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 sectoral 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.

Keywords: Expectations, pricing, production networks, monetary policy, survey data
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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 essential for effective monetary policy formulation. Despite extensive research, most papers face challenges in identifying the NKPC parameters. By using disaggregate data and direct measures of expectations, I establish that the (positively sloped) Phillips Curve has not disappeared, as it has been claimed when using aggregate data (Coibion and Gorodnichenko 2015; Del Negro, Lenza, et al. 2020).

In this paper, I present a novel approach to estimating Sectoral Phillips Curve (SPCs) based on a theoretical microfounded framework, utilising a unique confidential survey dataset. My contribution is threefold: First, I address prevalent weak identification issues by employing direct measures of firms' expectations, along with industry-level data on prices and salary costs. This disaggregated approach uncovers a robust positive response of inflation to both expected inflation and labour costs. Specifically, I find that the slope of sectoral inflation with respect to labour costs is 0.1, while the response of sectoral inflation to expected inflation is 0.6. These findings indicate that the theoretically predicted Phillips Curve holds true when utilising disaggregate data, thereby challenging claims derived from aggregate data or weak proxy measures.

Second, I include micro-level time-varying data on intermediate goods shares using input-output tables. This integration highlights a significantly greater inflation response to costs than traditional models suggest, emphasizing the critical role of sectoral linkages and intermediate goods—factors often overlooked in conventional Phillips Curve analyses. To my knowledge, this is the first study to estimate SPCs using both direct measures of firms' expectations and detailed input-output data.

Third, by applying panel time series methods with sector-specific coefficients I uncover large sectoral heterogeneity in SPC parameters. I explore the sources of this heterogeneity, revealing that market concentration significantly influences the sensitivity of inflation to expected future inflation. Specifically, sectors with higher competition appear to react less to their own expectations, instead closely tracking their competitors' prices.

Identifying the Phillips Curve parameters — i.e. the sensitivity of current inflation to expected future inflation and to firms' costs — presents several challenges. Many of these challenges are related to the data used as proxies and model specification issues. A common data-related challenge arises from the lack of available data on firms' expectations. This makes it difficult to identify the actual sensitivity of current inflation to expected future inflation. In the literature to date, expectations have primarily been approximated using actual inflation, professional forecasts, households' or rational expectations. However, these proxies have been largely criticised for being weak instruments (Coibion, Gorodnichenko, and Kamdar 2018). Firstly, using survey-based expectations mitigates the risk of weak proxies and resulting bias in the estimation. Secondly, accurately identifying and understanding this parameter is crucial for monetary policy formulation, given that inflation expectations are a powerful tool for controlling inflation.

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) find significant and positive slopes using regional data, while Imbs et al. (2011) and Byrne et al. (2013) do so with sectoral data.

The novelty of this paper stems from combining industry-level data with direct measures of firms' expectations, supplier prices, and salary costs. This approach addresses the challenges associated with aggregate data, indirect measures of expectations, and other weak proxies. By utilising a unique survey dataset produced by the UK's Confederation of British Industry (CBI) and the Bank of England (BoE), which provides quarterly data on narrowly defined industries since 2009, I leverage direct measures of firms' inflation expectations, which are not commonly available.

This study also highlights the advantages of using salary cost data as a forcing variable instead of output, as emphasised in Gagliardone et al. (2023a). Many studies resort to proxy measures — such as the output gap or labour share — due to a lack of firm-level labour cost data, often yielding negative Phillips Curve slopes. Such a negative slope may be indicative of a low elasticity of marginal cost to the output gap rather than a low response of inflation to costs. Therefore, using salary costs mitigates this identification problem. Additionally, I employ industry-level prices from the survey to track inflation over time and serve as proxies for supplier prices. The integration of these micro-level inputs costs with input-output tables enables the estimation to effectively capture the influence of production networks on the industry-level inflation process. However, while survey data offers more realistic insights, it may be subject to measurement errors. I address this concern through two methods: first, by showing that, on average, survey-based data on industry-level inflation aligns closely with official data, and second, by incorporating sector fixed effects.

Potential weak identification of the Phillips Curve may also arise from model misspecification. To navigate this, I estimate the SPC based on two microfounded frameworks that differ primarily in their production functions and the transmission of nominal rigidities. The first framework, termed the *Labour-cost SPC*, primarily focuses on labour costs as the source of cost variation and builds on the work of Imbs et al. (2011) (henceforth IJP). My estimation of the *Labour-cost SPC* diverges from IJP in various ways: I study 52 industries in the UK, including those in manufacturing, distributive, retail, and services sectors. Furthermore, I use survey-based industry-level prices, direct measures of expectations, and salary costs.

The second framework, referred to as the *Full-cost SPC* emphasises the inclusion of intermediate goods alongside labour in the production function. Building on Rubbo (2023), I derive the Full-cost SPC expression, which features equivalent reduced-form parameters as the Labour-cost SPC. The Labour-cost SPC assumes that firms experience price stickiness due to infrequent price adjustments. In contrast, the Full-cost SPC shows that the industry's inflation response to costs is influenced not only by its own infrequent price adjustments but also by those of its suppliers. Industries are affected by both common and idiosyncratic shocks and face asymmetric nominal rigidities and production costs when setting prices and wages. The estimation of the *Full-cost SPC* reveals a markedly higher response of industry-level inflation to firms' costs compared to the *Labour-cost SPC*, around 0.5. This difference arises from the inclusion of intermediate goods costs and embedded sectoral linkages.[1]

Methodologically, panel analysis introduces the potential issue of unobserved common shocks affecting industries. Neglecting these common effects can lead to correlated errors with industry-specific variables. To mitigate this, I employ the Common Correlated Effects (CCE) estimator proposed by Chudik and Pesaran (2015), which effectively reduces cross-sectional dependence. By controlling for CCEs, I address the strong cross-sectional dependence that could distort my results.

Moreover, the traditional assumption of sectoral homogeneity in the Phillips Curve can lead to misleading and inconsistent results, such as higher inflation inertia and lower significance of costs. By estimating industry-specific parameters through the SPCs, I uncover substantial heterogeneity in the strength of the slope and the role of expectations across industries.

Upon unmasking the sectoral heterogeneity, I delve into its underlying sources, focusing on industry characteristics often overlooked in the existing frameworks. While the micro-

[1]IJP acknowledge the importance of sectoral linkages but don't explicitly model them. They implement the Seemingly Unrelated Regression Equations (SURE) correction to capture cross-sector interdependencies.

foundations of the SPC predicts sectoral heterogeneity in parameters, they fall short of providing a 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.

These findings are particularly relevant given the complexities in inflation dynamics observed over the past decade. They contribute to a more nuanced understanding of the inflation process by accounting for potential sectoral transmission of rigidities and shocks. In both frameworks, the average parameters indicate positive and significant values, underscoring the role of expectations and lagged inflation.

These findings are particularly relevant in light of the complex inflation dynamics observed over the past decade, where the average parameters within both frameworks reveal positive and significant values. This underscores not only the positive slope of the Phillips Curve but also the critical roles played by both expectations and lagged inflation in explaining current inflation. Specifically, the Full-Cost framework enhances our understanding of the inflation process by considering the potential transmission of sectoral rigidities and shocks, offering deeper insights into inflation dynamics.

The implications of these findings extend to current policy discussions, especially concerning the impact of inflation expectations on actual inflation and the sources of sectoral heterogeneity. The critical role of inflation expectations in the recent high-inflation episodes is emphasized in Reis (2023), who critiques the use of professional forecasts and median household surveys for capturing inflation persistence. Reports by the IMF (2023) suggest that the efficacy of monetary policy may diminish in the face of prolonged inflationary supply shocks if inflation's sensitivity to expectations is muted. Furthermore, IMF (2022) notes that a more backward-looking inflation, with lesser emphasis on future expectations, requires more pronounced and rapid policy response to mitigate escalating inflation. 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 share 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), Hazell et al. (2022), and Fitzgerald et al. (2024), 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 industry-level data.

While prior studies in the literature (Leith and Malley 2007; Imbs et al. 2011; 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 (2019), which estimates aggregate Phillips Curves using survey data from households. 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 industries 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 theory behind the two proposed SPC frameworks. 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 Theoretical Frameworks

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. In the second part I introduce the *Full-cost SPC* using elements from Rubbo (2023) which explicitly models the production network.

2.1 Labour-cost SPC

The *Labour-cost SPC* is analogous to the aggregate NKPC, but instead of being nationwide, it provides sector-specific parameters.[2] 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 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.1.

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

where

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

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^{π}_{kt}, is a cost-push shock.

The factor h_{kt} is a labour adjustment which depends on the elasticity of substitution across varieties, η, and the labour share $(1 - a_{kt})$.[3]

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

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

[3]The parameter η is included in the demand function, as described in Appendix A.1

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

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

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, denoted as α_k, is allowed to vary across sectors.[4] Prices in sector k are comprised by $(1 - \alpha_k)$ share of firms that have updated prices at time t and a α_k share of firms that have maintained last period's prices. As they anticipate a delay before the next price change, firms form expectations about future costs. They then optimally set their prices at P_{kt}^* as a mark-up over their marginal costs. Therefore, the sectoral price level in period t is calculated as:

$$P_{kt} = \alpha_k \, P_{k\,t-1} + (1 - \alpha_k) \, P_{kt}^* \tag{3}$$

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

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

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

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.

[4] One 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.

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.

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

This framework captures sectoral linkages through micro-level intermediate input shares and incorporates the concept that nominal rigidities might emerge from other sectors' stickiness. Firms 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:[5]

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

Equation 4 represents the sectoral inflation rate process, jointly explained by sector-level marginal costs $\hat{\mathbf{mc}}_t$, net of same sector lagged prices $\hat{\mathbf{p}}_{t-1}$, and sector-level inflation expectations. Bold letters indicate vectors, implying that the variable applies to all sectors, leaving the subindex k unnecessary. Capital letters represent matrices, and the parameter $\tilde{A}$ corresponds to the diagonal of sector-level price stickiness.

For illustrative purposes, considering two sectors or industries, 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

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

in sector 2.[6] In reality, matrix $\tilde{A}$ will be of size $k \times j$.

$$\hat{\mathbf{mc}}_t = (1 - \mathbf{a})\,\hat{\mathbf{w}}_t + \Lambda\,\hat{\mathbf{p}}_{jt} - log\mathbf{Z}_t \tag{5}$$

Equation 5 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 4 and Equation 5 and after working out the algebra, I obtain the expression shown in Equation 6.[7]

$$\hat{\boldsymbol{\pi}}_t = (I - \Lambda\,\tilde{A})^{-1}\boldsymbol{\beta}(1 - \tilde{A})\,\boldsymbol{E_t}\hat{\boldsymbol{\pi}}_{t+4} + (I - \Lambda\,\tilde{A})^{-1}\tilde{A}\;\hat{\mathbf{s}}_t^F \tag{6}$$

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

$$\hat{\mathbf{s}}_t^F \equiv (1 - \mathbf{a}_t)\,\hat{\mathbf{w}}_t + \sum_j \lambda_{kjt}\,\hat{\mathbf{p}}_{jt} - (1 - \lambda_{kkt})\hat{\mathbf{p}}_{t-1} \tag{7}$$

Expression 7 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 6, I obtain the *Full-cost SPC*, which is

[6] Following the original paper, the tilde in $\tilde{\alpha}$ (and $\tilde{A}$) indicates that α (and A) is adjusted by the discount factor β.

[7] In Appendix A.2 I show the derivation of the system with 2 sectors for illustrative purposes.

equivalent to the *Labour-cost SPC* but accounting for the sectoral linkages:

$$\hat{\boldsymbol{\pi}}_t = \boldsymbol{\gamma}^{\boldsymbol{f}}\, \mathbf{E}_t\, \hat{\boldsymbol{\pi}}_{t+4} + \boldsymbol{\gamma}^{\boldsymbol{s}}\, \hat{\mathbf{s}}_t^F + \boldsymbol{\varepsilon}_t^{\pi} \tag{8}$$

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.

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. 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.[8] However, these methods have faced criticism, particularly regarding the issue of

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

weak instruments. A proposed solution is to use survey-based expectations, as suggested by studies like Nason and G. W. Smith (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.[9]

3.2 Industry-level Data

The empirical disconnect between inflation and output gap results from the successful and optimally set monetary policy, as elaborated in McLeay and Tenreyro (2019). 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 costs, thereby confirming that hypothesis. At the sector or 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 industries 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,

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

particularly when these costs exhibit high persistence.

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

If I were to estimate Equation 2, but with homogeneous coefficients across industries, and these coefficients were actually heterogeneous — $\gamma^f_k \neq \gamma^f$, $\gamma^b_k \neq \gamma^b$ and/or $\gamma^s_k \neq \gamma^s$ — the errors ε_{kt} would be correlated with the explanatory variables, as shown in Equation 9, resulting in biased estimated coefficients.

$$\varepsilon_{kt} = \Big[u_{kt} + (\gamma^f_k - \gamma^f)\, E_{kt}\{\hat{\pi}_{k\,t+4}\} + (\gamma^b_k - \gamma^b)\,\hat{\pi}_{k\,t-1} + (\gamma^s_k - \gamma^s)\, h_{kt}\,\hat{s}_{kt}\Big] \tag{9}$$

Therefore, I will estimate dynamic panel model with heterogeneous industry-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 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) developed by Chudik and Pesaran (2015).

3.4.1 Background:

The CCE estimator, is designed to address the challenge of Cross-Sectional Dependence (CSD) and enhance the estimation efficiency. This estimator introduces a correction technique to account for unobserved common factors, potentially correlated with industry-specific regressors.[10]

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.

[10]Proposed by Pesaran (2006) and expanded by Chudik and Pesaran (2015), CCE estimators perform well in models with lagged dependent variables and weakly exogenous regressors when augmented with sufficient lags and cross-sectional averages.

To provide further insight: certain shocks affecting the UK economy, such as Brexit and Covid, might have impacted various industries differently and simultaneously. The omitted factors constitute an unknown, fluctuating set of determinants that are correlated with inflation and the regressors.

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 effects are complemented by industry-specific "factor loadings" aimed to capture the differential impact across industries.

In order for the CCE Mean Group estimator to be valid, the industry-level equations of the panel must include a sufficient number of lags of cross-sectional averages (N_{lags}), leaving enough degrees of freedom for consistent estimation. Chudik and Pesaran (2015) suggests that $N_{lags} = \sqrt[3]{T}$. In this work, $T_{min} = 45$ and $T_{max} = 54$, which results in N_{lags} slightly above 3. This approach effectively reduces data dimensionality and prevents overfitting by focusing on the most influential factors affecting the variables of interest.

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

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

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 $g_{u,k} \neq 0$.[11]

3.4.2 Implementation

In the case of the *Labour-cost SPC*, I augment Equation 2 as follows:[12]

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

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

where Equation 10 includes 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

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

[12]In the case of the Full-Cost SPC, Equation 8 is expanded similarly.

inflation but also expected inflation and real marginal costs. 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.[13]

I compute cross-sectional averages z_t to approximate the time-varying covariates, as proposed in Chudik and Pesaran 2015. 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.[14] I also incorporate oil price inflation into f_t given its relevance for the UK (Batini et al. 2005). With the same rationale, I attempted to include real import prices, but they yielded insignificant results, likely due to their high correlation with oil price inflation.

Adding up to 3 lags of cross-sectional average proves to be sufficient to eliminate the strong cross-sectional dependence, as previously explained.

Next, I provide an illustrative framework for estimating Equation 10, which effectively mitigates 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, refer to the regression outputs in Table 2.

$$
\begin{aligned}
\pi_{kt} = {} & \alpha_k + \gamma_k^b\, \hat{\pi}_{k\,t-1} + \gamma_k^f\, E_{kt}\, \hat{\pi}_{k\,t+1} + \gamma_k^s\, h_{kt}\, \hat{s}_{kt} \\
& + \sum_{s=0}^{3} g_{1\,k}\, \overline{E_{k\,t-s}\, \hat{\pi}_{k\,t+4-s}} + \sum_{s=0}^{2} g_{2\,k}\, \overline{\hat{s}_{k\,t-s}} + \sum_{s=0}^{2} g_{3\,k}\, \hat{\pi}_{t-s}^{oil} + \varepsilon_{kt}^{\pi}
\end{aligned}
\tag{12}
$$

3.5 Further discussion on Cross-Sectoral Interdependencies:

Factors present in the studied frameworks, such as input-output production linkages and integrated factor markets can lead to cross-sectoral interdependencies. In the previous section I discussed the estimation of the SPCs while addressing cross-sector interdependencies through econometric techniques, without explicitly modelling the sectoral linkages, as it is also approached in other previous studies (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.

[13]See Eberhardt and Presbitero (2015) for an empirical application of these methods.
[14]See details in Correlation Table 6.

In my analysis of the Full-Cost SPC I complement the use of CCEs, which capture unobserved common factors, with input-output tables to account for observed sectoral linkages. This approach further alleviates the risk of cross-sectional dependence and captures the effects of intermediate goods shares and input prices throughout the supply chain.

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. (2023a) 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.

3.6.2 Time Series Properties

Temporal aggregation poses a common challenge in this literature due to differences in the frequency of the data. While the CBI perceived past and expected future inflation data are annual, the frequency is quarterly. To address potential correlation over time, I use lagged variables to instrument the regressors. This approach is supported by Mavroeidis et al. (2014), who emphasise the use of lags as instruments for robust inference.[15]

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 8 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 costs, and vice versa, as found by Gagliardone et al. 2023a.

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.

[15] Panel unit root tests reject that series are nonstationary, see Table 7.

3.7 Using Labour Costs Over Using Output Gap as Proxy

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.[16] 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.

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]

In this study, I use firm-reported data of salary costs from the survey as proxy for the slack measure. Industry-level nominal marginal costs are calculated as the average of the costs across firms of industry k.

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, and change in prices 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

[16] 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.

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

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 Panel[18]. 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 mining firms, and an over-representation of financial services 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.

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.[20] Further information available from the survey about firms' characteristics include

[18]The 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.

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

[20]Although the CBI survey began in 1958, the quantitative question on past and expected future price movements started being collected in 2008. This work focuses on data starting in 2009 given that very few

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 published 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 and studies firm-level prices. 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. The other difference is that the above mentioned authors use the question on firms' own-prices whereas this work uses the question on industry-level prices. More details below.

4.1.1 Inflation Expectations Question

The key question about perceived and expected own-industry inflation is framed identically in the four surveys: "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?".[21]

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%.[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] Interestingly, while only 8% of reports were above the 5% bucket during the stable inflation period 2009-2019, the share of reports above the 5% bucket rose to 25% when inflation

data points were collected in 2008.

[21]The question that is not used in this study, regarding own-firm inflation expectations, 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?"

[22]Specifically, the buckets for ITS are -8.1 to -10%; -6.1 to -8%; -4.1 to -6%; -2.1 to -4%;-0.1 to -2%; no change; 0.1 to 2%; 2.1 to 4%; 4.1 to 6%; 6.1 to 8% and 8.1 to 10%. The buckets for DTS, FSS and SSS are -4.1 to -5%; -3.1 to -4%; -2.1 to -3%; -1.1 to -2%; 0 to-1%; no change; 0.1 to 1%; 1.1 to 2%; 2.1 to 3%; 3.1 to 4% and 4.1 to 5%.

[23]Bank of England/Ipsos Inflation Attitudes Survey.

started increasing in the UK in 2020. This suggests that firms make use of the larger buckets and manual entry to report higher inflation rates.

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 2009q1 to 2022q2 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 C. 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. For my analysis, however, I focus on 52 industries for which I have a time series spanning more than 45 quarters. Each of these industries has at least 45 quarters of data, with some reaching up to 54 quarters. This approach offers several advantages. First, a long time series ensures a decent number of degrees of freedom even after incorporating lags in the regression analysis. Second, it allows for a more balanced panel. A long time series is also required to implement the CCE estimator in order to eliminate the strong cross-sectional dependence (as discussed in Section 3.4). However, this comes at the cost of some quarters being represented by only one firm's input rather than an average from multiple firms in the industry. This occurs in 158 instances, representing 5% of the panel.

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 6 and 7 in Appendix B, which illustrate the sectoral inflation expectations, averaged across firms within each 2-digit SIC category. Figures 7a and 7b 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.

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 (Figure 6a). However, a notable shift has occurred in recent times. By the end of 2021 (Figure 6b), the entire distribution of services expectations has skewed

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

towards higher expected inflation rates, being located by then between 0% to 6%. Interestingly, the industries with the highest expected sectoral inflation rates in this period were 55, 56, 63, 72, and 81, a departure from the trends observed in 2010.

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 comprehensive understanding of inflationary pressures.

4.2 Official Inflation vs. Survey-based Perceived Sectoral 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. I will explain the difficulties associated with each of them and why I choose the latter for SPC estimation.

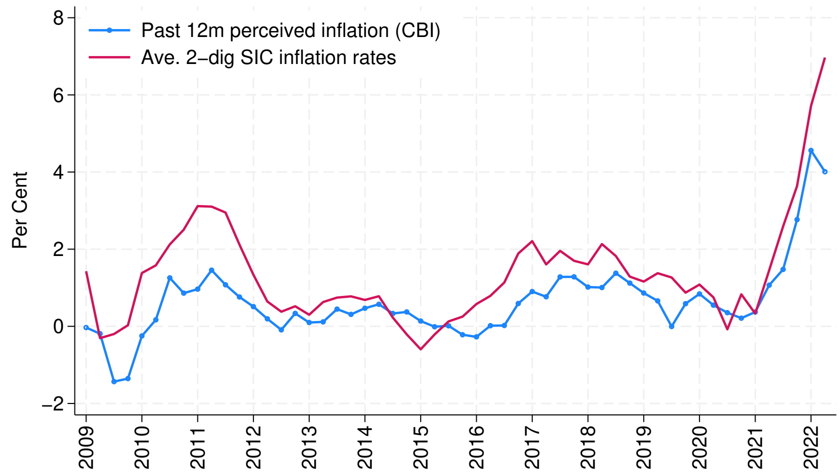
One challenge with using ONS inflation data is the lack of granularity at the 4-digit SIC level observed in the CBI reports. The ONS provides disaggregated Producers Price Indices (PPI) by SIC code for industrial sectors, while Consumers Price Indices (CPI) and Services Producer Prices Indices (SPPI) 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 10 and Figure 1 that survey-based sectoral inflation perceptions closely align with official inflation rates at the 2-digit SIC level. The correlation between the perceived (CBI) past inflation and the average of aggregate ONS inflation indices is 0.88, being the R-squared 0.78.

[25] For 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.

4.3 Measures of Cost

As discussed in Section 3.7, variations in production costs are the preferred measure to estimate the labour-cost SPC slope. For the sake of robustness, I have also tested the output gap, however not yielding a significant slope.

4.3.1 Labour Cost

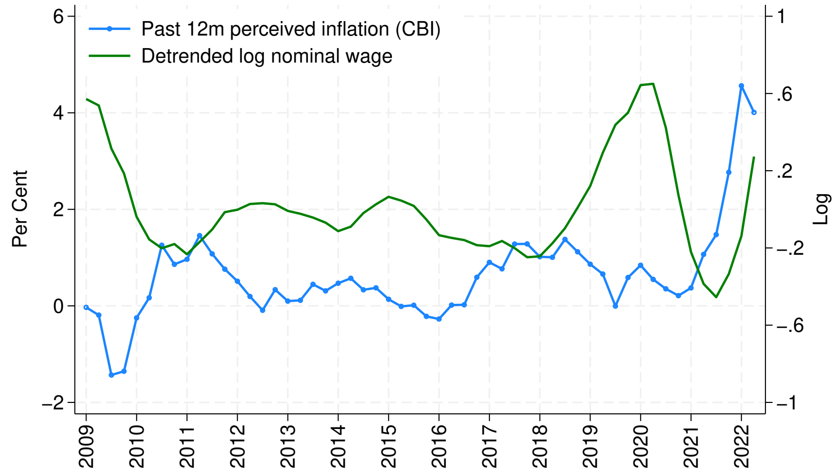
As it is standard in the literature, industry-level labour costs is calculated as the detrended log real wage.[26] To compute the detrended log real wage, denoted as $\hat{s}_{kt}$ and shown in Figure 2, I first compute the nominal wage series as levels from the survey-based "change in wage/salary cost 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 $\hat{w}_{kt} = w_{kt} - \overline{w}_k$ and detrended log price is represented as $\hat{p}_{kt} = p_{kt} - \overline{p}_k$. Lastly, the detrended log of the real product wage is defined as $\hat{s}_{kt} = \hat{w}_{kt} - \hat{p}_{kt}$, which I will often refer to simply as "Labour Cost".

[26]Also common in the literature is the use of the unit labour cost (ULC), the problem being for the UK is that it is not available at the 2-digit SIC level. See details in Appendix C.

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

[28]See a time series plot of the average real marginal cost in Figure 17 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.

4.3.2 Full Cost

In order to construct the measure of "Full cost" — defined in Equation 7 — 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 explain in the next section how I obtain the first two from the input-output table.

For the calculation of intermediate goods' prices, I first compute quarterly sectoral prices by dividing the perceived sectoral inflation from the CBI over the past 12 months by four, represented as $\pi^q_{kt} \equiv \frac{\pi^y_{kt}}{4}$. By indexing the price series with the first quarter data point as 100 and applying quarterly changes throughout the series, I generate a price level series for each 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 $\hat{p}_{kt}$.

4.3.3 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.

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*, I estimate the hybrid version of Equation 8, as follows:

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

5.1 Previous Research on Phillips Curve Estimation in the UK

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.

As suggested by Batini et al. (2005), I studied the relevance of foreign factors.[29] While oil price inflation and real import prices as regressors in the SPC did not yield statistically significant results, 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 2 and for the *Full-cost SPC* in Table 3. In both cases, the three columns indicate different specifications: Column 1 shows the estimation of a pooled model assuming homogeneous coefficients for all industries, 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 common factors to control for CCEs, labelled the "Full model". All models incorporate industry-level fixed effects.

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.

The addition of up to three lags of cross-sectional averages to eliminate strong cross-sectional dependence proves to be sufficient as the CD test shows a p-value of 0.42 in the case of the Full model. This result suggests that it is not necessary to add extra lags for the cross-sectional averages.

As discussed in section 3.6.2, we may worry that perceived past inflation may be simultaneously determined with inflation expectations and salary costs, and that the annual measure of expectations may lead to serial correlation in the error term. To address the endogeneity risk, I use lagged variables as instruments, following the approach of Gagliardone et al. 2023b. Table 8 shows the relevance of these instruments. Lagged expectations significantly explain current expectations, showing the expected sign and reflecting the time overlapping effect due to annual changes. The conversion of the labour cost series from an-

[29] See details on the open-economy framework in A.3.

Table 2: *Labour-cost SPC*

	Pooled [1]	MG [2]	Full model [3]
	Dependent variable: CBI sectoral inflation		
Expected sectoral inflation (γ^f)	1.02***	0.80***	0.63***
	(0.21)	(0.08)	(0.11)
Lagged sectoral inflation (γ^b)	0.35***	0.23***	0.17***
	(0.10)	(0.04)	(0.04)
Labour cost (γ^s)	0.06**	0.07*	0.13***
	(0.02)	(0.04)	(0.04)
Heterogeneous/Homogeneous Coeff.	Homogeneous	Heterogeneous	Heterogeneous
FE (k)/CCE	FE(k)	FE(k)	FE(k) + CCE
Observations	2,507	2,507	2,507
Number of groups	52	52	52
RMSE	2.24	2.16	1.64
CD test (p-value)	0.00	0.01	0.42

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. Dataset is restricted to 52 industries with time series spanning between 45 and 54 quarters. Data 2009q1-2022q2. S.E. in parenthesis (robust in model 1). *** p<0.01, ** p<0.05, * p<0.1.

nual to quarterly terms shows that only one lag is statistically significant. Importantly, the lags of expectations have little predictive power on labour costs, and vice versa. For models [2] and [3], the usual IV test statistics are not available as these models are first partialled out from the CCEs. The tests conducted on Model [1] can be used as a reference since the same data and instruments are used in [2] and [3]. IV tests on Model [1] indicate that the instruments are not weak, and the model should provide reliable and consistent estimates.[30]

Comparing the three model specifications reveals that the Full model consistently yields the lowest Root Mean Squared Errors (RMSE) in both frameworks — the *Labour* and *Full-cost SPC*.[31] 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*.

[30]The Cragg-Donald Wald F statistic of 59.91 is well above the critical value of 13.97 for a 5% maximal IV relative bias. Additionally, the null hypothesis of underidentification is rejected, with the Kleibergen-Paap LM statistic at 56.43 and a p-value of 0.00.

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

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, i.e. 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 $\gamma^f : 0.7^{***}$.[32] 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 $\gamma^b : 0.1$ and $\gamma^f : 1.6^{***}$, while McLeay and Tenreyro (2019) reported $\gamma^b : 0.1^{***}$ $\gamma^f : 0.22$.

Table 3: *Full-cost SPC*

	Pooled [1]	MG [2]	Full model [3]
	Dependent variable: CBI sectoral inflation		
Expected sectoral inflation (γ^f)	0.87***	0.57***	0.56***
	(0.20)	(0.07)	(0.10)
Lagged sectoral inflation (γ^b)	0.32***	0.23***	0.16***
	(0.08)	(0.04)	(0.04)
Full cost (Labour and Int. goods) (γ^s)	0.32***	0.86***	0.89***
	(0.10)	(0.17)	(0.24)
Heterogeneous/Homogeneous Coeff.	Homogeneous	Heterogeneous	Heterogeneous.
FE (k)/CCE	FE(k)	FE(k)	FE(k) + CCE
Observations	2,436	2,436	2,436
Number of groups	52	52	52
RMSE	2.03	1.64	1.46
CD test (p-value)	0.00	0.00	0.42

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. Dataset is restricted to 52 industries with time series spanning between 45 and 54 quarters. S.E. in parenthesis (robust in model 1). *** p<0.01, ** p<0.05, * p<0.1.

Byrne et al. 2013 assume that $\gamma^f + \gamma^b = 1$ and argue that this assumption precludes the

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

existence of a long-run level trade-off between inflation and real marginal costs. Based on theory and the evidence presented above, we may expect that the forward- and backward-looking coefficients sum to one or less than one. In Table 11 I show that for the Labour-cost SPC, $\gamma^f + \gamma^b$ is below one only in the case of the Full Model [3]. In Model [2] the sum appears to be slightly above one, but it is not statistically significantly different from 1. The joint coefficient for the Full-cost SPC is below 1 in both models [2] and [3], and it is statistically significantly equal to 1 in both cases.

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. Importantly, while the average slope for the Full-cost SPC of 0.9 (see Table 3) seems too high, this average decreases to 0.5 when considering only the significant coefficients. Despite the lack of comparable estimates from the literature for the Full-cost SPC, a value of 0.5 appears more reasonable than 0.9. The reason for the insignificant or poorly defined industry-specific estimates is unknown. It could be due to specific dynamics or industry characteristics that we cannot control for in a panel estimation of a structural SPC relationship, or it might be related to shorter time series for some industries.

In Table 4 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. See some robustness analysis using different set of proxies for the CCEs and results for the sub-sample period before Covid in Section D.1.

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 is important to highlight the broad heterogeneity that exists across industries beneath these averages. In this section, I will delve into the results further, presenting

Table 4: Aggregate (nationwide) Phillips Curve regression

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

industry-specific parameters, obtained from the Full models in Table 2 and Table 3.

It is important to note that these industry-specific parameters were estimated as a panel to account for cross-sectional interdependencies and common factors. By aiming to estimate the SPC reduced-form parameters, the empirical specification is constrained to the micro-foundation previously discussed, at the cost of potentially not capturing specific dynamics or characteristics at the industry-level. Consequently, the industry-level estimates are not always significant or perfectly-defined, similar to the findings of Imbs et al. 2011.

Figures 3, 4 and 5 display the histogram distribution of the estimated parameters: the slope, the forward lookingness, and the backward-lookingness, respectively. In Appendix B I provide the specific parameters from the *Labour-cost* and the *Full-cost SPC* frameworks for each industry, along with the average parameters within each group.[33]

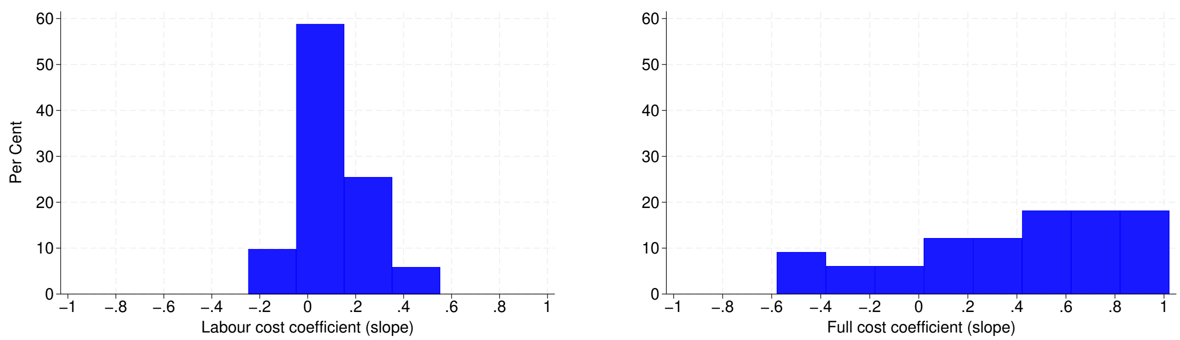
[33] With groups I refer to: Manufacturing, Distributive/Retail, Services, Financial Services.

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. This contrast underscores the significant impact of including intermediate goods costs in the pricing decisions, i.e. embedding the production networks into the pricing decisions yields a much larger responsiveness of inflation to costs for the majority of industries.

Figure 3: Industry-specific parameters: slope

(a) *Labour-cost SPC* γ^s (b) *Full-cost SPC* γ^s



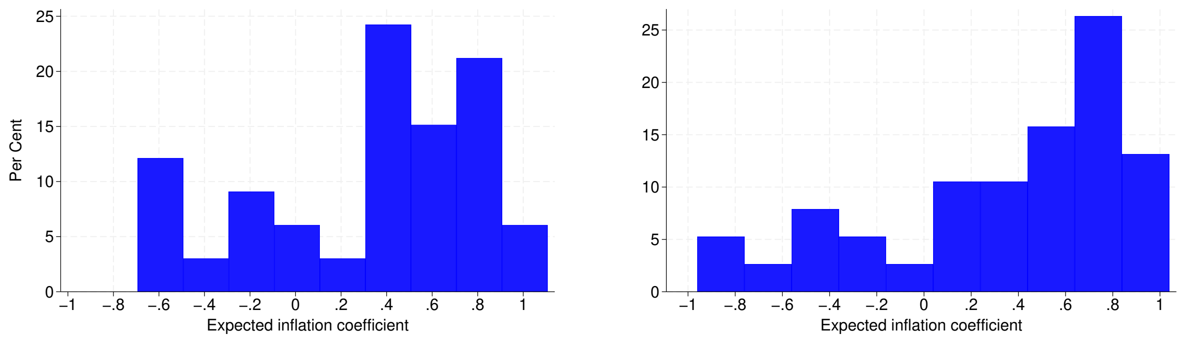
Upon examining whether differences in parameters can be explained by their broad group nature — e.g. manufacturing versus services industries — I find no discernible differences. For the *Labour-cost SPC*, the average parameter for manufacturing is similar to that of services, at around 0.1. While retail and financial services industries exhibit, on average, the lowest and almost null inflation response to costs (refer to Figure 8), 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) show similar patterns, emphasising 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 9). 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

(A) *LABOUR-COST SPC* γ^f (B) *FULL-COST SPC* γ^f

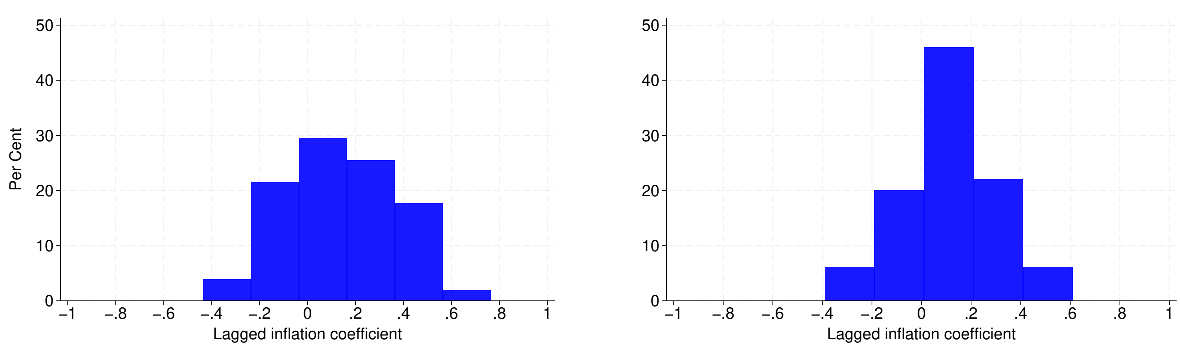


5.3.3 Backward-lookingness

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 10, 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.

FIGURE 5: INDUSTRY-SPECIFIC PARAMETERS: LAGGED INFLATION

(A) *LABOUR-COST SPC* γ^b (B) *FULL-COST SPC* γ^b



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

6 Determinants of Sectoral Heterogeneity in Price Setting

While the microfoundation of the SPC predicts heterogeneity across industries, it lacks a specific theoretical framework for explaining these differences. Here I will investigate industry-specific characteristics that may contribute to the observed sectoral heterogeneity, drawing on both theoretical aspects and empirical evidence from existing literature.

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 paper. At this stage, I will assess the estimated reduced-form industry-specific parameters, γ_k^f, γ_k^b, and γ_k^s.

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 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.

6.1.1 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 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.

6.1.2 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.

6.1.3 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.

6.1.4 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.

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

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. I will now explain how I proxy for these industry-characteristics and proceed then to test these potential determinants empirically.

6.2 Data

I will utilise the estimated parameters of forward- and backward-looking behaviour, and the SPC slope, obtained in Section 5, to understand how they respond to market structure and other industry characteristics.

6.2.1 Estimated Parameters Weighted by their Inverted Standard Errors

It is important to remember that the estimated industry-specific parameters exhibit various levels of estimation precision. This variability may be due to their estimation as a panel, without consideration of potential industry-specific characteristics or shocks that may affect certain industries and are yet not captured by the CCEs.

To ensure comparability, I will initially adjust the estimates based on their estimation precision. I will do so by applying weights to the parameters based on their standard errors. This approach is similar to Weighted Least Squares (WLS).[35] Since the standard errors are derived from the OLS estimation of the SPCs, they will be used to adjust the imprecise parameters. The weights w_k^p 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). Thus, the re-scaled weights $\overline{w}_k^p$ will be:

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

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

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

I show in Appendix E the weighted parameters by industry from the *Labour-cost SPC* and from the *Full-cost SPC*.

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

The weighted regression used is expressed as follows:

$$\widetilde{\gamma}_k^p = \beta_0 \widetilde{X}_k^0 + \beta_1 \widetilde{X}_k^1 + ... + \widetilde{u}_k \tag{14}$$

6.2.2 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.[36] I show the series for each industry from 2009 to 2021 in Figure 23 in the Appendix, but I use only the 2021 series for the panel analysis as it is the latest available and it does not vary much from previous years.

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

I then define the HHI for a given 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.

6.2.3 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:

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

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

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 15.

6.2.4 External Competition

Import penetration is calculated as total imports over total resources (production plus total imports), using the Input–Output tables.
I calculate the measure of import intensity as the percentage of costs that are imports, similar to Bunn et al. (2022), and the export intensity as the percentage of turnover that are exports, similar to Andrade et al. (2022).

6.2.5 Cost Structure

The "share of petrol over costs" and "share of energy over costs" are computed following the methodology outlined in Bunn et al. (2022). Costs are computed as the sum of intermediate consumption and compensation to employees. "Petrol" comprises Crude Petroleum, Natural Gas & Metal Ores Coke, and refined petroleum products, whereas "Energy" comprises Electricity, transmission and distribution Gas; distribution of gaseous fuels through mains; steam and air conditioning supply. These classifications are taken from The 'Combined Use' matrix with Industries' intermediate consumption. Additionally, the labour share is calculated as the ratio of compensation of employees to Gross Value Added (GVA). The data utilised for this analysis is sourced from the year 2021, selected due to the stability observed in the shares over the available sample period spanning from 2016 to 2021. Consequently, averaging over this timeframe is deemed unnecessary.

6.3 Regression Estimation Results

The regressions presented in Table 5 shed light on the association between the industry-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.

I focus primarily on estimates obtained from the *Labour-cost SPC* as its reduced-form parameters allow for more direct comparisons with own-industry characteristics. I present results from the *Full-cost SPC* in Table 17, despite their interpretation being less intuitive as the parameters embed interactions with other industries.

Table 5: Regression estimations (*Labour-cost SPC*)

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

Notes: This table presents the OLS panel estimation as reflected in Equation 14. The study includes 51 industries due to the absence of information on imports and exports for one industry. The dependent variables consist of the estimated parameters from the Labour-cost SPC obtained in Section 5 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 15. S.E. in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

The results presented in Table 5 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 above 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-stetting 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 Sectoral Phillips Curves: further discussion

A.1 SPC Derivation by IJP

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

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

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

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

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

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

where Z_{kt} is a time-varying sector-specific exogenous technology factor, labour is the only factor of production and h_{ikt} denotes hours worked. For the theoretical derivation, IJP assume that costs in steady state are as follows: $S_{ik\,t,t+j} = S_k = \eta/(\eta-1)$.

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

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

By taking the first order condition of Equation 18 and working on the algebra, I get the following expression:

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

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

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

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

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

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

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

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

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

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

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

A.2 Two Sector Illustration of *Full-cost SPC* Framework

I will first present Equation 4 and Equation 5 in matrix form for two sectors for illustrative purposes. Hatted letters refer to variables expressed as log-linearised deviations from the steady state.

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

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

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

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

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

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

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

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

Further combining terms to get expressions for the inflation rates:

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

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

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

Finally, I will express inflation rates in reduced form in terms of the full cost measure, $\hat{\mathbf{s}}_t^F$, and inflation expectations:

$$\hat{\boldsymbol{\pi}}_t = (I - \Lambda\,\tilde{A})^{-1}\boldsymbol{\beta}(1-\tilde{A})\,\boldsymbol{E_t}\hat{\boldsymbol{\pi}}_{t+4} + (I - \Lambda\,\tilde{A})^{-1}\tilde{A}\;\hat{\mathbf{s}}_t^F \tag{28}$$

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

A.3 Discussion on 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.

$$\pi_t = \gamma^f\,E_t\{\pi_{t+1}\} + \gamma^b\,\pi_{t-1} + \gamma^s\,s_t + \alpha_1\,z_{p\,t} + \alpha_2\,(p_t^W - p_t) + \alpha_3\,s_{L\,t} + \alpha_4\,p_{m\,t} + \alpha_5 \Delta n_t + \varepsilon_t^\pi \tag{29}$$

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.

Appendix B Additional Figures and Tables

Table 6: Correlation table

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

Notes: This table displays correlation levels for the main studied variables. "IG" represents Intermediate Goods. Refer to Section 4.3 for details on how I construct the "Labour Cost" and the "Full Cost"

Table 7: Panel Stationarity Test: Pesaran (2007) CIPS

Specification with constant								
Lags	CBI inflation	*(p)*	Labour cost	*(p)*	Expected inflation	*(p)*	Full cost	*(p)*
0	-24.1	0.0	-7.4	0.0	-26.9	0.0	-13.8	0.0
1	-13.8	0.0	-8.9	0.0	-16.3	0.0	-9.9	0.0
2	-8.3	0.0	-8.8	0.0	-10.4	0.0	-8.3	0.0
3	-5.2	0.0	-7.9	0.0	-8.0	0.0	-6.2	0.0
4	-3.2	0.0	-6.2	0.0	-4.5	0.0	-4.5	0.0
Specification with constant and trend								
Lags	CBI inflation	*(p)*	Labour cost	*(p)*	Expected inflation	*(p)*	Full cost	*(p)*
0	-25.9	0.0	-3.2	0.0	-27.9	0.0	-10.4	0.0
1	-14.4	0.0	-4.9	0.0	-15.8	0.0	-6.5	0.0
2	-7.9	0.0	-5.1	0.0	-9.1	0.0	-5.6	0.0
3	-3.3	0.0	-4.2	0.0	-6.3	0.0	-3.4	0.0
4	-0.2	0.4	-2.8	0.0	-1.5	0.1	-1.1	0.1

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. Results suggest to reject the null hypothesis, indicating that a statistically significant proportion of the industries are stationary.

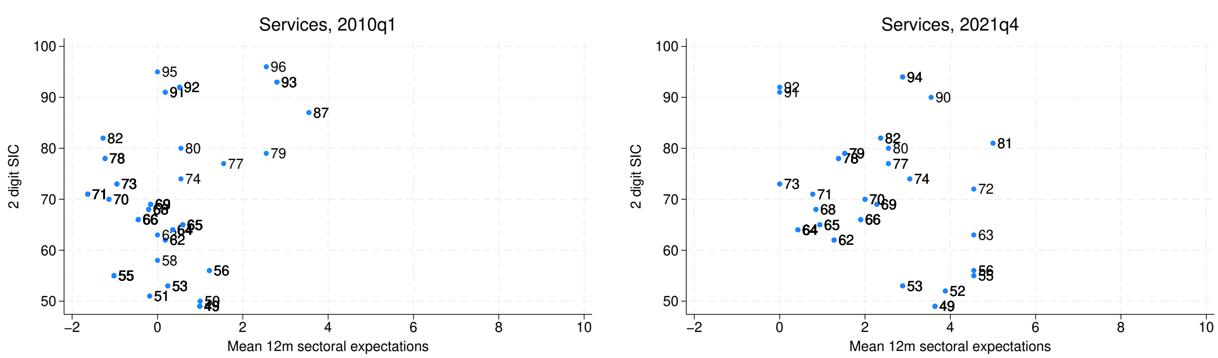
Table 8: Relevance of instruments

Dependent Variable:	*Expected inflation* [1]	*Expected inflation* [2]	*Labour Cost* [3]	*Labour Cost* [4]	*Full Cost* [5]	*Full Cost* [6]
Exp. inflation (1st lag)	0.23***	0.20***		0.01		-0.09***
	(0.03)	(0.03)		(0.01)		(0.01)
Exp. inflation (2nd lag)	0.13***	0.11***		-0.04***		0.01
	(0.03)	(0.03)		(0.01)		(0.01)
Exp. inflation (3rd lag)	0.07**	0.11***		-0.02**		-0.02**
	(0.03)	(0.03)		(0.01)		(0.01)
Cost (1st lag)		0.29**	0.98***	0.97***	0.73***	0.81***
		(0.12)	(0.04)	(0.04)	(0.04)	(0.05)
Cost (2nd lag)		-0.07	-0.00	-0.06	0.08*	0.02
		(0.15)	(0.06)	(0.06)	(0.05)	(0.05)
Cost (3rd lag)		0.28***	-0.22***	-0.15***	-0.09**	-0.02
		(0.10)	(0.04)	(0.03)	(0.04)	(0.04)
FE	t & k	t & k	t & k	t & k	t & k	t & k
Observations	2,070	2,070	2,146	2,086	2,028	2,028
R-squared	0.44	0.47	0.77	0.78	0.59	0.64

Notes: OLS estimations. In specifications [1] to 4], the Cost variable corresponds to Labour Cost and in [5] and [6] to the Full Cost. 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 6: Sectoral inflation expectations - Services

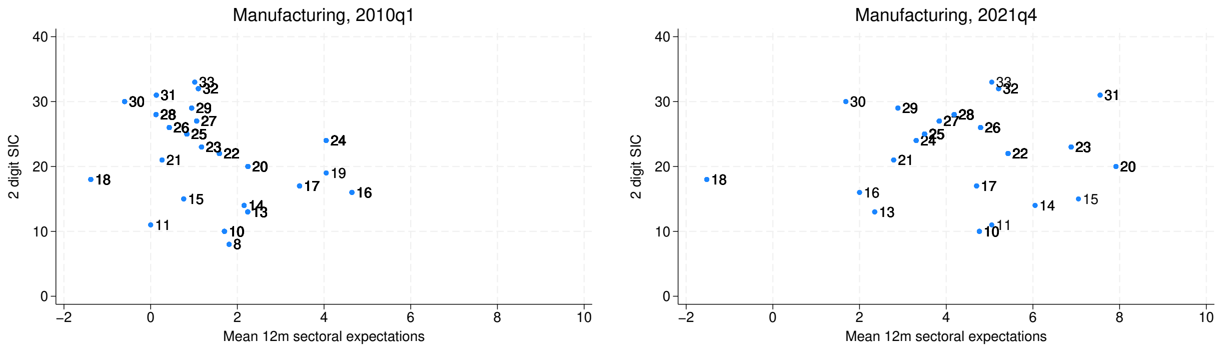
(a) (b)



Notes: Each dot represents the mean sectoral inflation expectations for each industry, calculated as the average of expectations across firms within each industry. The number next to the dot indicates the industry. Figures "a" and "b" show industries belonging to the services sector in 2010q1 and 2021q4, respectively.

Figure 7: Sectoral inflation expectations - Manufacturing

(a) (b)



Notes: Each dot represents the mean sectoral inflation expectations for each industry, calculated as the average of expectations across firms within each industry. The number next to the dot indicates the industry. Figures "a" and "b" show industries belonging to the manufacturing sector in 2010q1 and 2021q4, respectively.

Table 9: 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.

Table 10: Summary statistics

	2009-2020		*2021-2022q2*	
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

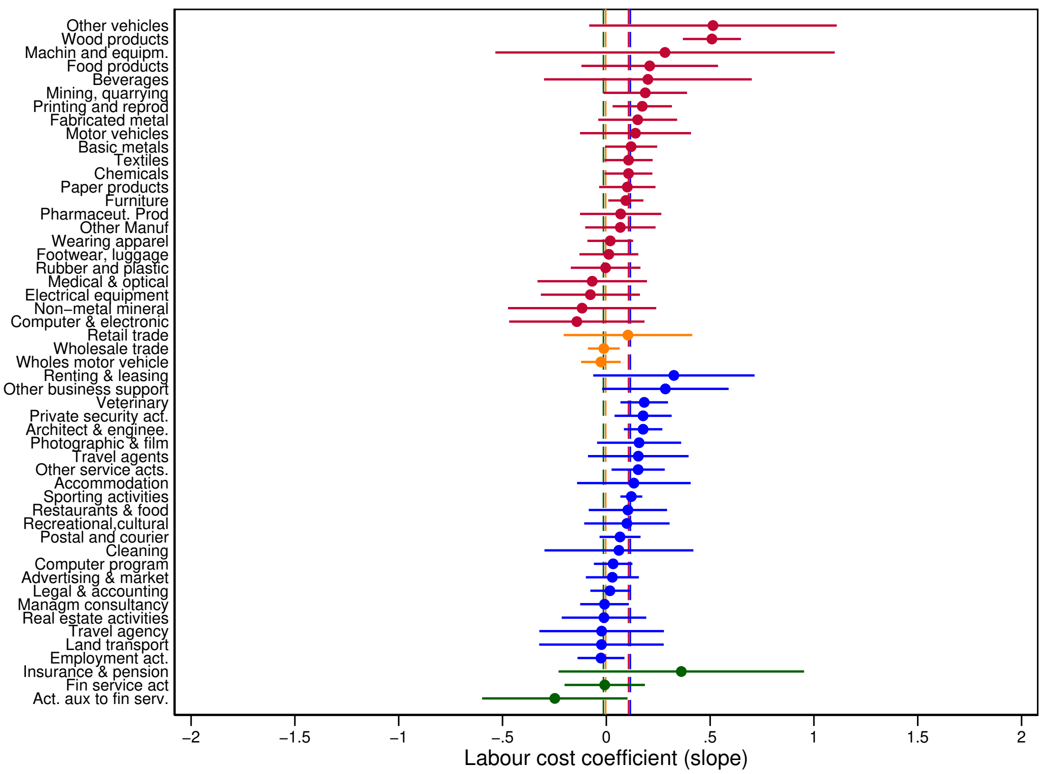
Notes: This table displays the mean and Standard Deviation (SD) of CBI survey data and ONS inflation series for the period 2009q1-2020q4 and the period 2021q1-2022q2.

Table 11: Joint Coefficients

	Labour-cost SPC			Full-cost SPC		
	Pooled [1]	MG [2]	Full Model [3]	Pooled [1]	MG [2]	Full Model [3]
			Joint Coefficients estimation			
$\gamma^b + \gamma^f$	1.38***	1.02***	0.80***	1.19***	0.80***	0.73***
S.E.	(0.14)	(0.07)	(0.09)	(0.15)	(0.07)	(0.09)
			Test $\gamma^b + \gamma^f = 1$			
P-value	0.01	0.74	0.03	0.20	0.00	0.00

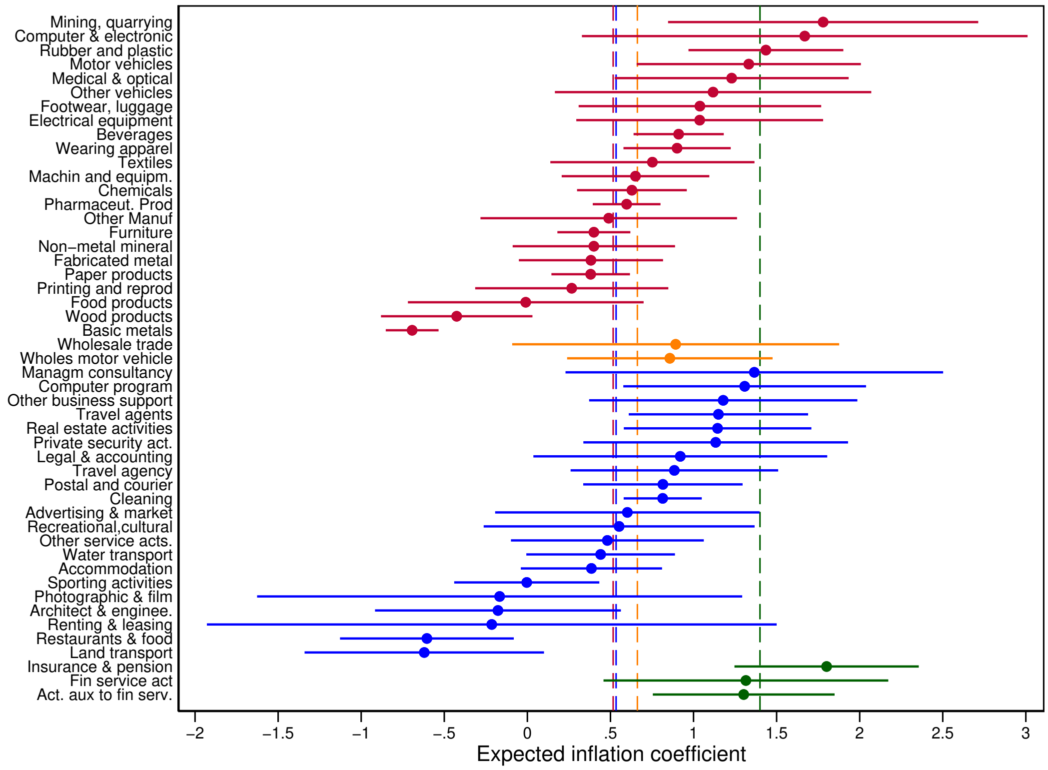
Notes: The top part of the table shows the sum of the coefficients with the standard errors in parenthesis. Significance levels are indicated as follows: *** p<0.01, ** p<0.05, * p<0.1. The bottom part of the table presents the p-values of the hypothesis test $H_0 : \gamma^b + \gamma^f = 1$.

Figure 8: Slope by industry (*Labour-cost SPC*)



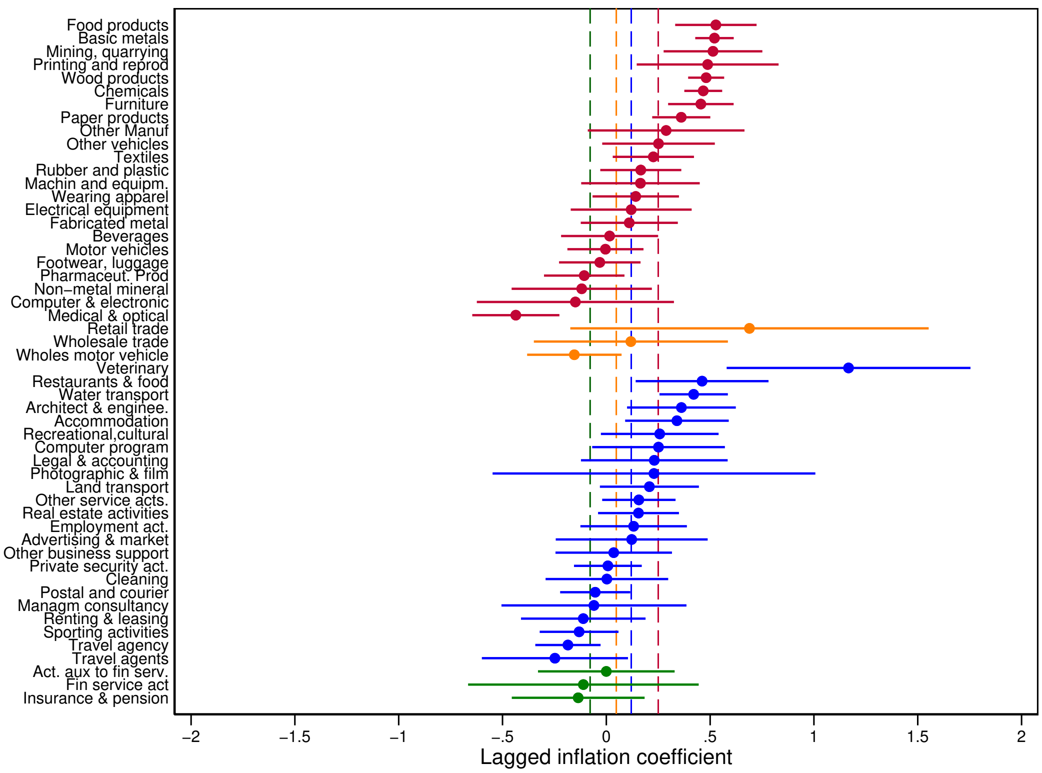
Notes: Industry-specific parameters related to labour costs from Model 3 (Table 2, through dynamic panels with CCE). These coefficients are net from common factor effects. Intervals are calculated as the mean +/- s.e.. The labels indicate the mean estimated coefficient for each industry. The dashed vertical 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 9: Role of expectations by industry (*Labour-cost SPC*)



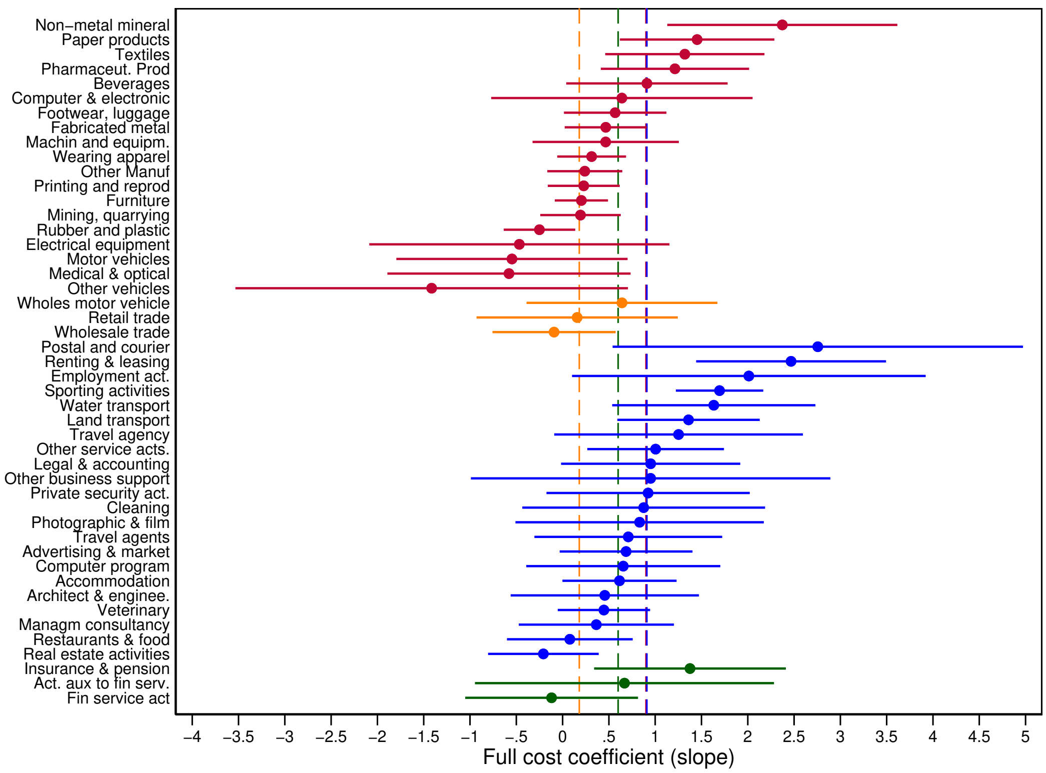
Notes: Industry-specific parameters related to inflation expectations from Model 3 (Table 2, through dynamic panels with CCE). These coefficients are net from common factor effects. Intervals are calculated as the mean +/- s.e. The labels indicate the mean estimated coefficient for each industry. The 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 10: Role of lagged inflation by industry (*Labour-cost SPC*)



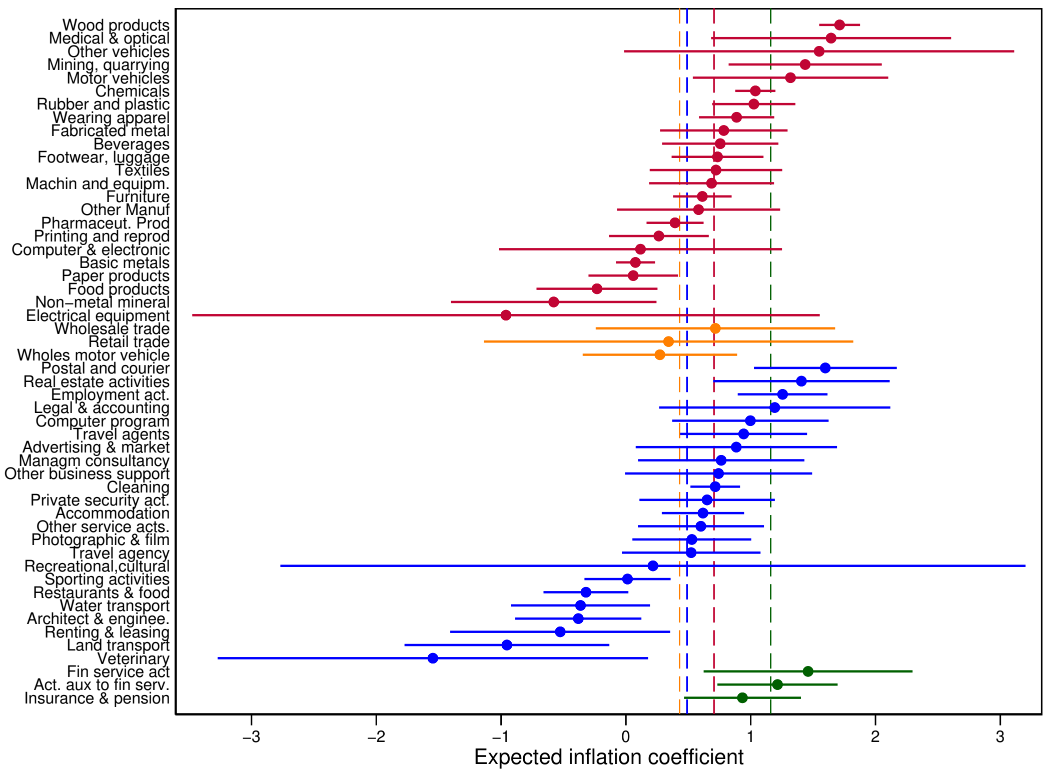
Notes: Industry-specific parameters related to lagged inflation from Model 3 (Table 2, through dynamic panels with CCE). These coefficients are net from common factor effects. Intervals are calculated as the mean +/- s.e. The labels indicate the mean estimated coefficient for each industry. The dashed 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 11: Slope by industry (*Full-cost SPC*)



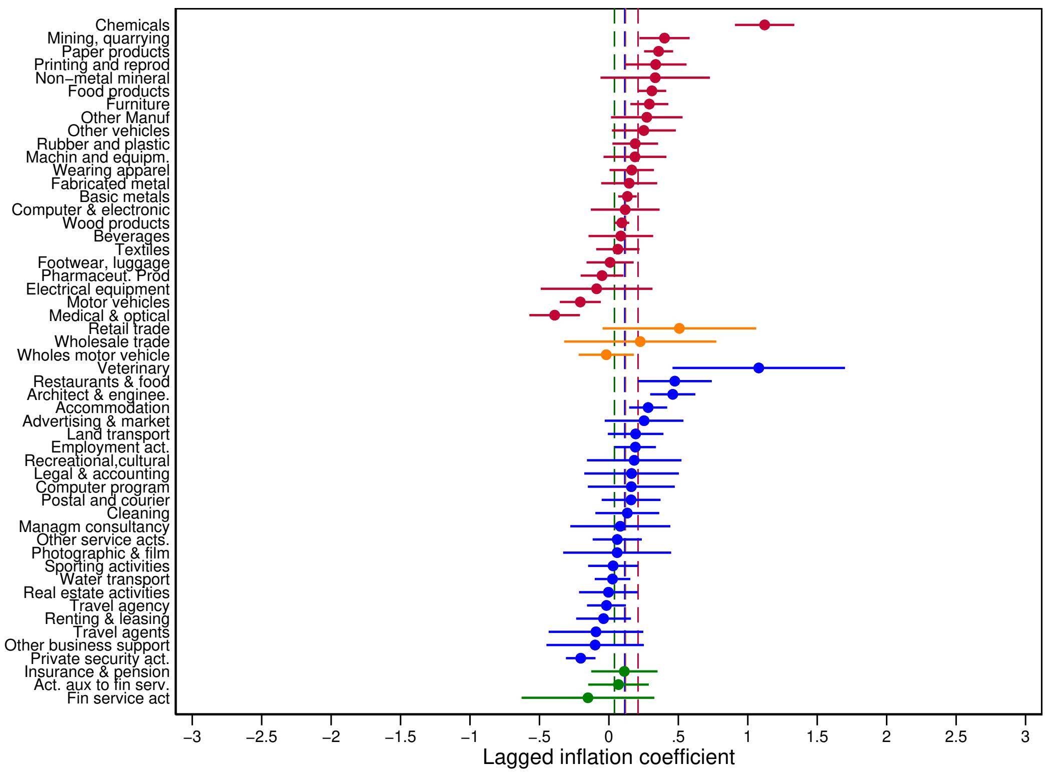
Notes: Industry-specific parameters related to the full cost measure from Model 3 (Table 3, through dynamic panels with CCE). These coefficients are net from common factor effects. Intervals are calculated as the mean +/- s.e. The labels indicate the mean estimated coefficient for each industry. The 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*)



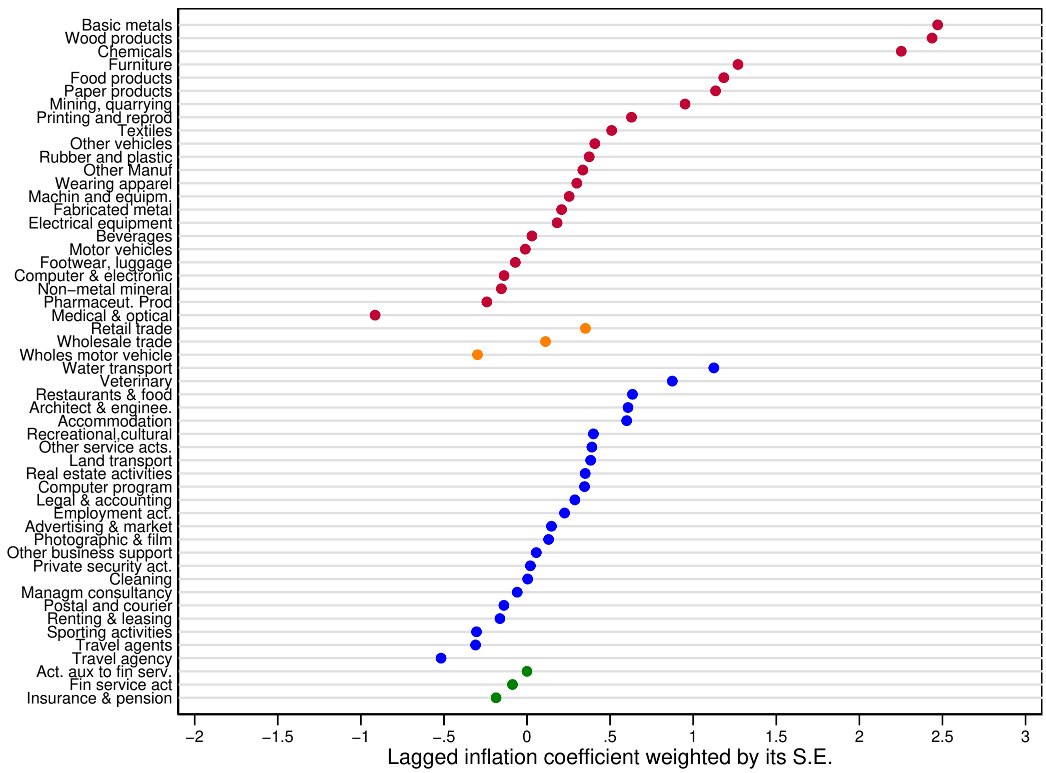
Notes: Industry-specific parameters related to inflation expectations from Model 3 (Table 3, through dynamic panels with CCE). These coefficients are net from common factor effects. Intervals are calculated as the mean +/- s.e. The labels indicate the mean estimated coefficient for each industry. The 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*)



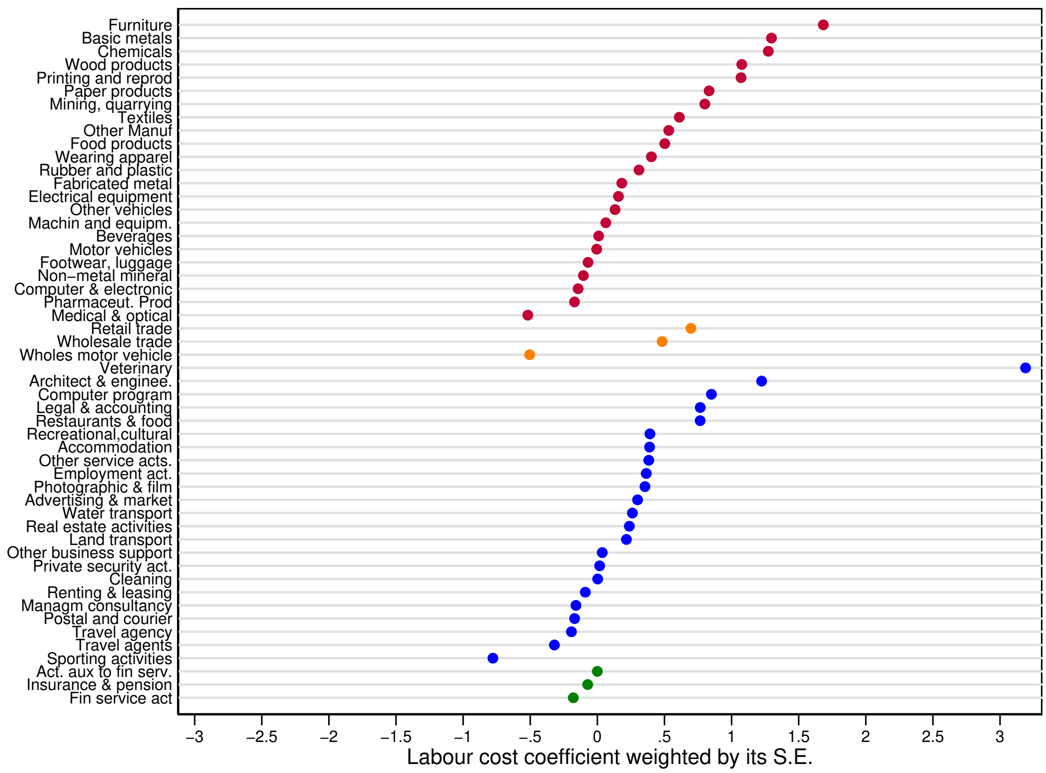
Notes: Industry-specific parameters related to lagged inflation from Model 3 (Table 3, through dynamic panels with CCE). These coefficients are net from common factor effects. Intervals are calculated as the mean +/- s.e. The labels indicate the mean estimated coefficient for each industry. The dashed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



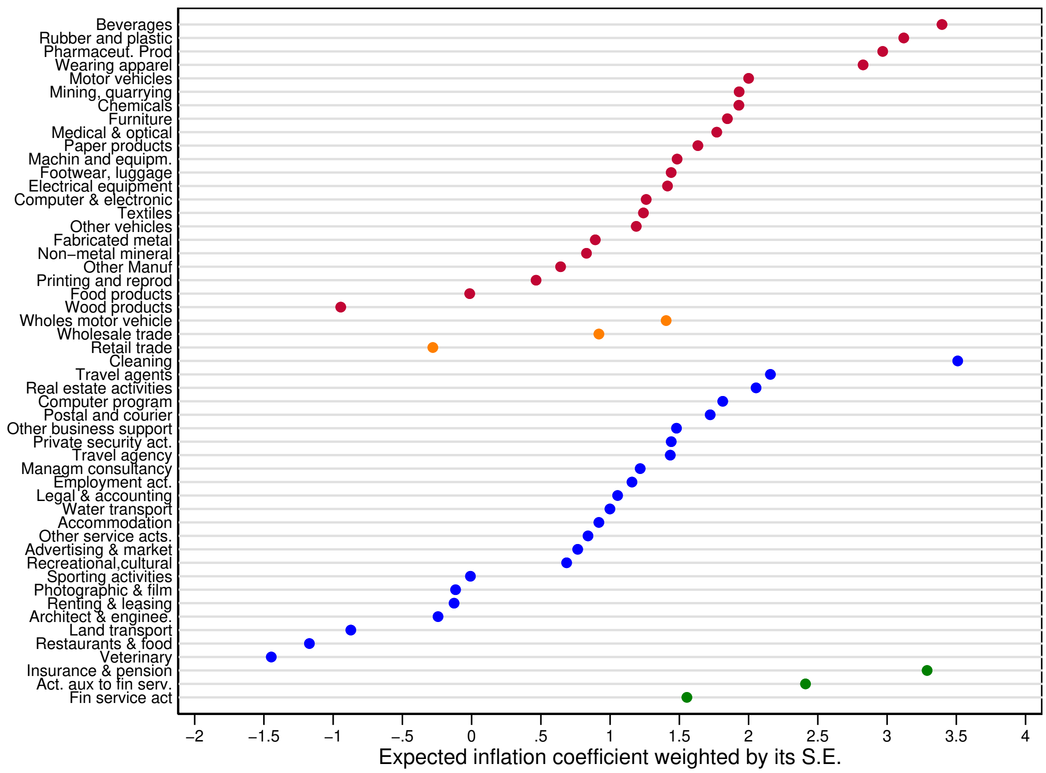
Notes: The parameters displayed in the figure have been weighted based on their inverted S.E. from the *Labour-cost SPC*. Red colour: Manufacturing; Orange: Retail; Blue: Services; and Green: Financial Services.

FIGURE 15: 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 16: 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.

Appendix C Data and Measurement

C.1 Discussion on 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. 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.

C.2 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.

C.3 Price Mapping

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	

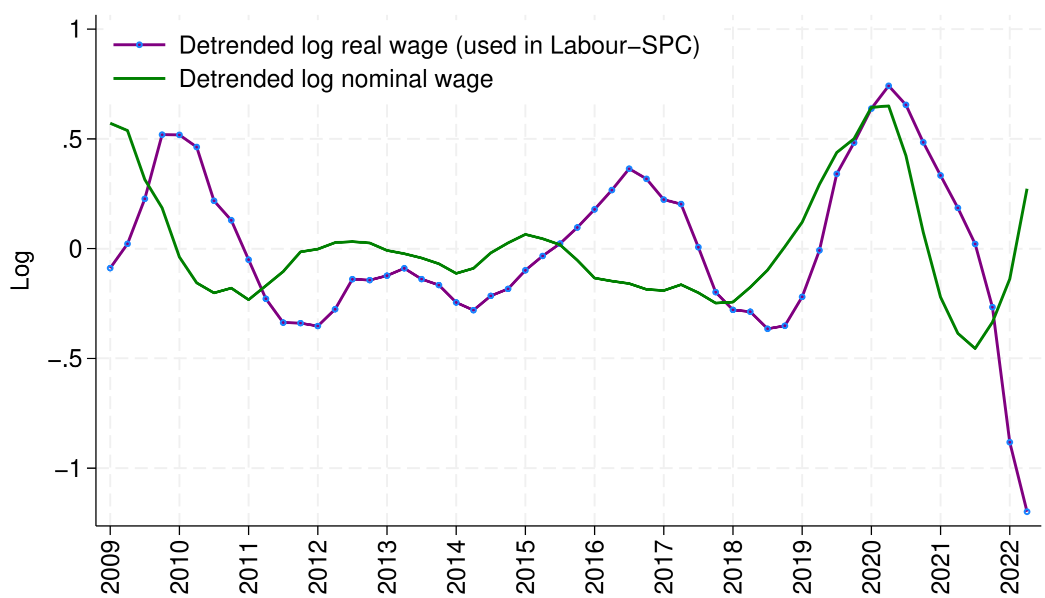
Notes: In the case of PPI and SPPI, the letter “x” indicates the availability of an inflation index related to the same SIC. When neither PPI nor SPPI has an inflation index available, then CPI indices are used. All three indices (PPI, SPPI, and CPI) are provided by the ONS.

C.4 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.

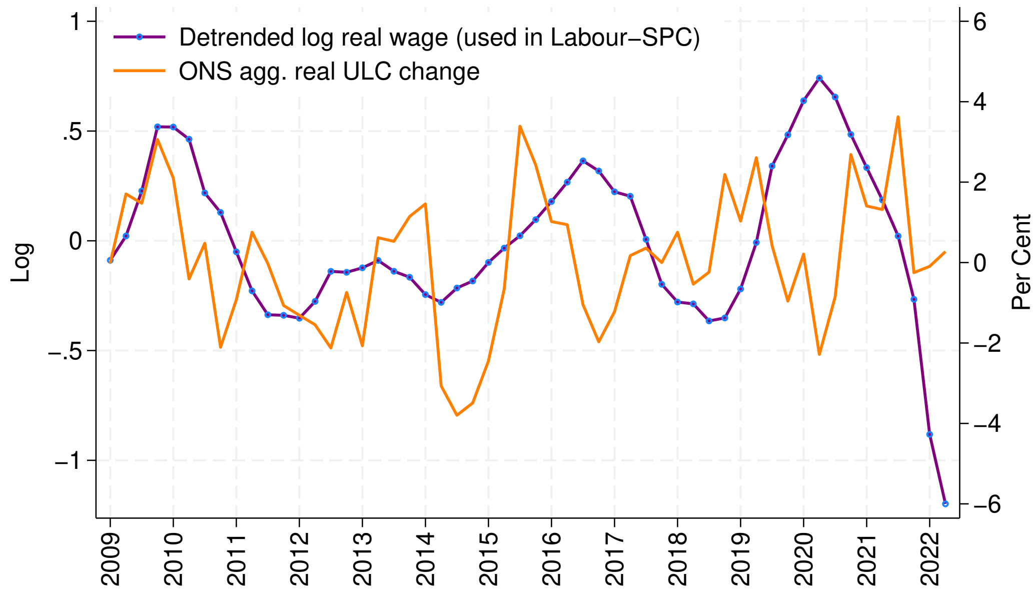
In Figure 17 I show the measure of detrended nominal wage cost (in log terms) alongside the measure of real detrended wage cost. The latter serves as a forcing variable for estimating the Labour-cost SPC. These two series align most of the time, reflecting low inflation, with minor gaps in 2010, 2016, and 2017. A notable difference becomes evident starting in mid-2021 due to the high inflation period.

Figure 17: 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 4.3.

Figure 18: 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.

C.5 Output Gap

The other measure I used as proxy for the slack measure for SPC estimation is the UK output gap calculated and provided by the Bank of England. See the time series in Figure 19. This measure was not statistically significant when used as a slack measure in the SPC estimation.

C.6 Other Data

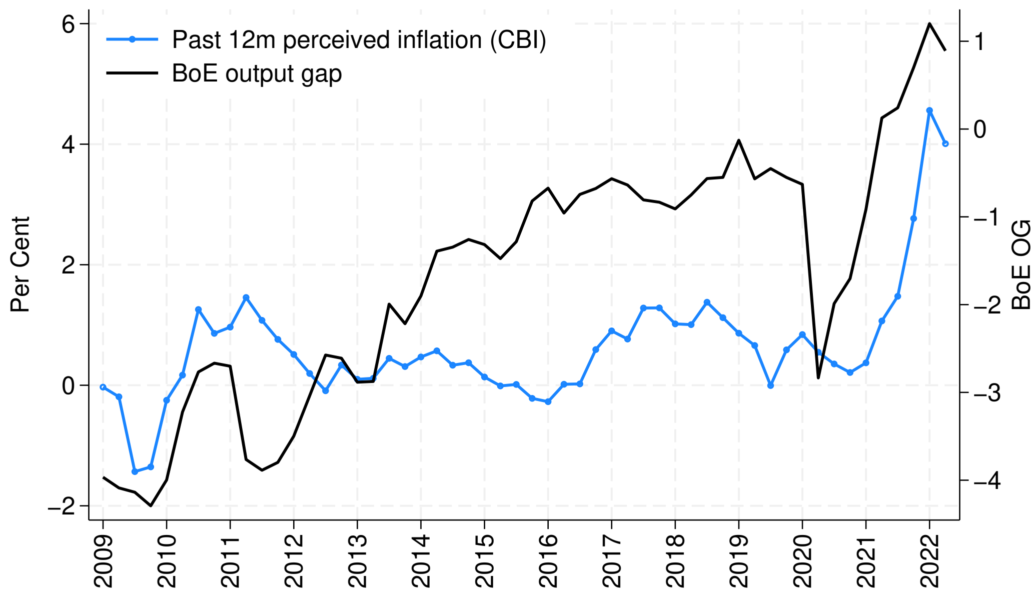
The real oil price inflation is the change in oil price adjusted by bilateral Foreign Exchange (FX) change. This measure is based on Roberts (1995), calculated as DCOILBRENTEU - DEXUSUK.

DCOILBRENTEU is the FRED[37] 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

[37]https://fred.stlouisfed.org/

Figure 19: 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.

An alternative measure for the labour share used in the estimations, as suggested by Batini et al. (2005): ln[((HAEA*A)/ABML)*100], where A = (E + SE)/E. E is given by BCAJ. The number of employee workforce jobs (seasonally adjusted), while SE is given by DYZN, the number of self-employment workforce jobs (seasonally adjusted). Note that the four letter codes refer to series produced by the ONS.

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

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

Appendix D Robustness

In this section I conduct some robustness analysis to test the strength of the results when cutting the sample before the high-inflation period, i.e. before the Covid-19 shock.

D.1 Regression Analysis - Subsample before 2020

Studying the subsample before 2020 presents the additional challenge of dealing with a shorter time series. This is particularly critical for estimating the industry-level coefficients. To ensure at least 22 degrees of freedom for each industry, I excluded industries 82 and 74. Model [1] in Table 14 presents the main specification studied in the paper (from model 3 of Table 2) with the same set of proxies for the CCEs (labelled as CCE_1) and the same time period. The coefficients are slightly different due to the exclusion of the two industries, but overall, the results are similar.

Model [3] examines the subsample before 2020 and exhibits strong cross-sectional dependence and an insignificant slope. The degree of forward-lookingness is much higher than the baseline estimates, while the degree of backward-lookingness is lower than the baseline estimates. To address the strong cross-sectional dependence, in Model [4] I reduced the number of common factors for the CCEMG estimation compared to Model [3]. First, this adjustment helps with the shorter sample, which provides fewer degrees of freedom. Second, by removing oil inflation from the proxies of CCEs, the results remain unaffected. While in Model [3] I cannot reject the strong cross-sectional dependence (p-value of 0.063), in Model [4], with the smaller set of proxies for the CCE (labelled as CCE_2), I can reject the strong cross-sectional dependence. Model [4] shows that the estimated coefficient for γ^f (0.85) is larger than when studying the full sample, while γ^b is slightly smaller (0.13). The slope is similar (0.13) but less significant. Overall, the results are quite stable, and $\gamma^f + \gamma^b$ is less than 1, which aligns with theoretical predictions.

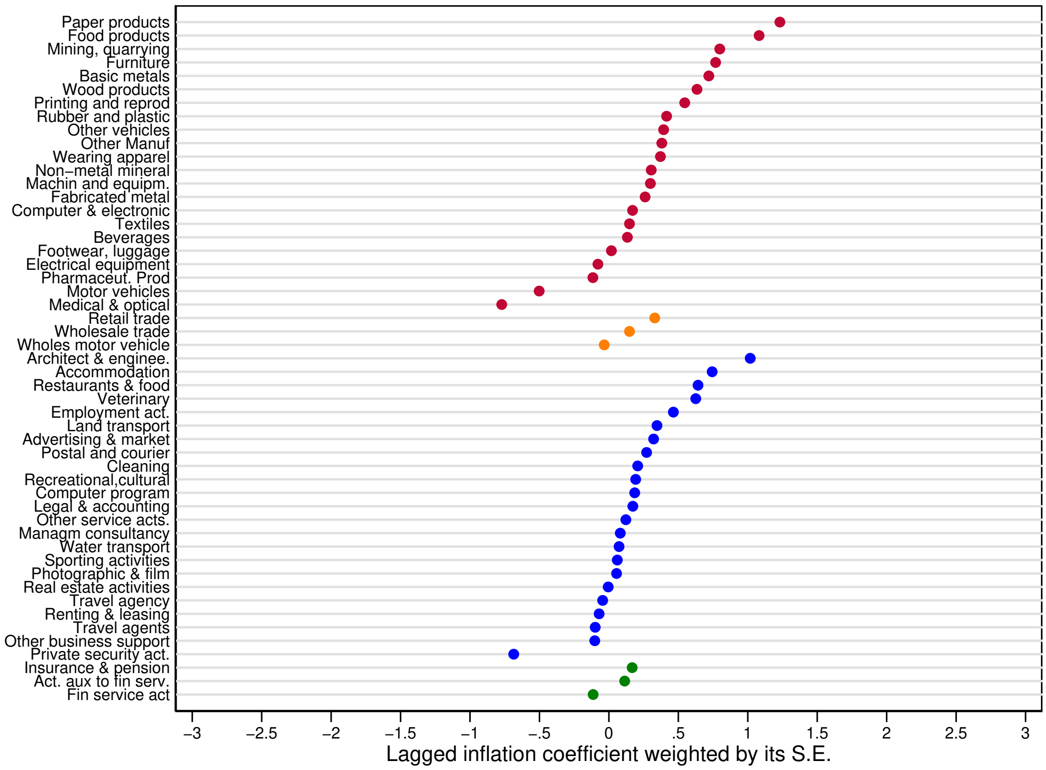
Table 14: *Labour-cost SPC*

	Full Model: CCEMG	Full Model: CCEMG	Full Model: CCEMG	Full Model: CCEMG
	[1]	[2]	[3]	[4]
	Dependent variable: CBI sectoral inflation			
	2009q1-2022q2		2009q1-2019q4	
Expected sectoral inflation (γ^f)	0.64***	0.64***	0.89***	0.85***
	(0.11)	(0.10)	(0.11)	(0.10)
Lagged sectoral inflation (γ^b)	0.17***	0.20***	0.09***	0.13***
	(0.04)	(0.04)	(0.03)	(0.04)
Labour cost (γ^s)	0.11***	0.14**	0.06	0.13*
	(0.04)	(0.06)	(0.04)	(0.07)
Heterogeneous/Homogeneous Coeff.	Heterog.	Heterog.	Heterog.	Heterog.
FE (k)/CCE	FE(k) & CCE_1	FE(k) & CCE_2	FE(k) & CCE_1	FE(k) & CCE_2
Observations	2,437	2,437	2,030	2,030
Number of groups	50	50	50	50
RMSE	1.62	1.76	1.46	1.66
CD test (p-value)	0.71	0.90	0.06	0.46

Notes: This table presents the OLS panel time-series estimation 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. Models [1] and [3] use a CCEMG estimator, implemented using cross-section averages proxied by ave. expectations (0 to 3 lags), ave. labour cost (0 to 2 lags) and oil inflation (0 to 2 lags); Models [2] and [4] use a CCEMG estimator, implemented using cross-section averages proxied by ave. expectations (0 to 3 lags) and ave. labour cost (0 to 3 lags). 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. S.E. in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

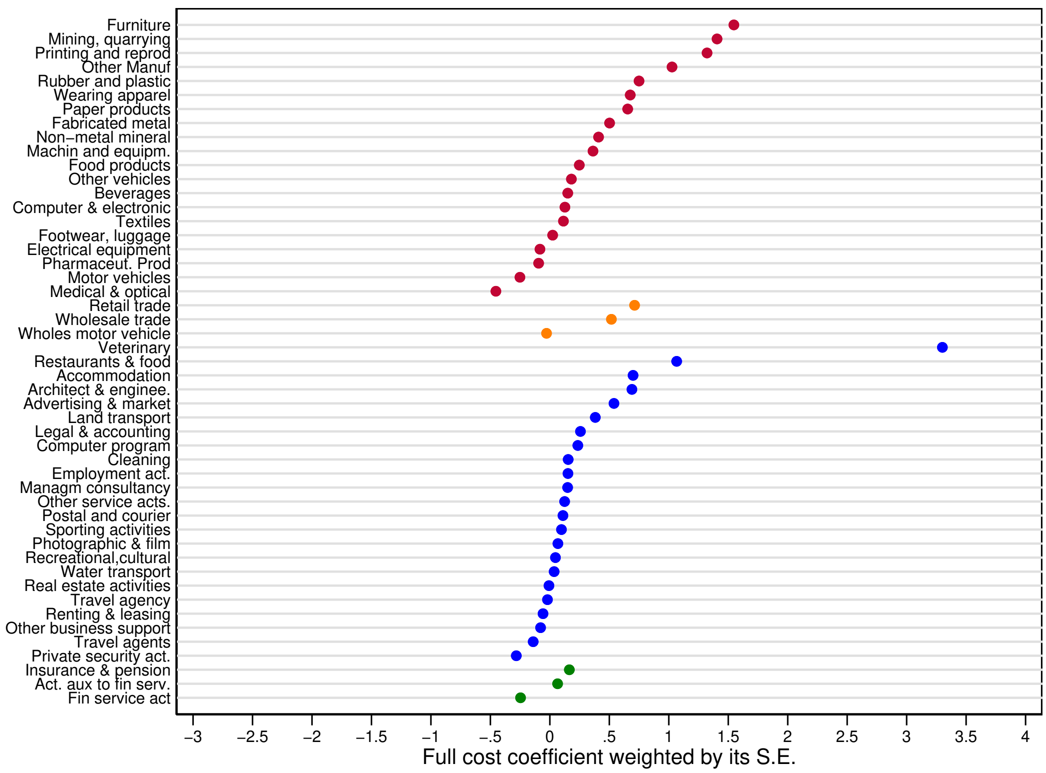
Appendix E Figures and Data

Figure 20: Weighted coefficient on lagged inflation (*Full-cost SPC*)



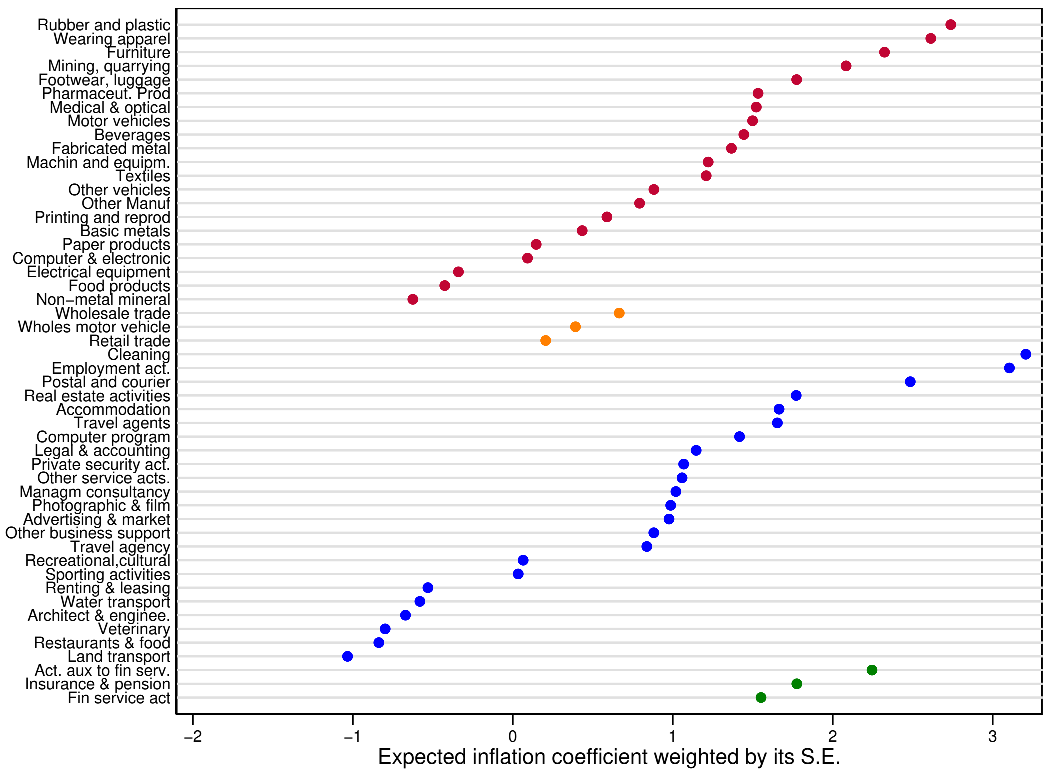
Notes: The coefficients presented in the figure have been weighted based on their respective S.E. from the *Full-cost SPC*. The Chemicals industry was excluded due to the estimated parameters falling outside the range of -3 to 3, adding them would distort the axis scales. This adjustment was made to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

Figure 21: 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 22: 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.

Figure 23: 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.

Appendix F Additional Results

Table 16: Regression estimations (*Labour-cost SPC*)

	γ^f [1]	γ^b [2]	γ^s [3]	γ^f [4]	γ^b [5]	γ^s [6]
		MC: CR5			*MC: HHI*	
Market concentration (MC)	69.44**	-16.73	23.63	1.48*	-0.61	0.05
	(29.82)	(13.04)	(19.77)	(0.85)	(0.42)	(0.38)
MC x Services Dummy	-15.12	-7.80	49.62	-1.14	-0.05	0.67
	(78.56)	(22.06)	(46.79)	(2.35)	(0.54)	(1.48)
Share of imports over supply	-0.16	0.57*	0.20	0.04	0.60*	0.10
	(0.53)	(0.33)	(0.13)	(0.51)	(0.32)	(0.11)
Share of energy over costs	-8.25	7.90***	6.33	-7.16	7.69***	5.70
	(7.15)	(2.57)	(6.08)	(7.01)	(2.60)	(5.53)
Share of petrol over costs	-13.38***	2.50	-1.12	-12.53**	2.48	0.45
	(4.51)	(1.72)	(3.86)	(4.67)	(1.49)	(3.61)
ULC variability	0.41	0.59	-1.67	0.75	0.51	-0.70
	(2.15)	(0.64)	(1.01)	(1.68)	(0.60)	(0.78)
Market concentration (MC) Beta	0.48	-0.36	-0.29	0.34	-0.39	-0.29
MC x Services Dummy Beta	-0.04	-0.04	0.15	-0.08	0.03	0.10
Imports over supply Beta	-0.06	0.27	0.25	0.01	0.31	0.22
Energy over costs Beta	-0.23	0.45	0.34	-0.20	0.46	0.31
Petrol over costs Beta	-0.60	0.31	0.04	-0.56	0.27	0.04
ULC variability Beta	0.05	0.01	-0.17	0.08	-0.03	-0.13
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 14. The dependent variables consist of the estimated parameters from the Labour-cost SPC obtained in Section 5 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. The bottom panel shows the Standardised Coefficients (Betas), which are valuable for assessing the relative importance of regressors. Inputs used in these regressions are shown in Table 15. S.E. in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table 17: Regression estimations (*Full-cost SPC*)

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

Notes: This table presents the OLS panel estimation as reflected in Equation 14. The dependent variables consist of the estimated parameters from the Full-cost SPC obtained in Section 5 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. Standard Errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table 15: Industry characteristics by industry (2dig-SIC)

	CR5	HHI	Share of petrol over costs	Share of energy over costs	Share of imports over supply	ULC variability
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 5. The correlation between the HHI and the CR5 is 0.95.

F.1 Robustness Analysis

In this section, I conduct a robustness analysis to test the strength of the results shown in Table 5. First, I run the regressions without the weighting adjustment, and second, I run the median regressions.

Table 18 shows the results from the unweighted regressions. The degree of forward-looking behaviour (γ_f) remains positively associated with market concentration, although the association is less significant. Similarly, the share of energy costs and share of petrol costs exhibit the same negative relationship with respect to γ_f. However, petrol is no longer significant, while energy becomes significant. These results suggest that the weighting approach does not substantially alter the results.

Table 18: Unweighted Regression estimations (*Labour-cost SPC*)

	γ_f (1)	γ_b (2)	γ_s (3)	γ_f (4)	γ_b (5)	γ_s (6)
	MC: CR5			*MC: HHI*		
Market concentration (MC)	0.26	0.02	-0.04	1.66	-0.21	-0.05
	(0.48)	(0.17)	(0.20)	(1.30)	(0.43)	(0.44)
MC x Services Dummy	-2.06*	0.28	-0.21	-4.97	0.26	-1.28
	(1.11)	(0.43)	(0.28)	(4.22)	(1.18)	(1.12)
Share of imports over supply	-0.00	0.00	-0.00	0.00	0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Share of energy over costs	-0.22***	0.08**	-0.06	-0.17**	0.07*	-0.06
	(0.08)	(0.04)	(0.05)	(0.07)	(0.04)	(0.05)
Share of petrol over costs	-0.07	0.01	0.07	-0.09	0.02	0.07
	(0.07)	(0.02)	(0.07)	(0.07)	(0.02)	(0.07)
ULC variability	0.03	-0.00	0.01	0.02	0.00	0.01
	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Observations	51	51	51	51	51	51
R-squared	0.24	0.13	0.19	0.15	0.11	0.22

Notes: This table presents the OLS panel estimation as reflected in Equation 14, but without weighting. The dependent variables consist of the estimated parameters from the Labour-cost SPC obtained in Section 5 for each industry. The observations refer to the number of industries. 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. S.E. in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

While Table 5 presents the results from OLS regression, which shows the average effect, Table 19 displays the results from the median regression, which indicates the effect at the median. The degree of forward-looking behaviour (γ_f) remains significant and positively associated with market concentration. Similarly, the share of energy costs and share of petrol costs exhibit the same negative relationship with respect to γ_f. However, petrol is no longer significant, while energy becomes significant, similar to the results found in the unweighted regression. Overall, these results suggest that the main findings are robust to both the unweighted analysis and to calculating the median regression.

Table 19: Median Regression estimations (*Labour-cost SPC*)

	γ_f (1)	γ_b (2)	γ_s (3)	γ_f (4)	γ_b (5)	γ_s (6)
		MC: CR5			*MC: HHI*	
Market concentration	103.15***	2.31	17.27	2.19***	0.01	0.34
	(26.30)	(21.27)	(37.27)	(0.64)	(0.67)	(0.84)
MC x Services Dummy	-87.39	-27.99	32.19	-1.16	-0.76	-0.68
	(116.16)	(31.54)	(41.72)	(8.82)	(6.79)	(6.72)
Share of imports over supply	-0.24	0.07	0.00	-0.08	0.35	-0.06
	(0.30)	(0.30)	(0.92)	(0.40)	(0.37)	(0.28)
Share of energy over costs	-17.98**	8.26***	10.13	-13.16	7.97**	10.59*
	(7.86)	(3.07)	(7.09)	(8.89)	(3.75)	(6.29)
Share of petrol over costs	-7.15	3.49	1.95	-9.41	2.16	1.99
	(8.52)	(2.75)	(4.36)	(9.52)	(5.05)	(8.67)
ULC variability	2.40	0.05	-0.84	1.47	0.67	-0.21
	(1.99)	(0.76)	(1.30)	(2.59)	(1.39)	(1.98)
Observations	51	51	51	51	51	51

Notes: This table presents the OLS panel estimation as reflected in Equation 14, but for the median instead of the mean. The dependent variables consist of the estimated parameters from the Labour-cost SPC obtained in Section 5 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 15. S.E. in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.