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

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October 26, 2023

Preliminary and Incomplete

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Abstract

I examine price-setting behaviour across 52 sectors in the UK by estimating Sectoral Phillips Curves (SPCs) using heterogeneous panel methods. First, I enhance the identification of the SPC by using a confidential survey dataset on direct measures of firms' expectations, labour costs, and supplier prices; thus alleviating a very common weak identification issue discussed in the literature. Second, I take into account input-output linkages, which are typically overlooked in traditional Phillips Curve estimations. I find significant and positive SPC parameters, reaffirming the importance of future expected inflation in firms' price setting and the key role of sectoral data in identifying the Phillips Curve slope. Also, I find larger slopes when sectoral linkages are taken into account. Third, I uncover substantial heterogeneity across industries in terms of forward- and backward-looking behaviour, and cost responsiveness. Delving into potential sources of heterogeneity, expectations play a larger role in the price-setting decisions of firms in more concentrated sectors.

JEL: C21, C23, E31, E70

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1 Introduction

The recent global surge in prices has brought back general attention to the question of inflation. To understand, and ultimately control inflation, central banks typically rely on the Phillips Curve. This relationship helps explain current inflation rates as resulting from firms' expected future inflation and firms' costs.

In this paper, I use a unique survey dataset of firms' inflation expectations to answer the two following research questions: (1) Can I obtain more precise estimates of the Phillips Curve? This study employs three approaches: (i) using survey and sectoral based data on direct measures of expectations, suppliers prices, and salary costs, (ii) incorporating input-output tables to account for production networks, and (iii) employing richer model specifications. Through these approaches, I find positive and significant parameters on the sensitivity of inflation to firms' expected future inflation and to their costs. I establish that the Phillips Curve slope has not disappeared when using sectoral and survey-based data. Additionally, including input-output linkages increases the responsiveness of prices to costs. I also find large sectoral heterogeneity in the Phillips Curve parameters, which highlights the risk of overlooking inflation dynamics and the sectoral linkages by using aggregate data..

Upon unmasking this large heterogeneity across sectors, the second research question is: (2) What are the primary sources of sectoral heterogeneity in the Phillips Curve? Can this heterogeneity be associated with industry characteristics? I find that market concentration is one of the explanatory factors of the sensitivity of inflation to expected future inflation. This result sheds light on industry characteristics that have been overlooked in the estimations of traditional Phillips Curves. To the best of my knowledge, this is the first paper to study Phillips Curves using direct measures of firms' expectations.

Identifying the Phillips Curve parameters presents several challenges.[1] General lack of available data on firms' expectations makes it challenging to identify the sensitivity of current inflation to expected future inflation. In the literature to date, it has been mostly proxied by actual inflation or rational-expectations.[2] However, these proxies have been largely criticised for being weak instruments.[3] The proper identification and understanding of this parameter are essential for central banks, inflation expectations is a powerful tool for controlling inflation.

Employing aggregate data makes it challenging to identify the expected (positive) sign for 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.

[1] See Mavroeidis et al., 2014, Abbas et al., 2016 and Del Negro et al., 2020 for more details.

[2] Some examples: Gali and Gertler, 1999, Leith and Malley, 2007, Maćkowiak et al., 2009, Imbs et al., 2011, Byrne et al., 2013.

[3] See e.g. Byrne et al., 2013 and Nason and Smith, 2005.

The flat or negative slope obtained when employing aggregate data is because monetary policy aims to offset aggregate demand shocks by raising interest rates, which leads to lower inflation. This does not hold when using more disaggregate data as the central bank cannot directly offset regional or sectoral shocks.[4]

This paper exploits the micro data from the Confederation of British Industry (CBI) surveys, which contain quarterly data of narrowly defined industries in the UK. This dataset is available over a relatively long sample period since 2009 and provides direct measures of firms' inflation expectations, which are not commonly available. Unlike other studies that use proxies like professional or household expectations[5], actual inflation, or rational expectations, using survey data mitigates the risk of weak proxies and bias in the estimation. Another improvement in the identification comes from using data on salary costs from the survey. Most studies rely on measures like the output gap or labour share due to the unavailability of firm-level labour cost data.[6] This study also uses sector-level prices from the survey to track sectoral inflation over time and to serve as proxies for supplier prices. By combining these micro-level intermediate goods costs with input-output tables, it accounts for the role of production networks in the sectoral inflation process. However, it's essential to acknowledge that, while survey data offers more realism, it may be subject to measurement errors. I address this issue by making comparisons with official aggregate data for robustness.

Furthermore, potential weak identification of the Phillips Curve might not only be due to poor data but may also stem from model misspecification. This represents my second contribution. To address this concern, I estimate a Phillips Curve model based on richer model specifications, thus challenging the traditional model.[7] One of the key assumptions of richer model specification is the inclusion of multiple and heterogeneous sectors within the economy, as I will capture empirically with micro-data. These sectors are affected by both common and idiosyncratic shocks and face asymmetric nominal rigidities and production costs when setting prices and wages. By modelling an economy with these assumptions, a Sectoral Phillips Curve (SPC) is obtained.

I estimate two SPC frameworks, mainly differing in their production functions. The first framework, originally developed by Imbs et al., 2011 (henceforth IJP) primarily focuses on labour costs as the main source of cost variation. The second framework, proposed by Rubbo

[4]McLeay and Tenreyro, 2019 and Hazell et al., 2022 have shown evidence of statistically and economically significant slopes by employing regional data. Imbs et al., 2011 and Byrne et al., 2013 also found positive and significant slopes using proxies of expectations.

[5]Coibion et al., 2018a.

[6]Gagliardone et al., 2023 and Rubbo, 2023 highlighted the advantage of using costs as forcing variable instead of output. They argue that the negative slope found when using the output gap may suggest a low elasticity of marginal cost to the output gap and not necessarily a low response of prices to costs.

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

(2023), incorporates the costs of intermediate goods. My analysis results indicate that including the costs of intermediate goods increases the responsiveness of prices to costs. This higher response is attributed to the inclusion of the sectoral linkages and additional nominal rigidities within the supply chain. These findings hold particular relevance during the recent inflation period[8], as they contribute to a better understanding of the inflation process. When it comes to the role of expectations and lagged inflation, the average parameters in both frameworks are quite similar, with positive and significant values.

Notably, my findings from both frameworks suggest that the slope has not disappeared and inflation responds positively and significantly to costs. To the best of my knowledge, this is the first work to estimate SPCs with survey and sectoral based data on direct measures of expectations, salary costs, and production networks. Therefore, the results might not be directly comparable to previous evidence.

Through the estimation of SPCs, this study also shows evidence of substantial heterogeneity across sectors in the strength of the slope and in the role of expectations. Allowing for heterogeneous coefficients thereby challenges previous assumptions of homogeneity in the traditional Phillips Curve. This finding is aligned with more recent works.[9] When homogeneity is imposed -and discrepant with the data-, estimations show potentially misleading and inconsistent results such as large inflation inertia and low significance of costs. IJP and Byrne et al., 2013 estimated labour cost-focused SPCs for manufacturing firms, showing evidence of the relevance of sector-level heterogeneity.

Another important aspect of the methodology I use for the estimation is that I employ heterogeneous dynamic panel data models with Common Correlated Effects (CCE) estimator to account for unobserved common factors. This correction technique helps mitigate the strong cross-sectional dependence across sectors.

On the second research question, I further investigate the primary sources of sectoral heterogeneity in the Phillips Curve, with a focus on some industry characteristics that have been overlooked in the estimated frameworks. The microfoundation of the SPC predicts sectoral heterogeneity in its parameters[10] but it does not provide a specific theoretical framework for explaining these sources of heterogeneities. 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.[11]

This paper's findings are relevant to current policy discussions concerning the impact of

[8]For an in-depth analysis of the recent inflation process in advanced economies, refer to Reis, 2023.

[9]Andrade et al., 2022, Byrne et al., 2013, Imbs et al., 2011, Maćkowiak et al., 2009, Leith and Malley, 2007.

[10]The key reduced-form parameters are the sensitivity of current inflation to expected future inflation and the Phillips Curve slope, while the main underlying structural parameters are the degree of price-stickiness, the degree of backward-lookingness, and the share of intermediate goods.

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

inflation expectations on current inflation and our understanding of the sources of sectoral heterogeneity. More backward-looking inflation expectations may need the monetary policy to lean more heavily and quicker against inflation to minimise the risks of further rising inflation (IMF, 2022). Additionally, weak identification of the Phillips Curve slope poses challenges for central banks in maintaining inflation on target, as the strength of the slope determines the necessary adjustment in nominal interest rates to meet the inflation target. Finally, monetary policy effects are larger and more persistent when accounting for the sectoral heterogeneity (Carvalho, 2006).

Related Literature. This paper connects to various areas of economic research, spanning inflation dynamics, Phillips Curve estimation, non-rational expectations, and heterogeneity in macroeconomics. The initial success of the Phillips Curve estimation relied on the utilisation of aggregate data, rational expectations, and proxies like labour cost or output gap to capture firms' cost pressure, as evidenced in Gali and Gertler, 1999, Sbordone, 2002, Rudd and Whelan, 2006. However, subsequent studies have cast doubt on the robustness of data choices and estimation methods. For instance, papers such as Coibion and Gorodnichenko, 2015, Del Negro et al., 2015, and Del Negro et al., 2020 found a disconnection between inflation and real activity, challenging the validity of the Phillips Curve.

A comprehensive review of the challenges tied to weak identification and instability in Phillips Curve estimation with aggregate data has been presented by Mavroeidis et al., 2014. They conclude that the estimation of the Phillips Curve using aggregate data is prone to a severe weak instruments problem. Consequently, they recommended exploring new identification methods and the use of alternative datasets, such as micro or sectoral data.

In that line, recent studies have proposed leveraging disaggregated data to enhance the identification of the Phillips Curve. For example, McLeay and Tenreyro, 2019 and Hazell et al., 2022 employed regional data, uncovering positive and significant Phillips Curve slopes. Importantly, my own findings, utilising sectoral data, corroborate these outcomes.

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.

While prior studies in the literature (Leith and Malley, 2007, Imbs et al., 2011 and Byrne et al., 2013) have employed sectoral data for Phillips Curve estimation, they have relied on indirect measures of expectations, i.e. actual inflation, or rational expectations, due to unavailability of direct measures of firms' expectations. The significance of using direct measures of expectations was firstly proposed by Roberts, 1995 and later emphasised by Adam and Padula, 2011. The adoption of subjective expectations in estimating the Phillips Curve aligns with a growing body of literature that acknowledges the role of non-rational expectations in firms' price-setting behaviour. Coibion and Gorodnichenko, 2015 and Coibion et al., 2018a illustrate considerable departures from full-information rational expectations among firms in New Zealand. In the UK, as evidenced by Boneva et al., 2020, the assumption of rationality is rejected using the same survey data employed in this study. Consequently, this study adopts the assumption of non-rational expectations and employs direct measures of expectations for Phillips Curve estimation. Other recent evidence of heterogeneous expectations within the UK context is presented in Meeks and Monti, 2022, which estimates aggregate Phillips Curves using survey data from households and firms. Therefore, this is the first study to estimate the Phillips Curve using sectoral data in conjunction with survey-based firms' expectations.

The relevance of expectations was originally stressed by Friedman, 1968 and more recently reaffirmed by Werning, 2022 and Hazell et al., 2022. The former explores the effect of expectations on inflation through theoretical approaches, highlighting a near one-for-one pass-through from inflation expectations to current inflation, especially when assuming price stickiness a 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.

Regarding the sources of asymmetries across sectors in price-setting behaviour, Andrade et al., 2022 and Klenow and Malin, 2010 offer valuable insights in these areas which I explain in detail in Section 6.

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

2 The Economics of Price-Setting Behaviour and Sectoral Heterogeneity

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

One notable limitation of IJP's framework is the omission of sectoral interactions within the theoretical setting. They approximate sectoral linkages empirically using econometric techniques to capture the cross-sectoral interdependencies. In my analysis, I take a step further and estimate SPCs with embedded production linkages in the production function. To do so, I introduce a second framework based on the SPC derived by Rubbo, 2023, explicitly modelling the production network. Using input-output tables, I use micro-level intermediate input shares to capture sectoral linkages, providing novel empirical evidence on how these interconnections influence the inflation process. More details on this second framework are provided in the second subsection.

2.1 Labour Cost-Focused SPC

Combining insights from Gali et al., 2001, Sbordone, 2002, and Woodford, 2003, but extending the analysis to encompass multiple sectors, IJP derived a sectoral hybrid New Keynesian Phillips Curve (NKPC).

Detailed derivation is provided in Appendix A. This expression is analogous to the aggregate Phillips Curve[12], but instead of being economy-wide, it yields sector-specific parameters:

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

This can also be expressed in the reduced-form:

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

where

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

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

[12]Microfounded in seminal works by Clarida et al., 1999, and Woodford, 2003.

degree of price stickiness (α_k), and the discount factor (β).

Some of the main assumptions in the IJP framework are:

- Optimal price setting by monopolistically competitive firms.
- Price updating follows a $(1-\alpha_k)$ probability distribution, similar to Calvo, 1983. Importantly, here the degree of price stickiness, α_k, is allowed to vary across sectors.
- The production function features labour as the only factor of production and sector-specific technology:
$$Y_{ikt} = Z_{kt}\, L_{ikt}^{1-a_{kt}}$$
where $1-a_{kt}$ represents the share of labour in sector k's value added
- Demand function:
$$Y_{ikt} = Y_{kt}\left(\frac{P_{ikt}}{P_{kt}}\right)^{-\eta}$$
In this equation, P_{ikt} is the price of firm i of good k chosen taking P_{kt} (price index in k) and Y_{kt} (AD) as given. The parameter $\eta > 1$ is the elasticity of substitution across varieties within sector k, and assumed homogeneous across sectors.
- A constant frictionless markup μ.
- Perfect competition in labour markets, i.e. labour is undifferentiated and fully mobile across industries.

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

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

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

In line with Gali et al., 2001, IJP advocates a marginal cost-focused Phillips curve. They claim that this setting directly captures the impact of productivity gains on inflation. However, other studies support the use of the output gap as a measure of economic activity. In Subsection 3.8, I will explore the upsides and downsides of each approach in greater detail.

Real marginal cost is defined as: $S_{ikt} = \Psi'(Y_{ikt})/P_{ikt}$. For the theoretical derivation, IJP assume that costs in steady state are as follows: $S_{ik\,t,t+j} = S_k = \eta/(\eta-1)$.

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

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

$$\mu = 1.1$$

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

An important drawback of this framework is its omission of sectoral interactions within the theoretical framework. I will then introduce Rubbo's framework explicitly modelling the sectoral linkages.

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

By explicitly modelling the sectoral linkages, Rubbo, 2023 claims that price rigidities compound at each step along the production chain, with price rigidity in the intermediate goods sector reducing the pass-through of wages into the final good producer's marginal cost. After combining equations from Rubbo's paper and working through the algebra, I obtain an equivalent expression to the SPC obtained by IJP (See Equation 7 below).

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

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

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

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

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

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

The main expressions[14] I use from Rubbo are the following[15]:

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

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

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

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

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

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

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}.

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

I approximate the full cost measure, s^F_{kt}[16], by using: the labour share for each sector, $(1 - a_{kt})$, the intermediate goods share bought by sector k from sector j, λ_{kjt}, and sector

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

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

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

j's intermediate goods' prices, $\hat{p}_{jt}$[17].

By further reducing the expression in Equation 5, I obtain the equivalent to the SPC:

$$\pi_{kt} = \gamma_k^s \, \hat{s}_{kt}^F + \gamma_k^f \, E_t \, \pi_{k\,t+4} + \varepsilon_{kt}^{\pi} \tag{7}$$

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

Let's compare the sets of structural parameters from IJP and Rubbo and temporarily ignore the discount factor and the indexation rate (ω in IJP) for simplicity: One interesting difference is that in the traditional SPC setting, firms pricing behaviour in sector k respond to expected inflation and costs based on their own degree of price stickiness. However, in the extended version of the SPC that incorporates production networks, the responsiveness of prices to expected inflation and to marginal costs is influenced not only by the nominal rigidities within the sector itself but also by its suppliers, considering the extent of sector k's purchases from these suppliers. I discuss this further in section 3.6.

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

2.3 Open Economy Features

The SPC frameworks presented in the previous sections do not consider the role of foreign factors such as the price of import prices, the price of oil, and the degree of openness. Abbas et al., 2016 show evidence that the open economy NKPC, which incorporates prices of imported goods, performs better in explaining the process of inflation dynamics for Australia, Canada, New Zealand and the UK.

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

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

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

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

To my knowledge, nobody has derived an open economy SPC framework. Therefore, this paper estimates the structural framework based on IJP and Rubbo, as well as some modified versions, combining elements from Batini et al., 2005. I show in Section 5 that these modifications, such as controlling for oil inflation and real import prices, improve the results in some cases, i.e. yield parameters more consistent with the theory.

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 and how I address them: using survey and sectoral based data on direct measures of expectations, suppliers prices, and salary costs; incorporating input-output tables to account for production networks; and employing heterogeneous dynamic panel data models with Common Correlated Effects (CCE) estimator to account for unobserved common factors. I will also delve into the tradeoff between using marginal cost and the output gap as proxies for the forcing variable. For a more comprehensive review of all challenges faced in Phillips Curve estimation, please refer to Mavroeidis et al., 2014 and Abbas et al., 2016.

3.1 Survey-Based Expectations

Most studies proxy expectations with instrumental variables (IV) or rational-expectations (RE)[18] mainly due to the lack of available data on firms' expectations. However, these methods have faced criticism, particularly regarding the issue of weak instruments. A proposed solution is to use survey-based expectations, as suggested by studies like Nason and Smith, 2005, Byrne et al., 2013, and Coibion et al., 2018b. 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"*.

The use of survey data as a proxy for inflation expectations in the Phillips Curve was introduced by Roberts, 1995. They found that using survey data yield the correctly signed (positive) and statistically significant slope. These estimates were statistically insignificant when actual future inflation is used as a proxy for inflation expectations. 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 IV or RE.

[18] Gali and Gertler, 1999, Leith and Malley, 2007, Maćkowiak et al., 2009, IJP, Byrne et al., 2013

Connecting the empirics with the theory, Adam and Padula, 2011 argue that 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). This condition entails that agents are unable to predict revisions in their own or other agents' forecasts. Coibion and Gorodnichenko, 2012[19] provide a test for this condition on survey-based expectations and fail to detect deviations from LIE.

For a comprehensive review of the role of expectations across various papers and specifications, refer to Mavroeidis et al., 2014.

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

3.2 Sectoral Data

By using sectoral data, I will address concerns related to simultaneity and the endogenous response of monetary policy in the estimation process.

Simultaneity Challenges: The estimation of the Phillips Curve faces several challenges, including the issue of distinguishing demand and supply shocks, as highlighted by Hazell et al., 2022. Supply shocks comove both inflation and unemployment positively. If the variation used to identify the slope of the Phillips Curve is contaminated by such shocks, the estimated slope will be biased.

Another challenge arises from the disconnection between inflation and real economic activity due to the dynamic response of monetary policy to inflationary pressures[20], as elaborated in McLeay and Tenreyro, 2019. This dynamic interplay between Aggregate Supply (AS) and Aggregate Demand (AD) can lead to a negative slope in the Phillips Curve when demand shocks are successfully mitigated, i.e. AD offsets the AS impact.

The Use of Cross-Sectional Data: To address these challenges, researchers have explored the use of cross-sectional data, such as regional or sectoral data, as a means to overcome these simultaneity issue. See McLeay and Tenreyro, 2019 for an example with regional data. Leveraging sectoral data provides a way to overcome the simultaneity issue, allowing for more accurate estimation of SPCs.

Addressing Remaining Simultaneity: However, remaining simultaneity could arise

[19]See also Coibion et al., 2018a for the derivation of the Phillips Curve with survey-based expectations.

[20]The slope of the Phillips Curve results from the interaction between Aggregate Supply (AS) and Aggregate Demand (AD). AS reflects the positive response of inflation to higher economic activity, while AD represents the central bank's goal to counteract demand shocks through monetary policy.

from the dependent variable being jointly determined with the explanatory variables for a given sector. For instance, current sectoral inflation may be explaining currently formed expectations, or vice versa. To address this common simultaneity problem, instrumental variable techniques are employed, including the use of lagged explanatory variables.

3.3 Heterogeneous Dynamic Panel Estimation

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

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

By estimating Equation 9 instead of Equation 10, upon any of the following being true: $\gamma_k^f \neq \gamma^f$, $\gamma_k^b \neq \gamma^b$ or $\gamma_k^s \neq \gamma^s$, then the errors ε_{kt} will be correlated with the explanatory variables and the estimated coefficients will be biased.

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

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

3.4 Addressing Cross-Sectoral Interdependencies:

Factors such as input-output production linkages and integrated factor markets can lead to cross-sectoral interdependencies. To address this concern, IJP implement the Seemingly Unrelated Regression Equations (SURE) correction, aimed at capturing cross-sector interdependencies. They assert that the SURE correction is a robust technique that accommodates common macroeconomic shocks, cross-sector linkages, and other factors influencing sectoral prices or marginal costs with contemporaneous correlations across industries. To enhance robustness, they also employ an alternative estimator proposed by Pesaran, 2006, which introduces a correction technique to account for unobserved common factors[21], potentially correlated with sector-specific regressors.

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

While Byrne et al., 2013 also utilise the CCE technique, they employ the weighted mean group (WMG) estimator which utilises observed sectoral weights. Both IJP and Byrne (2013) assume an exogenous autoregressive process for real marginal costs to identify the forward-looking term of inflation in the NKPC model, as direct measures of expectations are lacking. It is worth noting that while these research papers employ powerful tools to address cross-sector interdependencies, they do not explicitly model linkages between sectors, such as through an input-output structure. In contrast, I enhance the estimation of SPCs by accounting for sectoral linkages through input-output tables and eliminating the strong cross-sectional dependence through CCEs.

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

In the context of Dynamic Panel Mean Group Estimation, this study employs the Common Correlated Effects (CCE) estimator, a method closely aligned with the approach introduced by Chudik and Pesaran, 2015. The CCE estimator, initially proposed by Pesaran, 2006 and extended by Chudik and Pesaran, 2015[22] is designed to address the challenge of cross-sectional dependence (CSD) and enhance the efficiency of estimations. This section explores its application in the context of the estimation of the SPC.

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

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

To provide some intuition: it could be that some shocks that hit the UK economy such as Brexit and Covid affected several sectors simultaneously and differently, and are not necessarily captured by the production network. We should however think of these omitted factors not just as omitted variables, which we could in principle have included in the model,

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

but also as a set of unknown and time-varying determinants correlated with inflation and independent variables. Therefore, CCEs are also included in Rubbo's estimation equation.

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

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

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

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

Then, in the case of the IJP SPC, I augment Equation 2 as follows:

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

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

where π_{kt}, $\pi_{k\,t-1}$ and $E_{kt}\,\pi_{k\,t+4}$ are current, lagged, and expected sectoral inflation, respectively, all expressed in annual percentage change; $\hat{s}_{kt}$ is detrended real marginal cost, expressed in logarithm terms. These variables constitute the observable part of the model, with their parameter coefficients γ_k^b, γ_k^f, and γ_k^s allowed to differ across industries k. Equation 10 also includes sector fixed-effects, α_k, and a set of unobserved common factors f_t with sector-specific factor loadings g_k. These common factors not only drive inflation but also expected inflation and real marginal costs. As explained in Eberhardt and Presbitero, 2015, the parameters γ_k^b, γ_k^f, and γ_k^s are not identified unless I find some way to approximate the unobservable factors in the error term u. Following Chudik and Pesaran, 2015, I compute cross-sectional averages z_t to approximate the time-varying covariates.

Equation 10 is then estimated using various sets of covariates to eliminate strong CSD while monitoring regression dimensionality, considering the limitations of the sample size.

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

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

The initial set of cross-sectional averages, following the methodology's literature, are computed on the model's explanatory variables: inflation, expected inflation, and the cost measure. Due to the high correlation between the first two variables[25], including just one is sufficient. Additionally, in line with empirical evidence mentioned in the previous section, I incorporate additional time-varying covariates, specifically real import prices and oil price inflation.

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

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

3.6 Sectoral Linkages Through Input-Output Tables

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

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

Therefore, the degree of price stickiness in industry k is directly explained by the same-industry characteristics, i.e. reasons for having low-frequency in price adjustment, or indirectly by the price stickiness coming from the supplier. Intuitively, a non-sticky industry is willing to update prices every quarter but buys goods only from a very rigid industry which only updates prices annually. Hence, the non-sticky industry will exhibit low-frequency

[25] See details in Correlation Table 7.

price updates. A non-sticky industry could be thought of as an industry not tied to annual contracts or an industry with very high market power. Conversely, a sticky industry could be due to using annual contracts/indexation or being part of a very competitive market.

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

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

3.7 Other Potential Identification Concerns

Shifting Trend Inflation: It is standard in the derivation of the Phillips Curve to assume that trend inflation is constant. This implies that shifts in trend inflation may confound the identification of the parameters. Gagliardone et al., 2023 uses time fixed effects to control for shifting trend inflation. I propose using CCEs as an enhanced object compared to time fixed effects to control for potential shifting trend inflation. While the CCEs are also time-components, proxied through a common factor across sectors, the panel technology which implements them have the advantage of allowing for heterogeneous loadings associated to each sector.

Time Series Properties: One common challenge in this literature is related to the overlapping periods of the variables, as the perceived and expected inflation measures refer to annual changes while the frequency is quarterly. To address the potential correlation over time, I employ lagged variables[26] to instrument out the regressors.

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

It is also the case that inflation expectations are simultaneously determined along with the current inflation rates. By conducting a first-stage regression, the resulting fitted value mitigates the endogeneity issue. I show in Table 8 the potential endogenous variables regressed on their lags. In the case of expectations, all coefficients have the expected sign and are highly significant, reflecting the time overlapping effect. The labour cost series has been converted from an annual to a quarterly measure. This is reflected in the short-dated correlation, as only one lag is statistically significant. It is also noteworthy that the lags of expectations have practically no predictive power on labour costs, and vice versa.

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

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

survey-based data.

3.8 Proxy for the Slack Measure: Output Gap or Marginal Cost

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

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

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

Sbordone, 2002 uses data on the average level of unit labour cost in the US economy as a measure of nominal marginal cost and proves that no other measure of marginal cost is better than unit labour cost. Regarding marginal costs vs. average costs, she illustrates two different classes of factors that might cause average and marginal cost to vary differently: 1) in the presence of a 'real wage bias': the marginal cost of hours is not equal to the wage, or 2) in the presence of a 'productivity bias': the growth rate of the effective variable input is larger than the growth rate of total labour hours, which is used to compute unit labour costs. In her paper, she proposes some ways to account for these potential biases.

Moreover, the expression with real marginal cost more directly generalises to models such as the multisector one studied here. The expression obtained for the SPC by Woodford, 2003 contains both relative prices and aggregate output gap[27] whereas the sectoral inflation equation which uses the real marginal cost (instead of the output gap) does not require relative prices. Sector-level nominal marginal costs are calculated as the average of the costs across firms of sector k. Therefore, I use firm-reported data of salary costs from the survey as proxy for the slack measure.

4 Data and Descriptives

4.1 Survey of Firms' Expectations

The Confederation of British Industry (CBI) suite of business surveys comprises four surveys[28] completed by firms operating in the UK. It gathers information from thousands of

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

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

firms on inflation expectations at the sector level, both retrospectively and in expectation, along with other firm-level outcomes such as output, investment, capacity, and inventories. The same firms are being targeted on a quarterly-basis but their completion is voluntary.

Table 1: Summary of CBI survey data

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

[1] Number of firm's reports per quarter: 2009-2020 mean 650 (max:813, min:451); 2021-2022 mean 388 (max:464, min:314)
[2] Calculated using turnover data reported by firms through the CBI surveys and sector-level statistics from the ONS.

Although the CBI survey began in 1958, the quantitative question on past and expected future price movements started being collected in 2008[29]. The CBI collects this information through supplementary questions managed jointly with the Bank of England (BoE). The CBI-BoE dataset is an excellent source of data regarding firms' inflation expectations, given its panel structure which allows to track firms over a significant period of time. It provides quarterly reports about perceptions since 2009, 1-year ahead expectations since 2009 and 2-year ahead expectations reports since 2014. Further information available from the survey about firms' characteristics include their location, industry activity (by SIC code), firm size (based on employee numbers), among others.

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

4.1.1 Inflation Expectations Question

The key questions about prices in the four surveys are framed identically. The question about future expectations is "What has been the percentage change over the past 12 months in the general level of output prices in the UK markets that your firm competes in, and

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

what is expected to occur over the next 12 months and the following 12 months?". And the question about past inflation is "What has been the percentage change over the past 12 months in your firm's own average output price for goods sold into UK markets and what is expected to occur over the next 12 months?

Respondents are asked to report their expectations and perceptions about price movements by selecting from one of the ten buckets within the range -10% to 10% (ITS)[30] whereas for DTS, FSS and SSS[31] are -5% to 5%. Additionally, in the four surveys they can answer zero or enter a point estimate manually. The range studied in this work, which spans from -10% to 10% has proven to be highly advantageous in capturing the rising inflation period 2020-2022, compared to the households survey[32] which had the highest bucket at 5%.

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

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

4.1.2 Stylised Facts from CBI Survey Data

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

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

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

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

[32]Bank of England/Ipsos Inflation Attitudes Survey

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

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

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

4.2 Official Inflation vs. Survey-based perceived Inflation

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

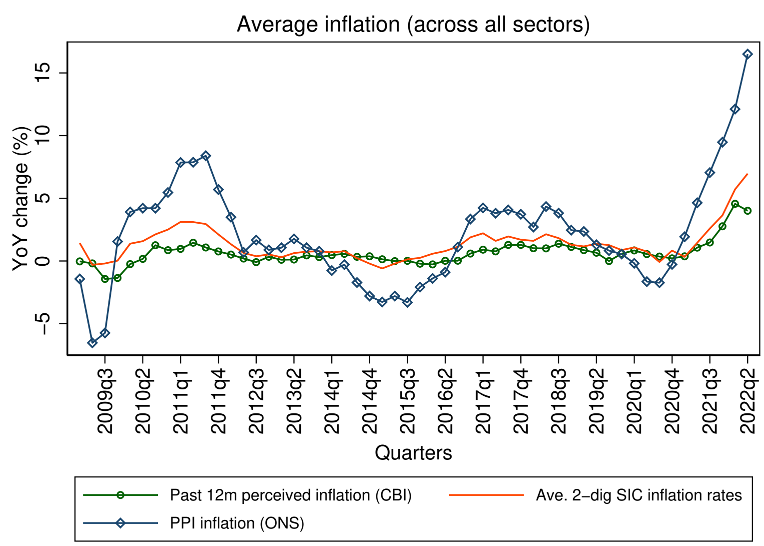
The key challenge with using the Office for National Statistics (ONS) inflation data is that the price indices are not available at the level of disaggregation (4-digit SIC) that is observed in the CBI reports. The ONS provides disaggregated Producers Price Indices (PPI[34]) by SIC code for industrial sectors. For non-industrial sectors, the Consumers Price Indices (CPI) and Services Producer Prices Indices (SPPI) could be used[35].

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

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

Regarding the survey-based reports, the CBI elicits firms' expectations regarding "changes in the general level of output prices in the UK markets that your firm competes in", without specifying the sector. This lack of specification raises the challenge of precisely identifying the exact "markets" with which each firm competes. While one could assume that these markets align with the 4-digit SIC code that firms report at the end of the questionnaire, this assumption may introduce bias. The interpretation of these markets by firms could be related to the locations where they sell their goods or services, where they source their inputs, or where they recruit their labour force. However, I show in 2 that the survey-based perceived sectoral inflation is a good proxy for the official actual inflation rates. The average of CBI perceived inflation reports follows quite closely the average of official 2-digit SIC inflation rates.

Figure 1: Measures of Sectoral Inflation



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

4.3 Input-Output Tables

The ONS produces input-output tables with the amount of expenses as a share of income spent on employees and spent on intermediate inputs bought from other industries. The input-output tables are available at an annual frequency. From these tables I derive the share of labour expenses and the share of intermediate goods expenses for each 2-digit SIC industry to build the production network matrix.

Share of labour cost and share of intermediate inputs costs:

$$Totalcost_k = Intermediatecosts_k + CompensationtoEmployees_k$$

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

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

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

4.4 Measures of cost

4.4.1 Labour Cost

I explored two measures for sectoral labour costs: the log detrended real wage, constructed using survey-based changes in salary costs, and a measure of unit labour cost (ULC) provided by the ONS[36]. The log detrended real wage, denoted as $\hat{s}_{kt}$ and shown in Figure 2, is calculated using the nominal wage series constructed from the survey-based "change in wage/salary cost per person employed". Subsequently, I compute the log deviations from the steady state[37]. To obtain a real measure, I deflate it by prices, also constructed based on the survey-based inflation data. This is represented as $\hat{s}_{kt} = s_{kt} - \overline{s}_k$ and $\hat{p}_{kt} = p_{kt} - \overline{p}_k$. The real wage measure yields positive and significant slope, as predicted by the theory. These results are presented in Section 5.

4.4.2 Full Costs

In order to construct the measure of cost that I use for the estimation of Rubbo's framework[38], which I will refer to as "Full costs", I require specific data elements: the labour share for each sector, $(1 - a_{kt})$, the intermediate goods share bought by sector k from sector j, λ_{kjt}, and sector j's intermediate goods' prices, $\hat{p}_{jt}$. I have explained in Section 4.3 how I obtain the first two from the input-output table, LS_k and $ICshare_{kj}$, respectively.

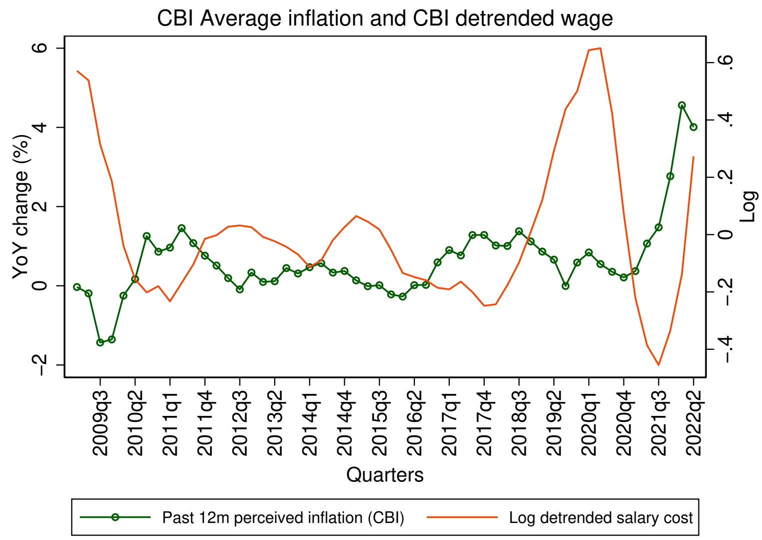
The process of calculating intermediate goods' prices involves several steps. First, I compute quarterly sectoral prices by dividing the perceived sectoral inflation reported by CBI over the past 12 months by four, represented as $\pi^q_{kt} \equiv \frac{\pi^y_{kt}}{4}$. By indexing the price series with the first quarter data point as 100 and applying quarterly changes throughout the series, I generate a price level series for each sector on a quarterly basis. Lastly, I calculate

[36] Details on how the ULC measure was constructed can be found in Appendix D

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

[38] As expressed in Equation 5

Figure 2: Inflation and CBI nominal wage



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

the natural logarithm of this series and detrend it by subtracting the sample mean price for each sector, resulting in $\hat{p}_{kt}$.

4.4.3 Market Concentration (Herfindahl-Hirschman Index)

To identify the industrial structure, I calculate the standard measure of concentration, the Herfindahl-Hirschman Index (HHI). As I am not aware of any ongoing production of these indices for UK firms, I constructed the HHI using turnover data from FAME BvD[39]. I show the series for each industry from 2009 to 2021 in Figure 28, but I use only the 2021 series for the panel analysis as it is the latest available and it does not vary much from previous years.

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

I then define the HHI for a given sector k as follows: $HHI_k = \sum_{f=1}^{n} (s_f)^2$ (summing up all firms f in each industry). HHI<0.1 suggests an unconcentrated industry, $0.1 <$HHI< 0.2 moderately concentrated and HHI> 0.2 highly concentrated.

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

4.5 Other Relevant Aspects About the Data

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

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

5 Sectoral Phillips Curves Estimation

In this section I show the estimation output of the two SPC frameworks: IJP's and Rubbo's. Each framework is estimated for 52 sectors. To calculate the expectations variable, I use the sector-weighted average of firms' reports, with the number of employees serving as weights. This approach offers the advantage of producing a balanced sample without any firm-level outliers.

For the IJP framework, I estimate the reduced-form parameters using Equation 2:

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

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

Based on Rubbo's framework, and referring to the derived Equation 7, I estimate the following specification:

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

The hybrid version will be as follows:

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

5.1 Previous Research on Phillips Curve Estimation in the UK

The validity of the aggregate Phillips Curve in UK data has been confirmed by Batini et al., 2005 through econometric techniques to estimate unobserved expectations and by Meeks and Monti, 2022 using households expectations. In the UK context, Byrne et al., 2013 represents the only available evidence of SPC estimation, also relying on econometric methods to proxy unobserved expectations. To the best of my knowledge, this is the first study to estimate SPC using direct measures of expectations from UK firms.

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

5.2 Can I enhance the identification of the Phillips Curve?

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

In table 3 I present the results of the SPC estimation using only labour costs as a forcing variable, and in Table 4, I incorporate labour costs with micro-level intermediate goods costs, thereby accounting for production network effects in the inflation process. In both cases, the three columns indicate different specifications. Column 1 shows the estimation of a pooled model, which assumes homogeneous slopes for all sectors. Column 2 shows Mean Group (MG) estimation, with heterogeneous coefficients. Column 3 integrates all features: heterogeneous coefficients Mean Group estimation and CCE, I will call this the "full model". All models have sector-level fixed effects, and Model 3 is augmented with common factors to control for CCEs.

Upon comparing the three model specifications, the full model consistently yields the lowest Root Mean Squared Errors (RMSE)[40] in both frameworks. This suggests that allowing for heterogeneous coefficients across sectors and accounting for unobservable CCEs results in substantially lower average residual magnitudes. Additionally, considering pro-

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

duction networks in Rubbo's framework leads to a lower RMSE compared to the IJP framework.

In the full model from both IJP and Rubbo, the average coefficient coefficient for the role of expectations is approximately 0.6, and for lagged expectations, it's around 0.2. These estimates align with economic theory, which predicts that γ^f should be larger than γ^b, indicating that firms set prices in a more forward- than backward- looking way. Although not exactly comparable, similar parameters have been found in other studies that estimated Phillips Curves for the UK and the US.

Table 3: Labour cost focused SPC (IJP)

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

Note: This table presents the OLS panel time-series estimation results using the IV method. The averages of sector-specific parameters are reported. Expectations are calculated as weighted averages among all firms in each sector. Labour costs and expectations are instrumented using: lags (1, 2, 3) of expectations and lags (1, 3) of labour costs. The "Full model" uses a CCEMG estimator, implemented using cross-section averages proxied by ave. expectations (0 to 3 lags), and up to 2 lags of ave. labour cost and oil inflation; these proxies of CCEs are partialled out. RMSE is the square root of the ave. of squared errors and is defined in terms of the dependent variable. CD test: null hypothesis of weak Cross-Sectional Dependence. Data 2009q1-2022q2. S.E. in parenthesis (robust in model 1). *** p<0.01, ** p<0.05, * p<0.1.

In the UK, Meeks and Monti, 2022 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 $\gamma^b : 0.7^{***}$. Moreover, Boneva et al., 2020 estimated firm-level pricing equations using CBI expectations about their own prices and obtained $\gamma^f : 0.2 - 0.3$ (γ^b not explicitly reported).

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

The slopes differ between IJP and Rubbo's framework, consistent with their differing underlying parameters. In the IJP framework, the slope is around 0.1, capturing the responsiveness of prices solely to labour costs. In Rubbo's framework, the slope is around

0.9, indicating a larger responsiveness of prices to a full measure of costs which arise from both labour and intermediate goods.

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

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

Table 4: Full cost based SPC

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

Note: This table presents the OLS panel time-series estimation results using the IV method. The averages of sector-specific parameters are reported. Expectations are calculated as weighted averages among all firms in each sector. Costs and expectations are instrumented using: lags (1, 2, 3) of expectations and lags (1, 3) of costs. The "Full model" uses CCEMG estimator, implemented using cross-section averages proxied by ave. expectations (0 to 3 lags), and up to 2 lags of oil inflation; these proxies of CCEs are partialled out. RMSE is the square root of the ave. of squared errors and is defined in terms of the dependent variable. CD test: null hypothesis of weak Cross-Sectional Dependence. Data 2009q1-2022q2. S.E. in parenthesis (robust in model 1). *** p<0.01, ** p<0.05, * p<0.1.

5.3 Can we Unmask the Sectoral Heterogeneity in Price Setting Behaviour?

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

Sector-specific parameters are obtained using the full model from both frameworks. In Figures 3 through 8 I show the histogram distribution of the estimated parameters. In Appendix C, I present the parameters from IJP's and Rubbo's frameworks for each of the sectors, as well as the average parameters across sector within each group[41].

Figure 3: IJP γ_s

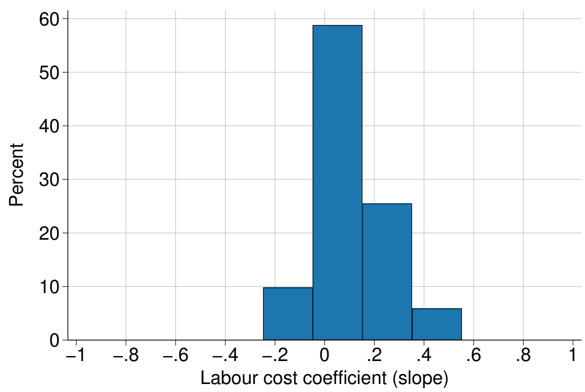


Figure 4: Rubbo γ_s

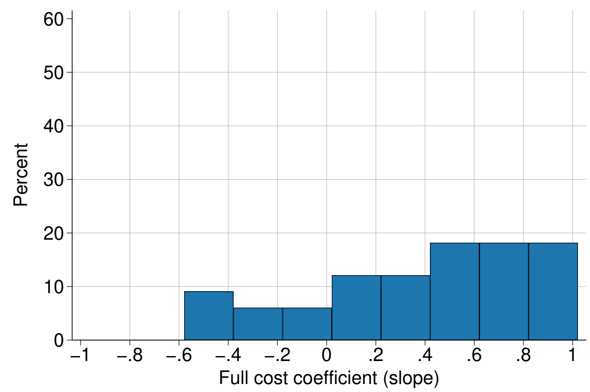


Figure 5: IJP γ_f

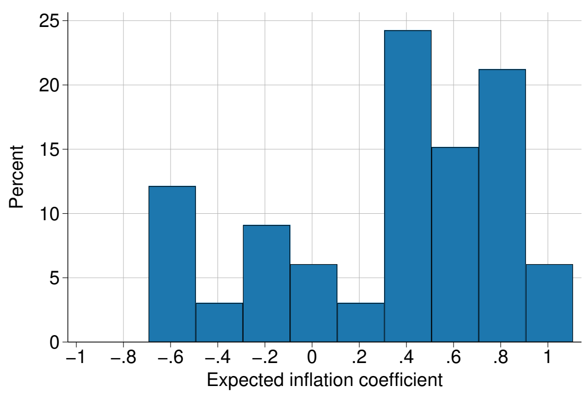
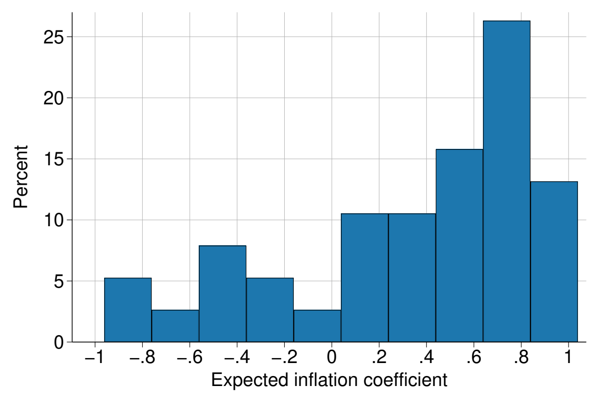


Figure 6: Rubbo γ_f



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

Additionally, based on Figure 5, we can see that while there is not a significant difference in the distribution of estimated parameters for the role of expected future inflation between frameworks. However, the figures in Appendix C reveal substantial differences across sectors, suggesting that industry-specific characteristics may be responsible for these

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

Figure 7: IJP γ_b

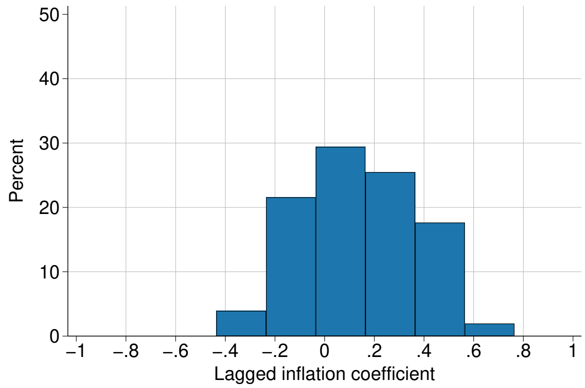
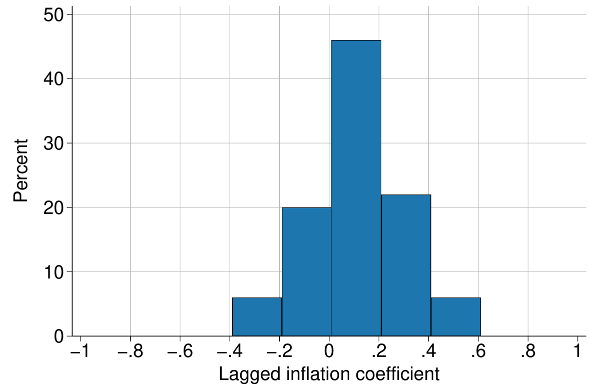


Figure 8: Rubbo γ_b



differences rather than their broad group classification.

In Figure 7, we can observe that the estimated parameters related to lagged inflation are mostly located between -0.5 and 0.5 in results from both frameworks. I will show in in Appendix C that some estimates are not statistically or not economically significant, suggesting that there might be industry-specific characteristics that the model is not accounting for. By comparing the sector-specific coefficients across groups, it doesn't seem to be a large difference on the average parameters across groups, i.e. the average among Manufacturing is 0.25 while the average among Services is 0.12. Yet, there's a wider heterogeneity across industries within each group, being the most persistent across Manufacturing: Food Products, and the least, Medical and Optical.

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

6 Determinants of Sectoral Heterogeneity in Price Setting Behaviour

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

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

6.1 Industry Characteristics and Sectoral Heterogeneity

While I am not aware of studies that explicitly explain industry characteristics potentially driving the SPC structural parameters, some papers have focused on their relationship with price stickiness (α). This parameter, sometimes proxied through the frequency of price changes, is behind all structural parameters in IJP's and Rubbo's frameworks[42]. The remaining parameters that influence the γ values include β[43], input shares in Rubbo's framework, and ϕ in IJP's framework (ultimately influenced by α, β, and ω).

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

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

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

6.1.1 Potential Sources of Sectoral Heterogeneity

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

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

[42]Refer to Equation 1 and Equation 27.

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

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

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

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

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

Other Relevant Factors: Additional factors have been studied by researchers examining price changes. For instance, Bils (2004) found an inverse relationship between the concentration ratio and the frequency of price changes, suggesting that more competition leads to more frequent price adjustments. Moreover, Kato (2021) reported a negative correlation between sectoral inflation persistence and market concentration, implying that increased market concentration is associated with an increase in γ^f. This correlation is due to changes in pricing complementarity as markets become more concentrated.

In contrast, Domberger, 1979 reports opposing findings: a positive relationship between the speed of price adjustment and market concentration. The author considers two plausible hypotheses: the first suggests that price coordination in concentrated industries is easier due to relatively low information and communication costs among sellers, potentially accelerating price adjustments. The second hypothesis relates to "administered prices" and posits that sellers in highly concentrated markets tend to adjust prices unilaterally either due to difficulties in oligopolistic collusion or through the use of mark-up pricing. While Domberger provides evidence supporting the first hypothesis, it is important to note that his study period (1963-1974) coincided with a period of rising inflation, characterised by mostly upward price movements. Furthermore, his sample predominantly consists of industrial sectors, whereas my sample includes also services and distributive sectors, reflecting a wider range of market structures.

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

6.2 Estimated Parameters Weighted by their Standard Error

In this section, I will utilise the estimated parameters of forward- and backward-looking behaviour, as well as the Phillips Curve slope, to understand how they respond to market structure and other industry characteristics. It's important to note that the estimated sector-specific parameters exhibit various levels of estimation precision[44]. 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)[45]. Since the standard errors are derived from the OLS estimation of the SPCs, they will be used to adjust the imprecise parameters. The weights will be determined by first calculating the inverse of the standard errors and then rescaling them to sum up to one.

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

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

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

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

I show in Figures 9, 10, and 11 the weighted parameters by sector from IJP framework[46].

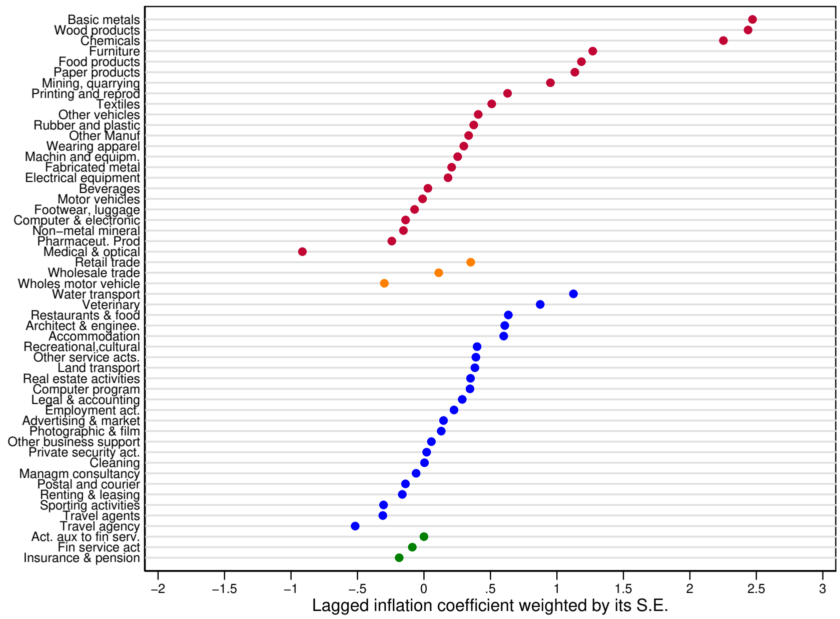
In the next section I will study the potential sources of heterogeneity using these weighted parameters. In order to do so, I will adjust the regression dependent variable and regressors by the precision of the estimates. By doing this, I am giving more weight to the less biased estimated sectors.

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

[45] 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).

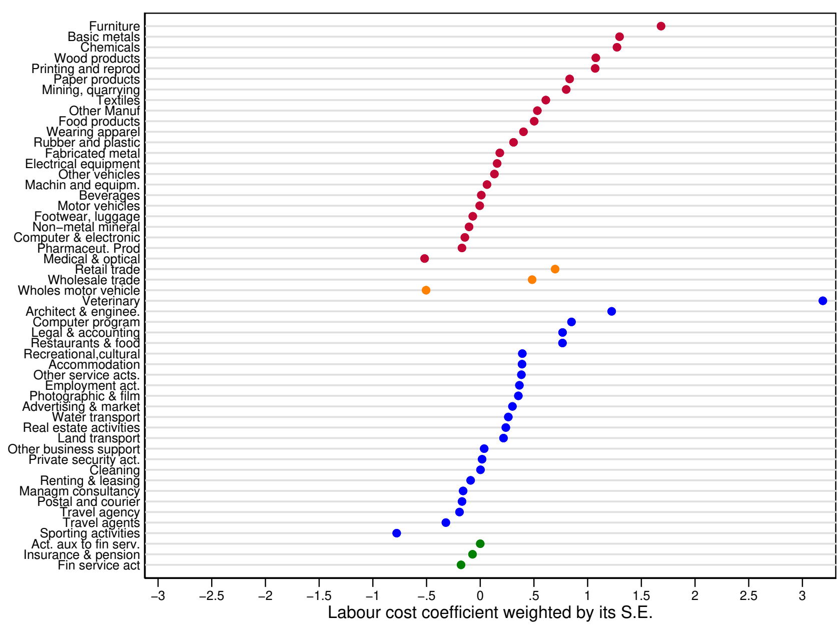
[46] In Appendix C I will show the estimated parameters from Rubbo's framework.

Figure 9: Weighted parameter on lagged inflation (IJP framework)



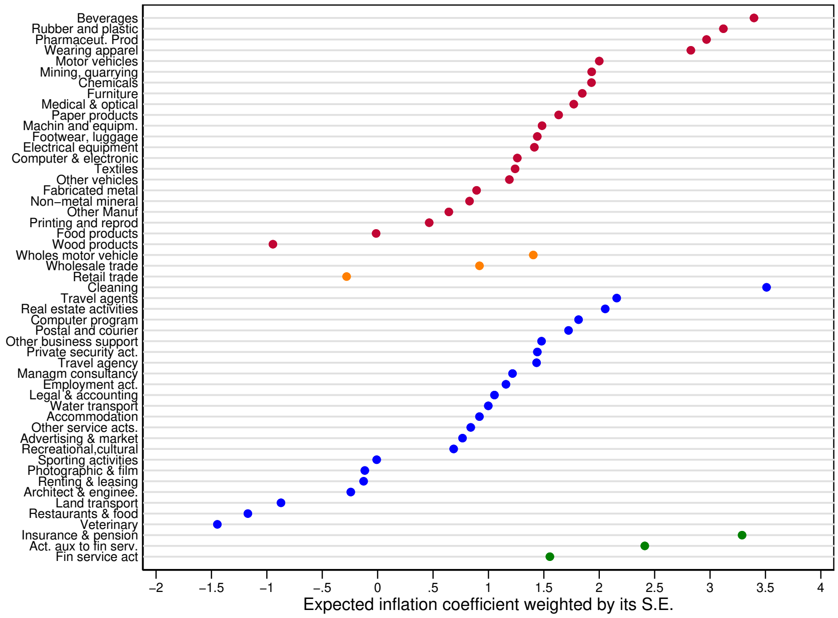
Note: The coefficients presented in the figure have been weighted based on their respective S.E. from IJP framework. Red colour: Manufacturing; Orange: Retail; Blue: Services; and Green: Financial Services.

Figure 10: Weighted parameter on labour cost (IJP framework)



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

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



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

The weighted regression used is expressed as follows:

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

6.3 Regression Estimation Results

The following regressions in Table 5 will shed light on the association between the sector-specific Phillips Curve parameters (γ_f corresponds to the role of expectations, γ_b corresponds to the degree of backward-lookingness, and γ_s refers to the slope) and selected industry characteristics, providing insights into potential sources of heterogeneity.

Table 5: Regressions estimations

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

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

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

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

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

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

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

These findings align with previous evidence suggesting that market concentration might be one of the sources of heterogeneity in the Phillips Curve price stickiness. They also imply that some of these sources may be better captured in Rubbo's model, based on the enhanced specification which captures the sectoral linkages, thereby yielding less scope for second-stage analysis.

7 Conclusions

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

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

The results also hold significant value for future research, aiding in addressing gaps in microfoundations for better specifying and identifying structural parameters. Additionally, these findings also provide insights for policymakers, especially concerning expectations management and communication. Monetary policy (MP) has more substantial and enduring effects when accounting for the asymmetries across sectors (Carvalho, 2006). These asymmetries in price change frequencies across sectors result in varying speeds of reaction to economic shocks. Moreover, more backward-looking inflation expectations may need the MP to lean more heavily and quicker against inflation to minimise the risks of further rising inflation (IMF, 2022).

Appendix A SPC derivation by IJP

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

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

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

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

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

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

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

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

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

By taking the first order condition of Equation 17 and working on the algebra, I get the following expression:

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Now, I will combine Equation 25 and 26, and ignore the productivity term just for brevity. This omission won't affect the results.

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

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

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

Further combining terms to get expressions for the inflation rates:

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

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

This 2-sector matrix illustration shows that inflation in sector 1 depends on a 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, s^F_{kt}, and inflation expectations:

$$\pi_{kt} = (I-\Lambda\,\tilde{A})^{-1}\tilde{A}\,(s^F_{kt}) + (I-\Lambda\,\tilde{A})^{-1}\beta\,(1-\tilde{A})\,E_t\pi_{k\,t+1} \tag{27}$$

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

Appendix C Additional Figures and Tables

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

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

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

Table 7: Correlation table

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

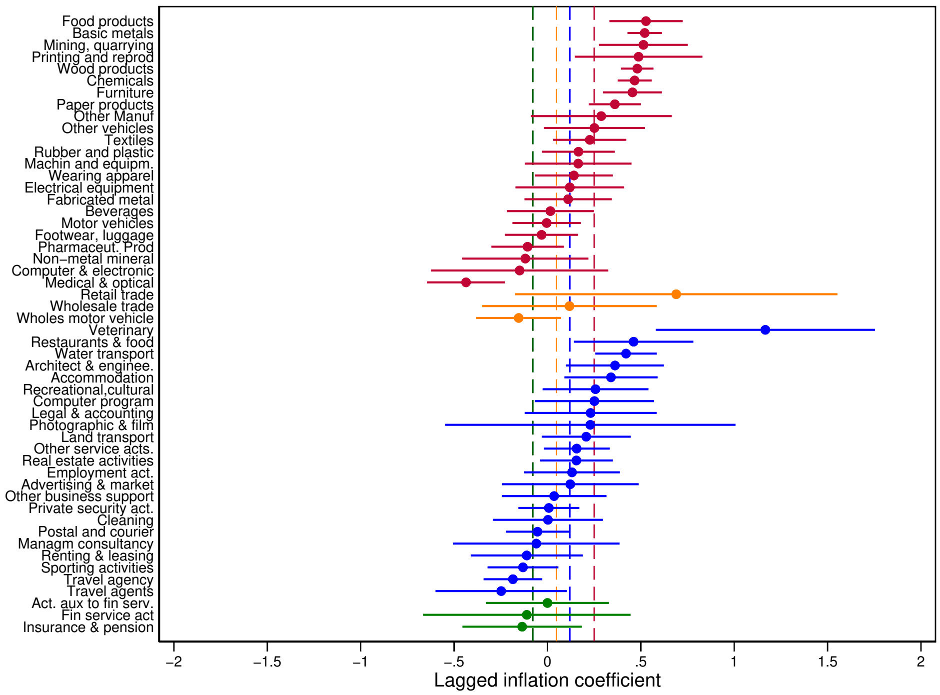
Note: This table reports correlation levels for the main studied variables. “IG” means Intermediate Goods.

Table 8: Relevance of instruments

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

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

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

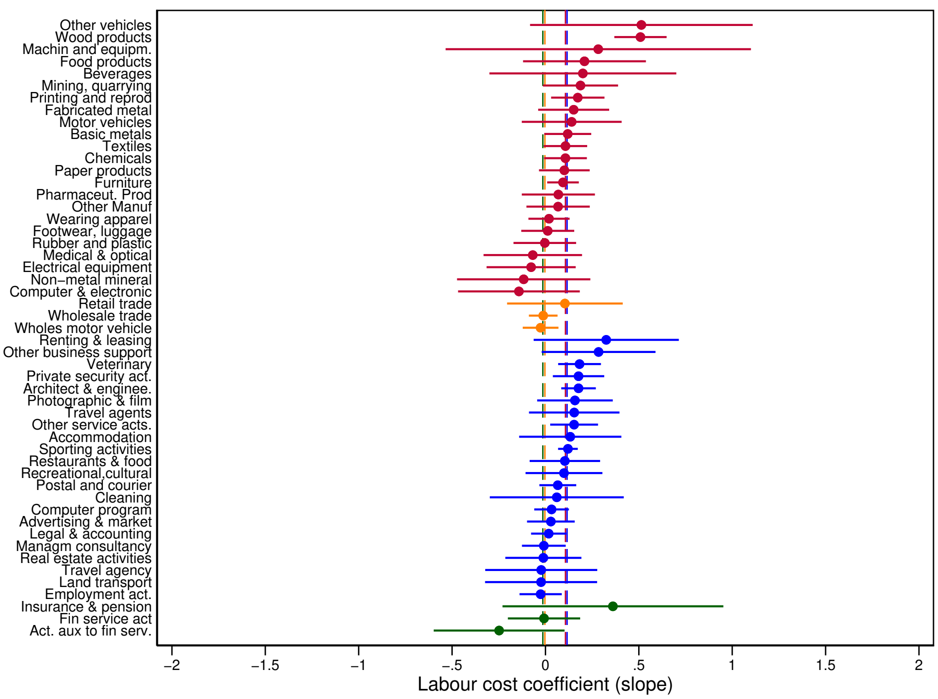


Note: Sector-specific parameters related to lagged expectations coefficients from Model 3 (Table 3, through dynamic panels with CCE). These coefficients are net from common factor effects. Intervals are calculated as the mean +/- s.e. The labels indicate the mean estimated coefficient for each sector.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

Figure 13 displays estimated sector-specific parameters very close to zero, ranging between -0.3 and 0.5. Only the estimated parameter for the Water Transport industry appears to deviate from the others (not included in the figure). These results are particularly relevant to the widely discussed point that labour is considered the only source of costs in these models. When including production networks, these estimated parameters are much further away from zero. See Figure 16 with parameters obtained from Rubbo's framework.

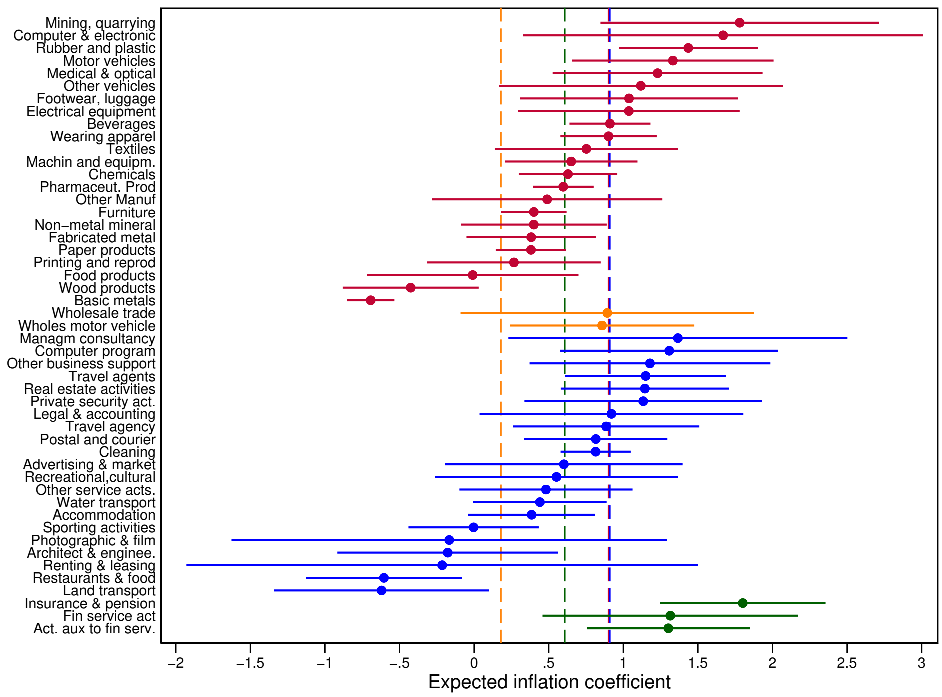
Finally, based on Figure 14, we can see that while there is not a significant difference in the average estimate between Manufacturing and Services firms, both at around 0.9, there are large differences within the groups. Certain Manufacturing sectors, such as Mining, Computer and Rubber have sector-specific parameters of around 1.4, suggesting that they are as forward looking as firms in Management Consultancy activities and the industries within the Financial Services group. This suggests that industry-specific characteristics may be responsible for these differences rather than their broad classification as Manufacturing or Services.

Figure 13: Slope by sector (IJP framework)



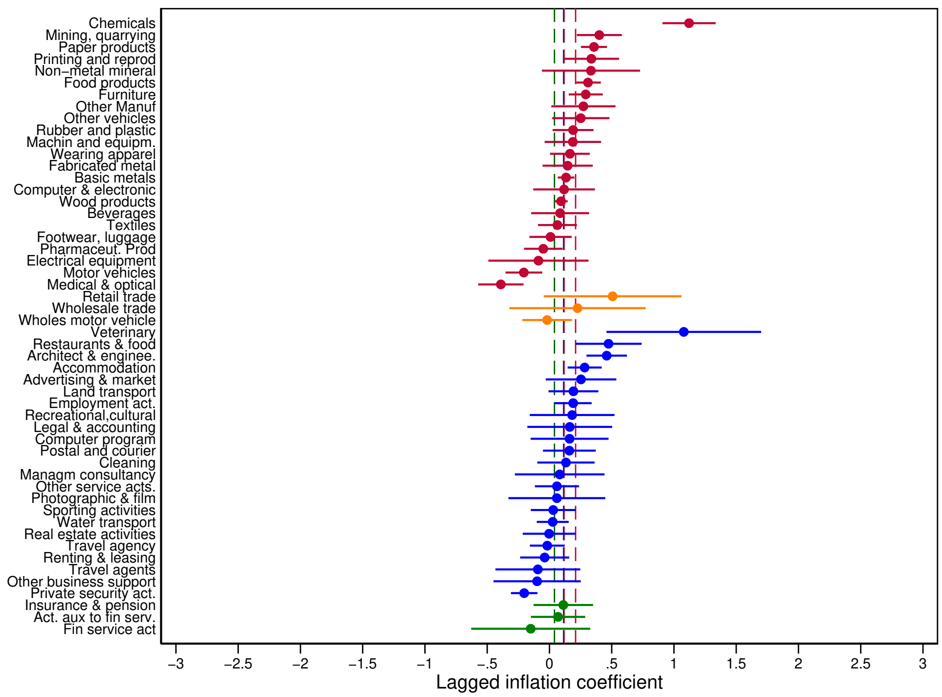
Note: Sector-specific parameters related to labour costs from Model 3 (Table 3, through dynamic panels with CCE). These coefficients are net from common factor effects. Intervals are calculated as the mean +/- s.e. The labels indicate the mean estimated coefficient for each sector. The dashed vertical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

Figure 14: Role of expectations by sector (IJP framework)



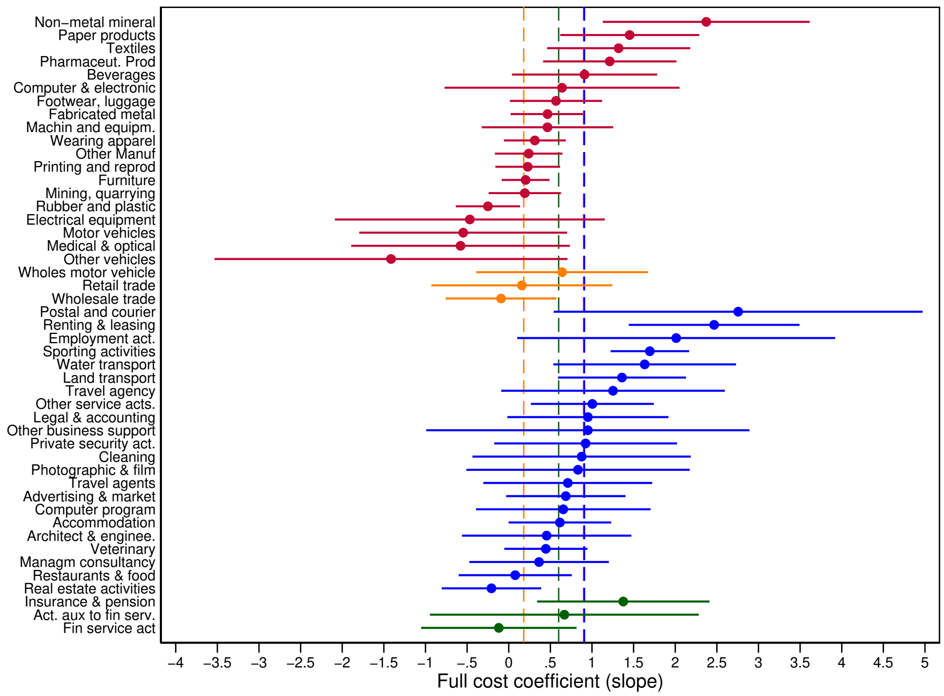
Note: Sector-specific parameters related to expectations coefficients from Model 3 (Table 3, through dynamic panels with CCE). These coefficients are net from common factor effects. Intervals are calculated as the mean +/- s.e. The labels indicate the mean estimated coefficient for each sector. The dashed vertical lines highlight the mean coefficient across each of the groups. Certain industries, such as Veterinary, Retail, and Employment Activities, were excluded due to parameter values falling in the range of -3 to -2 or 3 to 4, which would have distorted the axis scales. This adjustment was made to ensure comparability across figures. Red colour: Manufacturing; Orange: Retail; Blue: Services; and Green: Financial Services.

Figure 15: Role of lagged inflation by sector (Rubbo's framework)



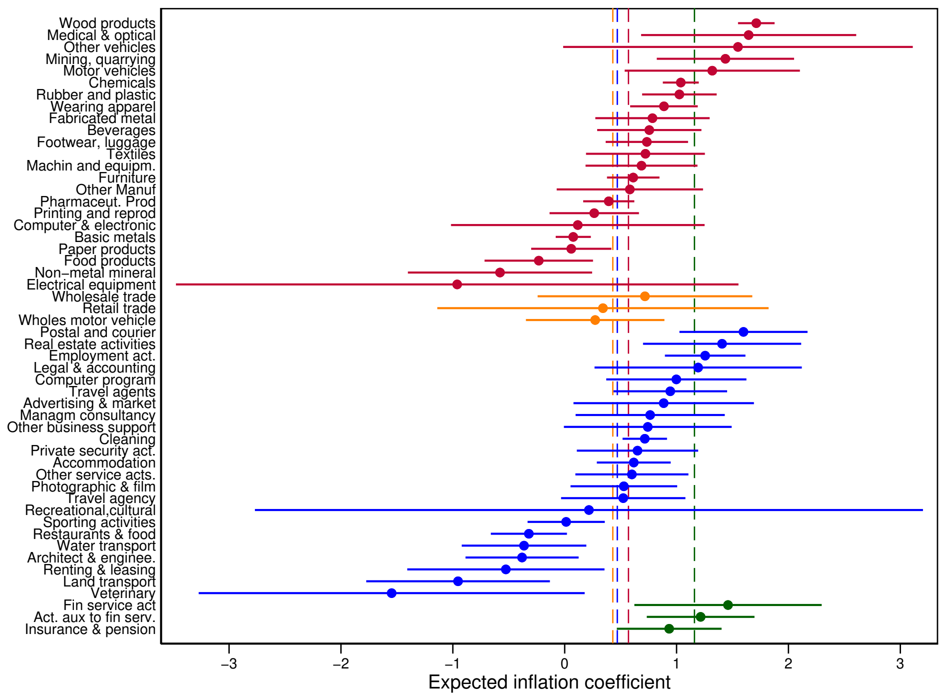
Note: Sector-specific parameters related to expectations coefficients from Model 3 (Table 4, through dynamic panels with CCE). These coefficients are net from common factor effects. Intervals are calculated as the mean +/- s.e. The labels indicate the mean estimated coefficient for each sector. The dashed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

Figure 16: Slope by sector (Rubbo's framework)



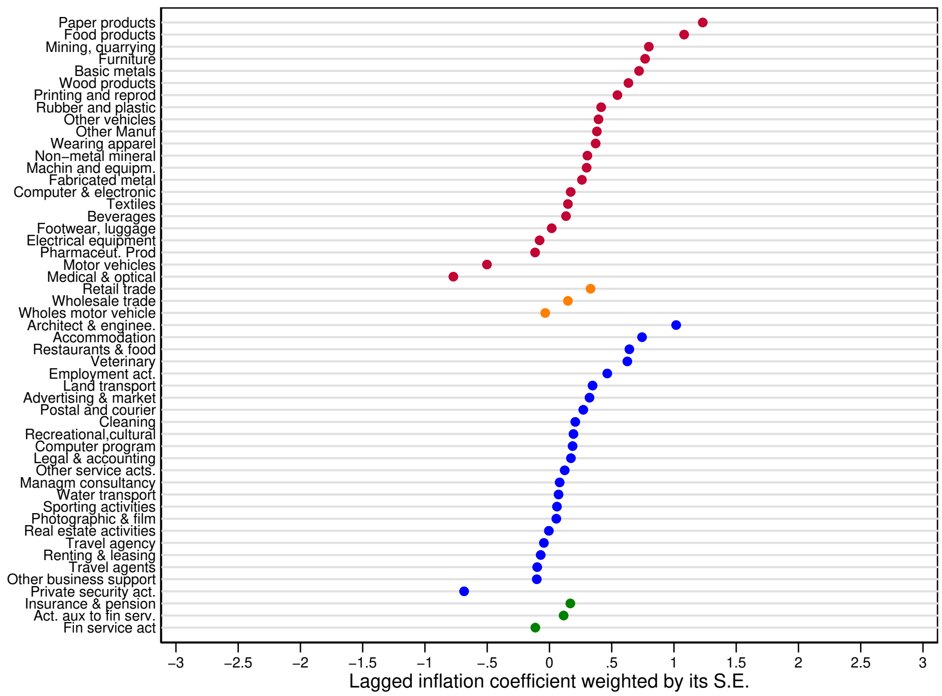
Note: Sector-specific parameters related to expectations coefficients from Model 3 (Table 4, through dynamic panels with CCE). These coefficients are net from common factor effects. Intervals are calculated as the mean +/- s.e. The labels indicate the mean estimated coefficient for each sector. The dashed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

Figure 17: Role of expectations by sector (Rubbo's framework)



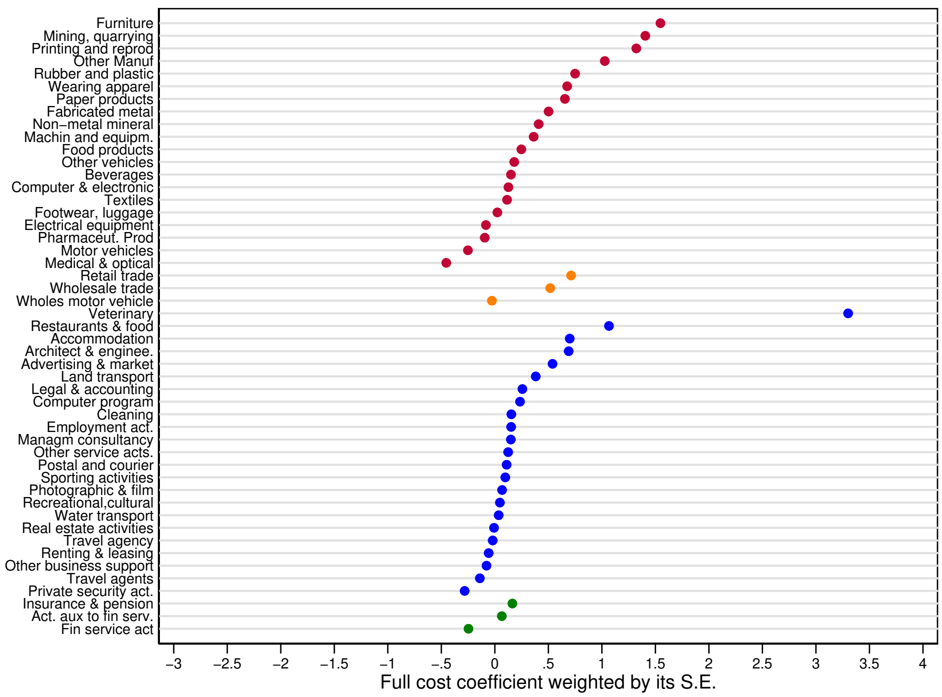
Note: Sector-specific parameters related to expectations coefficients from Model 3 (Table 4, through dynamic panels with CCE). These coefficients are net from common factor effects. Intervals are calculated as the mean +/- s.e. The labels indicate the mean estimated coefficient for each sector. The dashed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

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



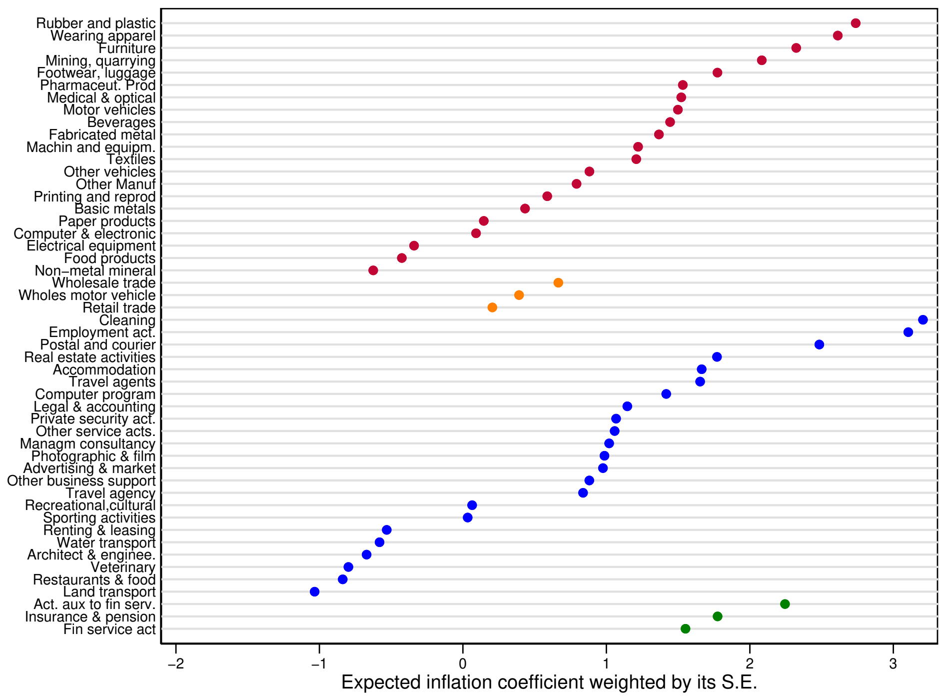
Note: The coefficients presented in the figure have been weighted based on their respective S.E. from Rubbo's framework. The Chemicals industry was excluded due to the estimated parameters falling outside the range of -3 to 3, adding them would distort the axis scales. This adjustment was made to ensure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

Figure 19: Weighted coefficient on Full cost (Rubbo's framework)



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

Figure 20: Weighted coefficient on expected inflation (Rubbo's framework)



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

Appendix D Data and measurement

D.1 Outliers detection and winsorisation scheme

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

Outliers are identified as

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

  Past industry prices(pi)

  Expected industry prices (ei)

  Salary cost (wi)

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

Method 1: percentiles and IQR are calculated across all firms within the same sector and within a given quarter.

Method 2: percentiles and IQR are calculated across all firms within the same sector and within 2 year rolling windows.

Rule: When Method 1 yields IQR=0, then Method 2 is used. This will be the case in 5 sector&quarters.

IQRs are calculated as:

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

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

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

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

Table 9: Summary of outliers

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

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

D.2 Price mapping

Table 10: Price mapping

				Available price indices
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	

D.3 CBI survey data

In the following figures I show expectations of sectoral inflation as an average of expectations cross firms for each 2-digit SIC. Figures 21 and 22 show that inflation expectations for services firms were centered between -2% and 4% in 2010, with sectors 79, 87, 93 and 96 close to the upper bound. More recently, the entire distribution of services expectations has shifted to the right. Figure 23 shows that inflation expectations for services firms are centred between 0% and 6%. The new upper bound is flanked by sectors 55, 56, 63, 72, and 81.

Figures 23 and 24 also indicate substantial sectoral heterogeneity. Services sectors have shown minimal response to the shocks endured by the UK over the past decade (Brexit, Covid, Ukraine war, and the resulting unstable inflation) compared to the response from manufacturing firms.

Figure 21

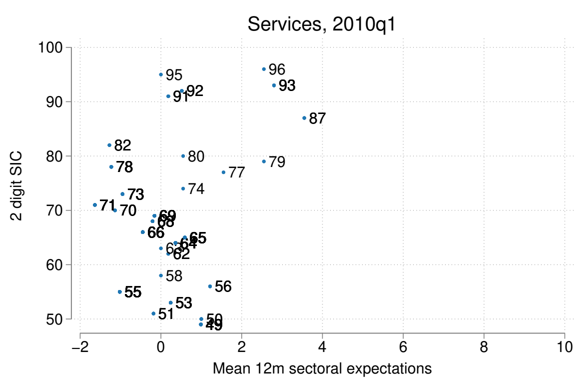


Figure 22

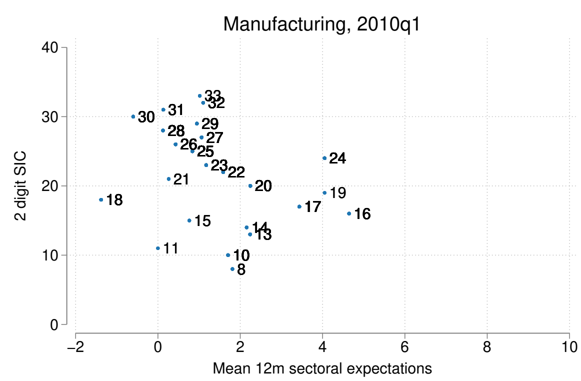


Figure 23

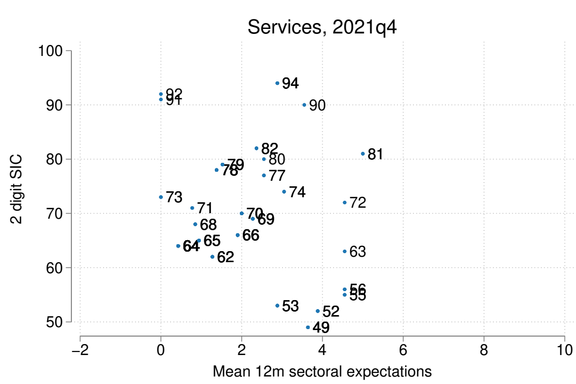
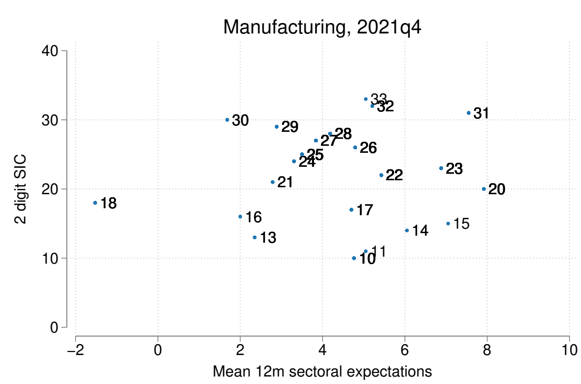


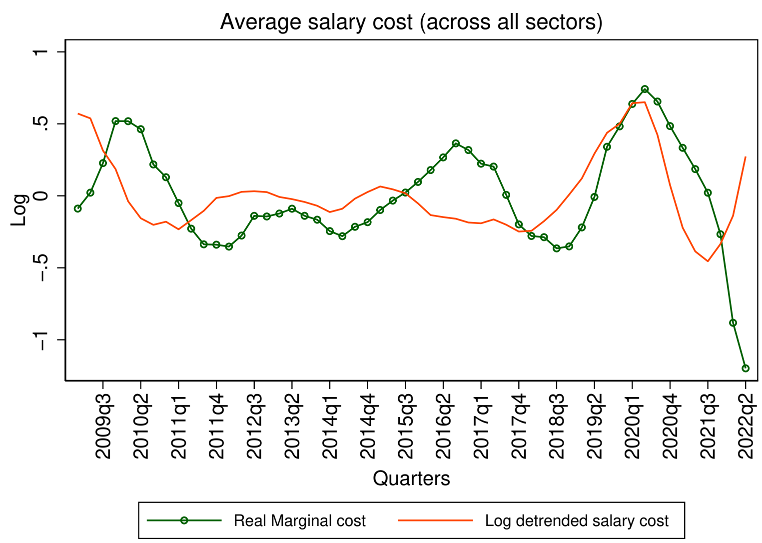
Figure 24



D.4 Measures of cost

The ULC measure provided by the ONS represents the nominal cost of labour input per unit of real (inflation-adjusted) economic output. It is the ratio of total nominal employment costs relative to output (divided by real gross value added (GVA)). The ULC data is not available at the 2-digit SIC level. The ONS provides 20 industry categories at the 2 digits SIC grouped as follows: 05to39, 45to98, 01to03, 05to09, 10to33, 35, 36to39, 41to43, 45to47, 49to53, 54to56, 58to63, 64to066, 68, 69to75, 77to82, 84, 85, 86to88, 90to93, 94to96, 97to98. I mapped these categories to the closest 2-digit SIC in the dataset.

Figure 25: Inflation and CBI nominal wage



Note: The log detrended nominal wage is calculated as the deviation of wage from the sectoral sample mean using the CBI survey-based "wage/salary cost per person employed".

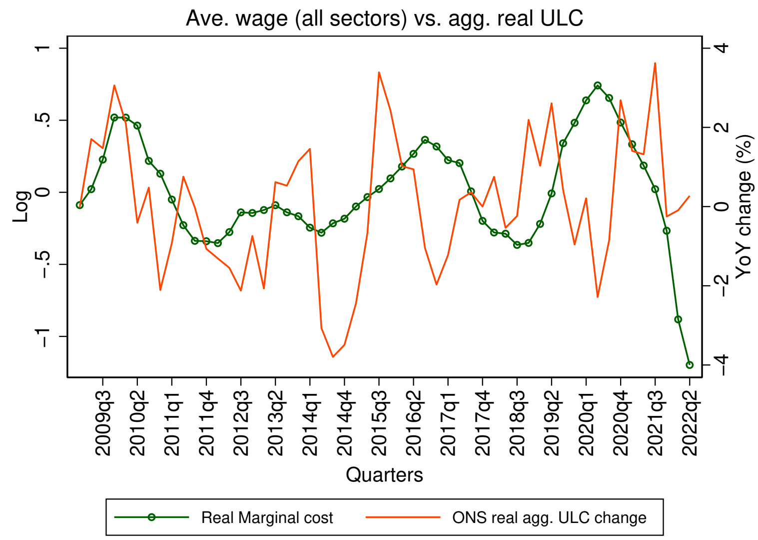
D.5 Output gap

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

D.6 Other Data

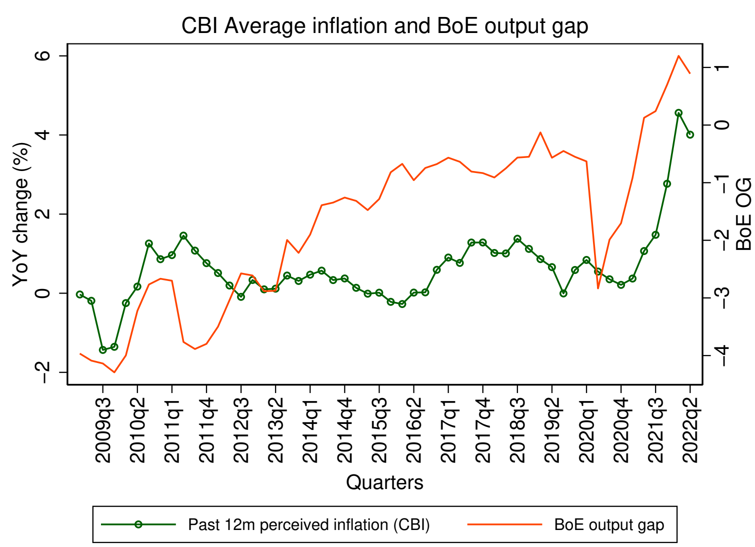
The real oil price inflation is the change in oil price adjusted by bilateral FX change. This measure is based on Roberts, 1995, calculated as DCOILBRENTEU - DEXUSUK. DCOILBRENTEU is the FRED series for Crude Oil Prices: Brent - Europe, Percent Change,

Figure 26: Inflation and CBI nominal wage



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

Figure 27: Inflation and BoE output gap



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

Quarterly (average of the quarter), Not Seasonally Adjusted. DEXUSUK is the FRED series for U.S. Dollars to U.K. Pound Sterling Spot Exchange Rate, Percent Change, Quarterly

(End of period), Not Seasonally Adjusted

An alternative measure for the labour share used in the estimations, as suggested by BJN: ln[((HAEA*A)/ABML)*100], where A = (E + SE)/E. E is given by BCAJ[47], the number of employee workforce jobs (seasonally adjusted), while SE is given by DYZN, the number of self-employment workforce jobs (seasonally adjusted).

Relative price of imports = ln[(IKBI/IKBL)*100] – GVA deflator[48], where IKBI is total imports (current prices), and IKBL is total imports (constant prices).

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

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

Figure 28: Herfindahl-Hirschman index (HHI) series

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

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

References

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

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

Afrouzi, Hassan and Saroj Bhattarai (2023). "Inflation and GDP Dynamics in Production Networks: A Sufficient Statistics Approach". URL: http://www.nber.org/papers/w31218.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Del Negro, Marco, Marc P. Giannoni, and Frank Schorfheide (2015). “Inflation in the great recession and new Keynesian models”. DOI: 10.1257/mac.20140097.

Del Negro, Marco et al. (2020). *What’s Up with the Phillips Curve?* Tech. rep.

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

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

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

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

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

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

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

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

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

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

Höynck, Christian (2020). *Production Networks and the Flattening of the Phillips Curve * Click here for latest version*. Tech. rep.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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