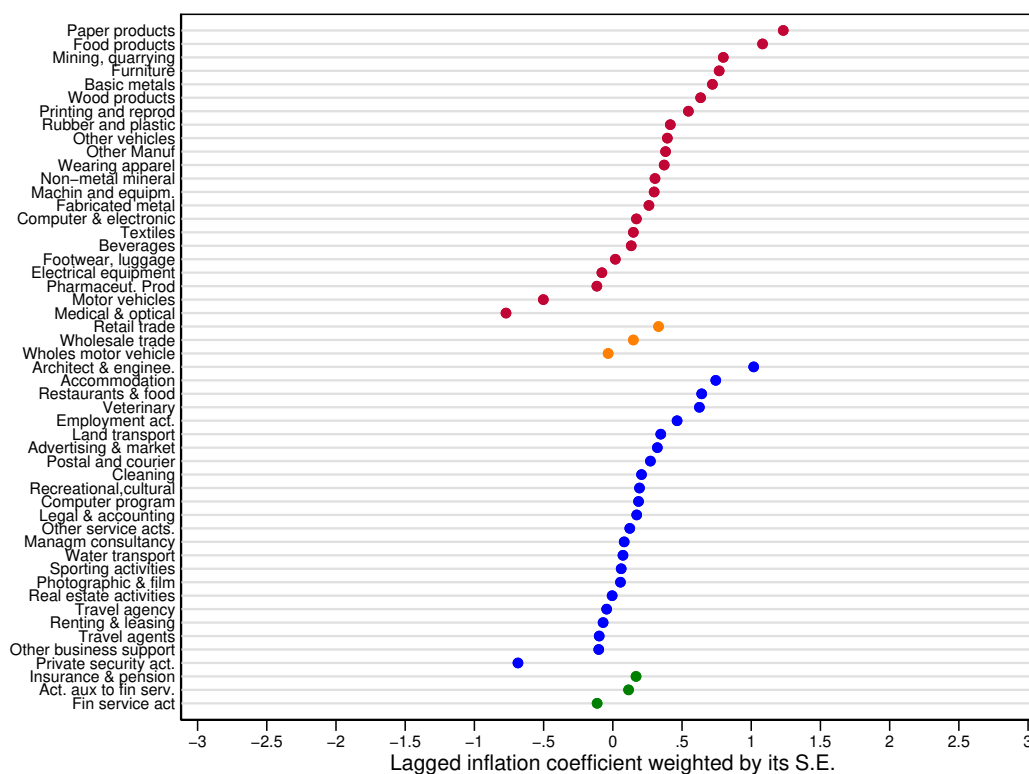
Notes: Industry-specific parameters related to lagged inflation from Model 3 (Table 5, through dynamic panels with CCE). These coefficients are net from common factor effects. Intervals are calculated as the mean \pm s.e. The labels indicate the mean estimated coefficient for each industry. The dashed 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 14: WEIGHTED PARAMETER ON LABOUR COST (*Labour-Cost SPC*)



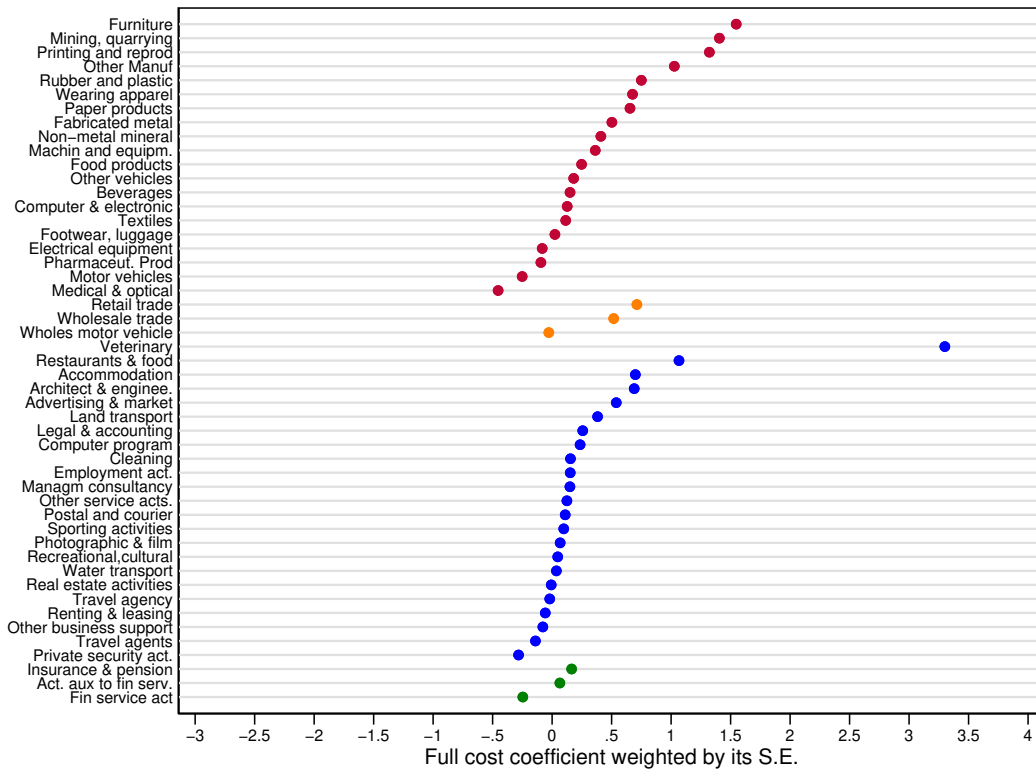
Notes: The parameters displayed in the figure have been weighted based on their inverted S.E. from the *Labour-Cost SPC*. Red colour: Manufacturing; Orange: Retail; Blue: Services; and Green: Financial Services.

FIGURE 15: WEIGHTED COEFFICIENT ON LAGGED INFLATION (*Full-Cost SPC*)



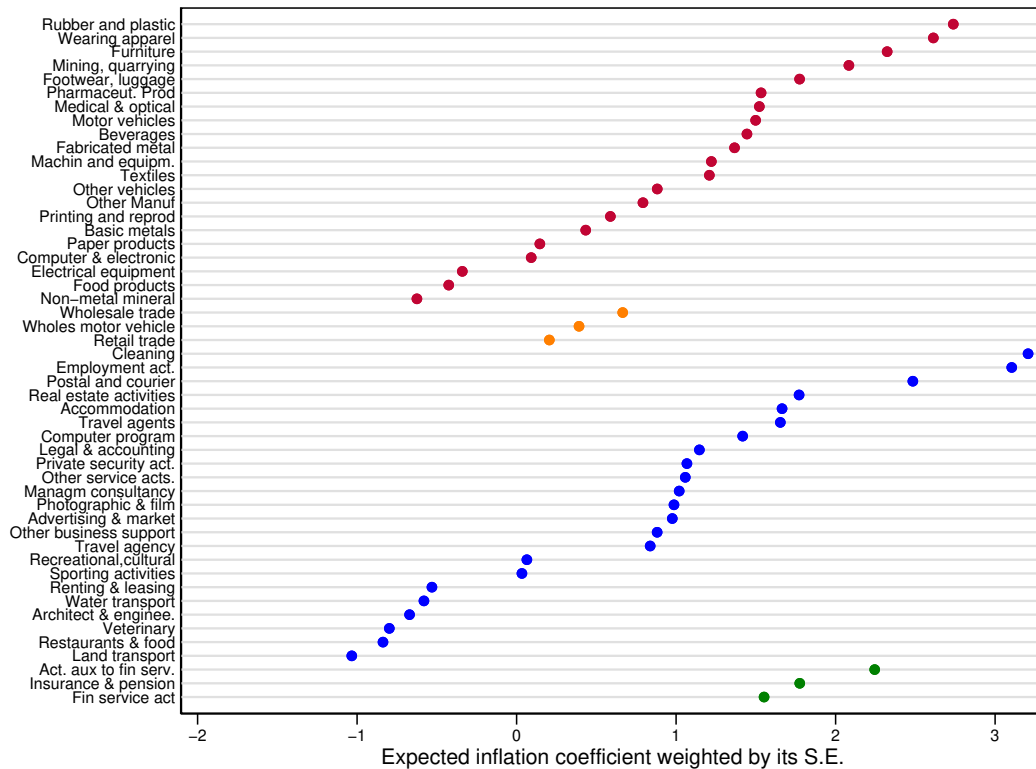
Notes: The coefficients presented in the figure have been weighted based on their respective S.E. from the *Full-Cost SPC*. The Chemicals industry was excluded due to the estimated parameters falling outside the range of -3 to 3, adding them would distort the axis scales. This adjustment was made to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

FIGURE 16: WEIGHTED COEFFICIENT ON FULL COST (*Full-Cost SPC*)



Notes: 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 17: WEIGHTED COEFFICIENT ON EXPECTED INFLATION (*Full-Cost SPC*)



Notes: 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.

TABLE 11: REGRESSIONS ESTIMATIONS (*Full-Cost SPC*)

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

Appendix D Data and measurement

D.1 Outliers detection and winsorisation scheme

Table 12 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 12: 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			

Notes: This table shows the number of identified outliers based on the “Past 12m sectoral inflation” reports from the CBI.

TABLE 13: PRICE MAPPING

2-dig SIC	2-digit SIC description	PPI	SPPI	CPI by COICOP
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	

Notes: In the case of PPI and SPPI, the letter “x” indicates the availability of an inflation index related to the same SIC. When neither PPI nor SPPI has an inflation index available, then CPI indices are used. All three indices (PPI, SPPI, and CPI) are provided by the ONS.

D.2 CBI survey data

FIGURE 18

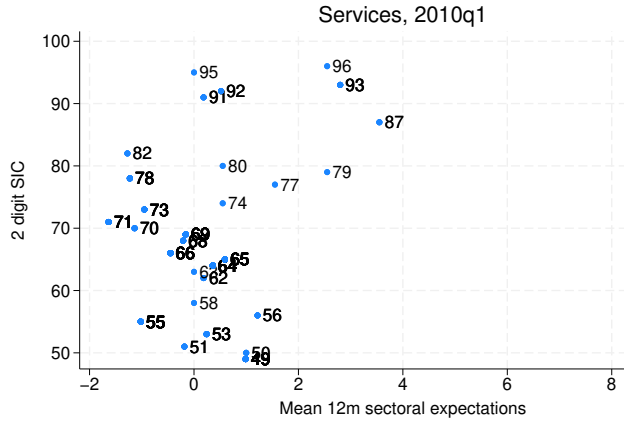


FIGURE 19

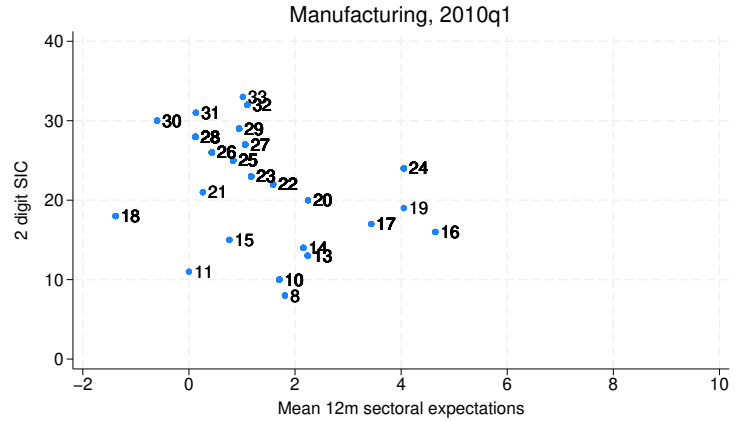


FIGURE 20

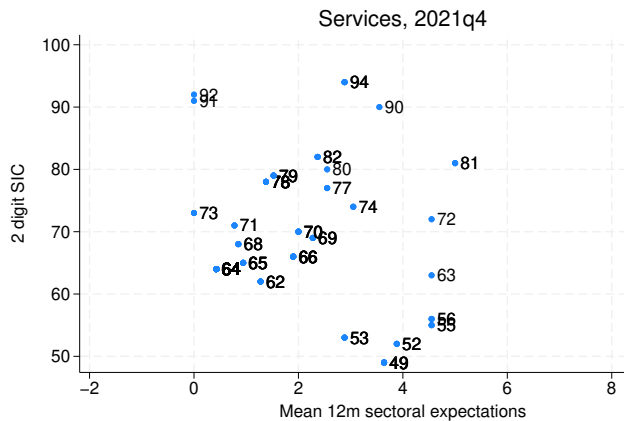
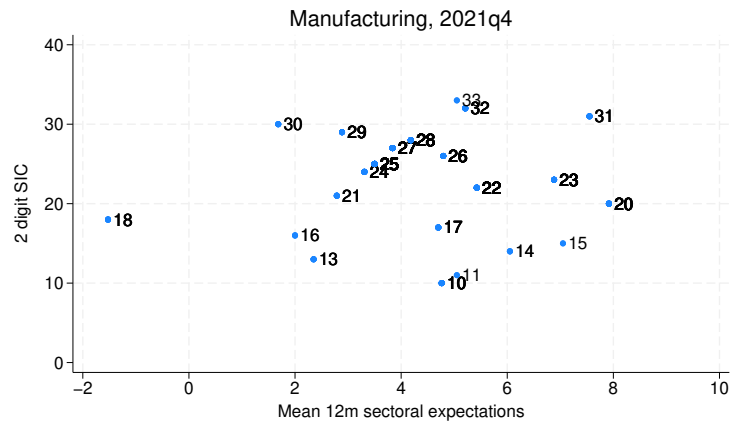


FIGURE 21

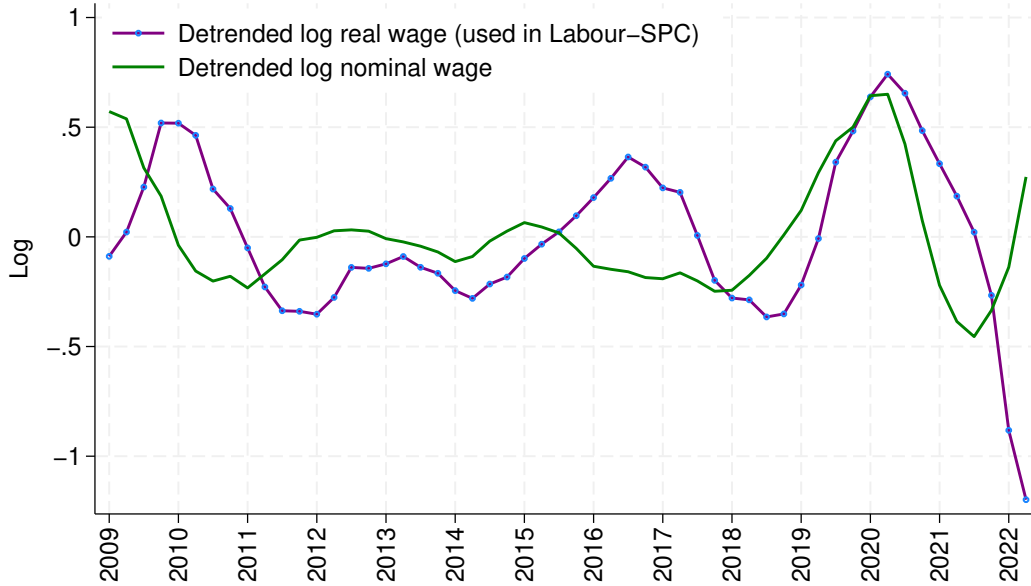


D.3 Measures of cost

The Unit Labour Cost (ULC) measure, as provided by the ONS, represents the nominal cost of labour input per unit of real economic output, adjusted for inflation. It is calculated by dividing total nominal employment costs by the real gross value added (GVA). However, it is important to note that the ULC data is not available at the 2-digit SIC level. The ONS provides 20 industry categories at the 2-digit SIC, grouped as follows: 05 to 39, 45 to 98, 01 to 03, 05 to 09, 10 to 33, 35, 36 to 39, 41 to 43, 45 to 47, 49 to 53, 54 to 56, 58 to 63, 64 to 66, 68, 69 to 75, 77 to 82, 84, 85, 86 to 88, 90 to 93, 94 to 96, 97 to 98. To align with the available dataset, I've mapped these categories to the closest 2-digit SIC codes.

In Figure 22 I show the measure of detrended nominal wage cost (in log terms) alongside the measure of real detrended wage cost. The latter serves as a forcing variable for estimating the Labour-Cost SPC. These two series align most of the time, reflecting low inflation, with minor gaps in 2010, 2016, and 2017. A notable difference becomes evident starting in mid-2021 due to the high inflation period.

FIGURE 22: REAL DETRENDED WAGE AND NOMINAL DETRENDED WAGE (AVERAGE ACROSS ALL INDUSTRIES)



Notes: For details on how I compute the measures of detrended log wage refer to Section 4.4.

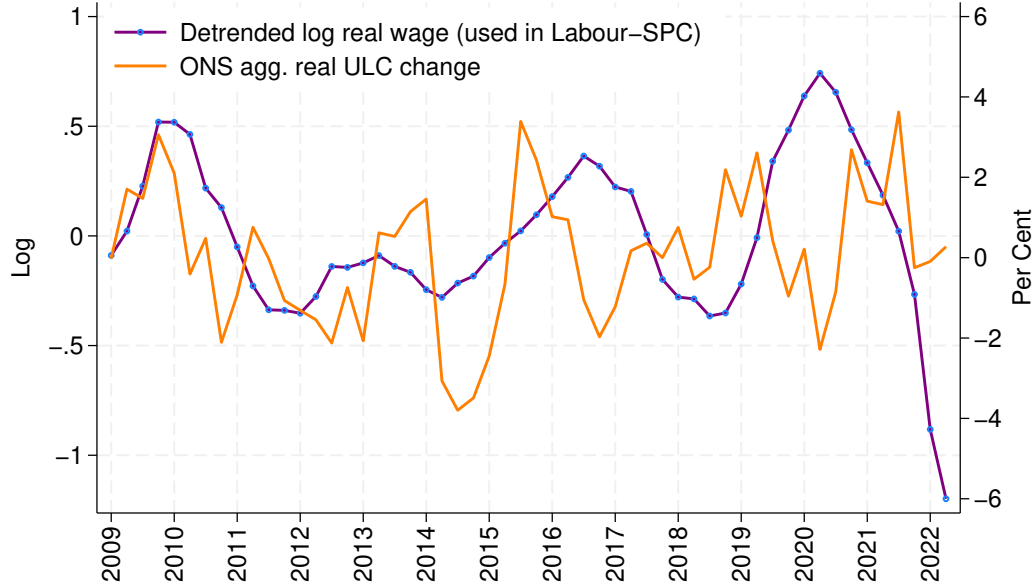
D.4 Output gap

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 24. This measure was not statistically significant when used as a slack measure in the SPC estimation.

D.5 Other Data

The real oil price inflation is the change in oil price adjusted by bilateral FX change. This measure is based on Roberts (1995), calculated as $DCOILBRENTU - DEXUSUK$. $DCOILBRENTU$ 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

FIGURE 23: AVERAGE REAL WAGE (ACROSS ALL INDUSTRIES) AND ONS AGGREGATE REAL ULC



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

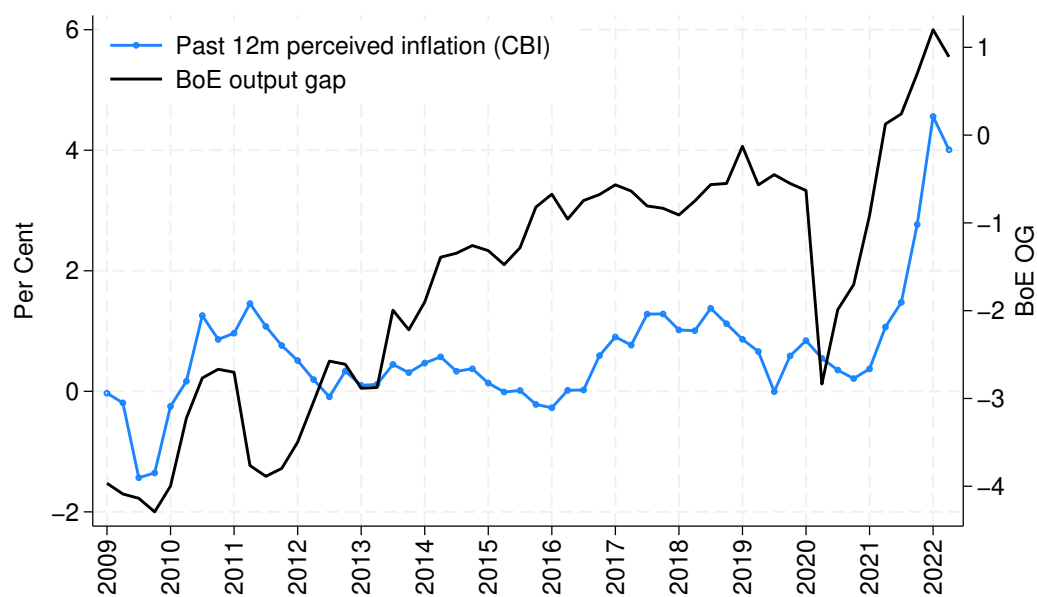
An alternative measure for the labour share used in the estimations, as suggested by BJN: $\ln[((HAEA \cdot A)/ABML) \cdot 100]$, where $A = (E + SE)/E$. E is given by BCAJ³⁷, the number of employee workforce jobs (seasonally adjusted), while SE is given by DYZN, the number of self-employment workforce jobs (seasonally adjusted).

Relative price of imports = $\ln[(IKBI/IKBL) \cdot 100] - \text{GVA deflator}^{38}$, where $IKBI$ is total imports (current prices), and $IKBL$ is total imports (constant prices).

³⁷Four letter codes refer to series produced by the ONS

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

FIGURE 24: CBI SECTORAL INFLATION AND BoE OUTPUT GAP



Notes: 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.

FIGURE 25: 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.

TABLE 14: INDUSTRY CHARACTERISTICS BY INDUSTRY (2DIG-SIC)

	CR5	HHI	Share of petrol over costs	Share of energy over costs	Share of imports over sup- ply	ULC variabil- ity
Mining, quarrying	0.94	0.24	4.19	3.72	11.62	24.84
Food products	0.23	0.02	0.36	1.97	21.68	3.52
Beverages	0.69	0.15	0.58	1.47	13.96	3.52
Textiles	0.45	0.06	0.20	1.77	33.58	3.52
Wearing apparel	0.66	0.26	0.07	0.70	37.34	3.52
Footwear, luggage	0.68	0.16	0.14	0.72	47.85	3.52
Wood products	0.32	0.03	0.49	1.89	27.55	3.52
Paper products	0.75	0.26	0.49	3.60	23.11	3.52
Printing and reprod	0.36	0.03	0.10	2.55	0.07	3.52
Chemicals	0.41	0.07	3.47	3.70	30.02	3.52
Pharmaceut. Prod	0.81	0.24	0.00	0.92	32.63	3.52
Rubber and plastic	0.16	0.01	0.19	2.88	37.60	3.52
Non-metal mineral	0.26	0.02	1.92	3.94	14.65	3.52
Basic metals	0.76	0.22	6.36	2.89	45.86	3.52
Fabricated metal	0.11	0.00	0.28	1.02	17.92	3.52
Computer & electronic	0.40	0.03	0.03	0.98	48.02	3.52
Electrical equipment	0.21	0.01	0.03	0.74	40.70	3.52
Machin and equipm.	0.47	0.07	0.13	0.93	37.42	3.52
Motor vehicles	0.69	0.14	0.09	0.80	35.45	3.52
Other vehicles	0.77	0.18	0.10	0.88	36.24	3.52
Furniture	0.23	0.02	0.32	1.21	25.55	3.52
Other Manuf	0.16	0.01	0.19	0.96	34.65	3.52
Medical & optical	0.50	0.15	0.99	0.86	9.66	3.52
Wholes motor vehicle	0.19	0.01	0.91	0.55	0.29	13.88
Wholesale trade	0.25	0.01	3.56	1.27	119.50	13.88
Land transport	0.33	0.03	6.17	1.32	4.47	19.37
Water transport	0.23	0.01	6.56	0.17	20.43	19.37
Aux transport activ	0.56	0.13	1.75	1.17	3.93	19.37
Postal and courier	0.88	0.30	4.12	0.05	3.24	19.37
Accommodation	0.33	0.03	0.24	4.88	14.56	33.32
Restaurants & food	0.49	0.14	0.06	2.11	2.48	33.32
Computer program	0.27	0.02	0.11	0.30	5.40	14.53
Fin service act	0.21	0.01	0.49	0.42	8.32	7.62
Insurance & pension	0.54	0.08	0.27	0.09	4.63	7.62
Act. aux to fin serv.	0.49	0.09	0.60	0.80	5.85	7.62
Real estate activities	0.13	0.01	0.39	1.62	0.90	12.88
Legal & accounting	0.29	0.02	0.34	0.61	6.09	8.97
Managm consultancy	0.18	0.01	0.36	0.35	24.40	8.97
Architect & enginee.	0.40	0.04	0.53	0.23	10.17	8.97
Advertising & market	0.40	0.04	0.11	0.17	11.20	8.97
Photographic & film	0.18	0.01	0.94	0.59	2.94	8.97
Veterinary	0.66	0.09	0.24	0.80	0.10	8.97
Renting & leasing	0.40	0.04	1.38	0.58	8.79	6.12
Employment act.	0.21	0.02	0.16	0.27	5.53	6.12
Travel agency	0.36	0.03	0.93	2.05	0.49	6.12
Private security act.	0.29	0.03	0.90	0.32	0.14	6.12
Cleaning	0.31	0.02	1.29	0.15	0.07	6.12
Other business support	0.17	0.01	0.48	0.37	39.53	6.12
Recreational,cultural	0.43	0.08	0.67	2.76	13.59	13.44
Sporting activities	0.23	0.02	0.23	2.59	2.48	13.44
Other service acts.	0.20	0.01	0.75	1.22	0.30	16.02

Notes: This table shows the inputs used for regressions shown in Table 7.