The Role of Expectations and Sectoral Heterogeneity in Price Setting in the UK *

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Abstract

This paper studies the price setting behaviour across sectors in the UK and the main determinants of the found heterogeneity. I first estimate the NKPC at the sector level using heterogeneous panel methods accounting for cross-sectional effects. This method allows to identify the NKPC parameters with significant and positive slope when using the output gap. The results also reveal that manufacturing firms are more forward-looking than services firms. Having unmasked the asymmetric degree of forward-lookingness across sectors, I investigate the main drivers using their cost and market structure. Among others, I find that the degree of concentration, the volatility in inflation and the labour share, they all have a positive effect on the relevance of expectations in the price setting decisions. This suggests that expectations play a larger role in the firms' price setting decisions when they face less competition.

JEL: C21, C23, E31, E70

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1 Introduction

Many modern macroeconomic models are explained by the New Keynesian Phillips Curve (NKPC). This relation was microfounded by Gali and Gertler, 1999 (henceforth GG) and Woodford, 2003. The NKPC describes how past inflation, expected future inflation, and a measure of real marginal cost or an output gap drive the current inflation rate. The NKPC has typically been estimated at the aggregate level, assuming homogeneity across firms and sectors. However, if there is heterogeneity across sectors in the data and homogeneity is imposed, the results will have an aggregation bias and yield inconsistent results [Pesaran and Smith, 1995; Barkbu et al., 2005].

Using more disaggregated data ameliorates the simultaneity bias in estimating aggregate NKPCs. As explained in McLeay and Tenreyro, 2019, one of the difficulties associated with identifying the Phillips Curve is that the monetary policy seeks to offset any demand shocks that might otherwise help identify the curve. But the central bank cannot offset regional or sectoral shocks using a national interest rate. McLeay and Tenreyro, 2019 and Hazell et al., 2022 showed evidence of a statistically and economically significant slope using regional data. Is the identification of the NKPC improved by using sectoral data as well? Can the heterogeneity across sectors be unmasked by using the NKPC framework? If so, among which sectors do expectations play a larger role? What are the main drivers of these sectoral asymmetries? Answering these questions not only contributes to the academic literature but also to the policymaking. I will show evidence that expected inflation plays a larger role among manufacturing firms, and in particular, among those facing less competition. This information can be used for policy purposes, as the monetary policy can affect inflation through the management of inflation expectations.

The first goal of this paper is to explain inflation dynamics across sectors in the UK. To do so, I estimate the NKPC at the sector level using heterogeneous panel methods. The NKPC has typically been estimated at the economy-wide level (among others, GG, Sbordone, 2002, Rudd and Whelan, 2006), assuming homogeneity across firms and sectors. More recent works have shown evidence against that assumption (Andrade et al., 2020, Byrne et al., 2013, Imbs et al., 2011, Maćkowiak et al., 2009, Leith and Malley, 2007). When homogeneity is imposed -and discrepant with the data-, estimations show potentially misleading and inconsistent results such as large inflation inertia and low significance of real marginal costs. Imbs et al., 2011 and Byrne et al., 2013 estimated the sectoral NKPC and obtained lower persistence of inflation and significantly large coefficients on real marginal costs, as compared to the aggregate level, thereby confirming the empirical importance of sector-level heterogeneity.

Having unmasked the asymmetric price setting behaviour across sectors, the second goal is to investigate its main sources. I do so by using the estimated sector-specific parameters of forward-lookingness from the NKPC and seeing how responsive they are to the industry-characteristics. Among others, I find a positive effect of the degree of concentration on the NKPC forward-looking parameters. This suggests that expectations play a larger role in the firms' price setting behaviour when their sector is more concentrated (in line with Leith and Malley, 2007). Also, sectors that face more volatile inflation seem to set prices based on their expectations. Lastly, labour share plays an important role in driving producer price setting, as argued by Andrade et al., 2020; Klenow and Malin, 2010.

A novel aspect of this work is the use of survey-data of firms' expectations to estimate the NKPC. The most common approach has been using system-built expectations, either IVs or rational-expectations (GG, Leith and Malley, 2007, Maćkowiak et al., 2009, Imbs et al., 2011, Byrne et al., 2013) mainly due to the lack of available data on firms' expectations. These methods have been under scrutiny and criticism regarding the problem of weak instruments (see e.g. Byrne et al., 2013 and Nason and Smith, 2005). I acknowledge that survey-based expectations are subject to a measurement error which is not present in estimations with system-built expectations. Yet, direct measures make the estimation more realistic and attenuate the statistical problems that might emerge from using weak instruments. To my knowledge, this is the first work to estimate the sectoral NKPCs with direct measures of firms' inflation expectations, thus the results won't be exactly comparable to previous evidence.

The results of the paper speak to recent policy debates on the relevance of inflation expectations in the firms' price setting behaviour and the heterogeneity across sectors. More backward-looking inflation expectations may need the monetary policy to lean more heavily and quicker against inflation to minimise the risks of further rising inflation (IMF, 2022). Also, monetary policy effects are larger and more persistent when accounting for the asymmetries across sectors (Carvalho, 2006).

Related literature. This paper contributes to the broad literatures on inflation dynamics, the estimation of the NKPC, non-rational expectations, and heterogeneity in macroeconomics. While the estimation of the national-level NKPC has been broadly documented, the literature has reached a limit on how much can be learned about the NKPC from aggregate time series. Mavroeidis et al., 2014 provides a comprehensive review of the literature and discusses the weak identification and instability in the estimation of the NKPC. I address some of these concerns in this paper:

- the use of more disaggregated data (McLeay and Tenreyro, 2019 and Hazell et al., 2022 use regional data);

- the relevance of forward-looking expectations (originally highlighted by Friedman, 1968, recently claimed in relevant works by Hazell et al., 2022, Werning, 2022, and in the recent speech by Mann, 2022);
- the importance of using direct measures of expectations, firstly suggested in Roberts, 1995, and studied more recently in Adam and Padula, 2011;
- particularly using firms' expectations, as exploited in Coibion and Gorodnichenko, 2015 & Coibion, Gorodnichenko, and Kamdar, 2018, and for the UK in Boneva et al., 2020;
- allowing for asymmetries across agents (Leith and Malley, 2007, Imbs et al., 2011 and Byrne et al., 2013 using sectors and Meeks and Monti, 2022 and Candia et al., 2021 for households);
- the sensitivity of inflation to the output gap (Gali and Gertler, 1999);
- and the study of the sources of asymmetries across sectors in the price setting behaviour and in the role of expectations (Andrade et al., 2022 & Klenow and Malin, 2010)

Outline. The rest of the paper is structured as follows. Section 2 explains the economics of price setting behaviour and the microfoundation of the sectoral NKPC. Section 3 explores some of the estimation and measurement issues found in previous works and proposes solutions to some of them. Section 4 details the data used for the estimations. Section 5 shows the results from the empirical estimation. Section 6 studies the determinants of the forward-looking parameters using industry-level characteristics. Section 7 concludes.

2 The economics of price-setting behaviour and cross-industry heterogeneity

2.1 Sectoral price setting behaviour for a closed economy

To explain sector-level inflation dynamics I use the sectoral NKPC similar to the one microfounded by Imbs et al., 2011 (henceforh IJP). This derivation combines ingredients from GG, Sbordone, 2002, and Woodford, 2003. IJP derive a disaggregate NKPC for each sector k (See Appendix A for a detailed derivation) and obtain a similar expression to the aggregate NKPC[1].

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

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

This expression suggests that inflation dynamics in each sector, $\pi_{k,t}$, is a function of past and expected future inflation, where sector-specific γ_k^b and γ_k^f are functions of the underlying deep parameters: the degree of backward lookingness in price setting, the degree of price stickiness, and the discount factor. Current-period inflation also depends on real marginal costs, $s_{k,t}^{avg}$. The error term $\varepsilon_{k,t}^{\pi}$, is a cost-push shock.

The structural coefficients obtained in the estimation of the sectoral NKPC are reflective of firms' pricing decisions. These are governed by the model proposed by Calvo, 1983[2]: in every period each firm has a probability $(1 - \alpha)$ of changing prices. Knowing that some time may pass before they next change prices, firms form expectations about future cost and demand conditions, as well as current ones, and optimally set their prices as a mark-up over their marginal costs.

The formulation by IJP (as it is the case for the aggregate NKPC derived by GG) uses a measure of real marginal cost instead of the output gap. They show evidence in favor of using the former as it directly accounts for the impact of productivity gains on inflation. Nonetheless, other papers provide arguments in favour of using the output gap as a measure of economic activity.

Woodford, 2003 develops a two-sector model and argues that the aggregate-supply relation between sectoral inflation and sectoral economic activity also depends on activity in the other sector, or alternatively on the aggregate output gap as well as the sectoral gap. Instead of writing the sectoral NKPC in terms of both aggregate and relative output gaps, one can write them in terms of the aggregate output gap (χ_t), and a relative-price gap (P_{Rt}). The hybrid equivalent expression would be:

$$\pi_{k,t} = \gamma_k^b \, \pi_{k,t-1} + \gamma_k^f \, E_t \, \pi_{k,t+1} + \gamma_k^s \, \chi_t + \xi \, P_{Rt} + \varepsilon_{k,t}^{\pi} \tag{2}$$

One way of accounting for the disparities in sectoral prices and their effect on other sectors is to add the average of other sectors' prices and other sectors' expectations through cross-sectional effects (as in Byrne et al., 2013). The tradeoffs between using the output gap and the real marginal cost have been largely discussed in the literature. I will explain this more in detail in section 3.

2.1.1 The sectoral NKPC framework allows to unmask asymmetries across sectors

Policymakers have struggled recently to understand why inflation dynamics differ from the predictions of workhorse models. Poor results has sparked a debate about the usefulness

[2] One advantage of Calvo's time-dependent framework (as opposed to state-dependent ones) is its explicit closed-form equation to describe the relationship between aggregate inflation and aggregate output.

of the aggregate Phillips curve framework for policy analysis (DelNegro et al., 2020, Hazell et al., 2022) and suggested to use dissagregate data: either regional or sectoral.

Also, aggregate dynamics can mask heterogeneous dynamics across sectors which might inform the policymakers for expectations and communication management. Monetary policy (MP) effects are larger and more persistent when accounting for the asymmetries across sectors (Carvalho, 2006). The asymmetries in the frequency of price changes across sectors lead to differences in the speed of reaction to a shock. Furthermore, more backward-looking inflation expectations may need the MP to lean more heavily and quicker against inflation to minimise the risks of further rising inflation (IMF, 2022).

2.2 Open economy NKPC framework

The baseline hybrid NKPC proposed by IJM does 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 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.

$$\pi_t = \gamma^f\, E_t\{\pi_{t+1}\} + \gamma^b\, \pi_{t-1} + \gamma^s\, s_t + \alpha_1\, z_{p,t} + \alpha_2\, (p_t^W - p_t) + \alpha_3\, s_{L,t} + \alpha \Delta n_t + \varepsilon_t^{\pi} \tag{3}$$

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

To my knowledge, nobody has derived the sectoral NKPC framework for an open economy. Therefore, this paper estimates the structural framework based on Woodford, 2003 and IJP as well as some modified versions, combining elements from Batini et al., 2005. I show in the empirical section that these modifications, such as using output gap instead of marginal cost, and adding oil inflation, might improve the results in some cases, i.e. yield parameters more consistent with the theory.

2.3 Determinants of the asymmetries in price setting

Having unmasked the asymmetric price setting behaviour across sectors, the next question is: what are the main drivers of those asymmetries? The closest work to this type of analysis is Leith and Malley, 2007, which estimated the NKPC structural parameters for US industries and found that market concentration (Herfindahl-Hirschman index) is positively correlated with the estimated measure of price stickiness. They argue that, the more concentrated an industry (less competition), the more sticky its price-setting behaviour and the more likely it is to set prices in a forward-looking manner. They also show evidence that industries are more backward-looking when output in that industry is more volatile.

Klenow and Malin, 2010 provide a (non-exhaustive) list of factors affecting the frequency of price changes investigated by researchers by the time of the publication of the handbook (2010), which include: inflation variability, the frequency and magnitude of cost and demand shocks, the structure and degree of market competition, and the price collecting methods of statistical agencies. Also, Bils and Klenow, 2004 studies the correlation between frequency of price change in different product categories and measures of market structure: the concentration ratio, wholesale markup, and rate of non-comparable substitutions in those categories and find that the first two measures are not significant after controlling for whether a good is raw/processed. They claim a positive relationship between the frequency of price changes and the degree of competition because firms therein face more elastic demand.

Kato et al., 2021 show evidence that sectoral inflation persistence is negatively correlated with market concentration. Their inflation persistence could be captured in the NKPC framework by γ^b. Given that the NKPC framework predicts that γ^b and γ^f move in opposite directions, these authors' findings might be interpreted as $\uparrow$ HHI & $\uparrow$ γ^f. Using US producer price data, they show that pricing complementarity (the sensitivity of individual prices to their competitor's prices) among monopolistically competitive firms decreases as market concentration increases. Intuitively, when the market is more concentrated, firms' products are more differentiated and less substitutable. As substitution becomes more difficult across products, the price of a firm's product becomes less sensitive to its competitors' prices. Thus, pricing complementarity becomes weaker.

Other relevant and related works examine the factors driving price changes instead of using the NKPC parameters. Vermeulen et al., 2007 shows evidence that firms with a higher labor cost share tend to change prices less frequently, whereas firms with higher energy cost share and non-energy intermediate goods change prices more frequently. Moreover, they find that the higher the degree of competition, the higher is the frequency of producer price changes.

Lastly, Domberger, 1979 finds the opposite results: a positive relationship between the speed of price adjustment and market concentration. He reflects on two plausible hypotheses: the first claims that price coordination in concentrated industries is much easier due to relatively low costs of information gathering and communication among sellers, potentially rising the speed of price adjustment; the second one is associated with "administered prices" and states that sellers in highly concentrated markets tend to adjust prices unilaterally either due to the difficulties of oligopolistic collusion or through the use of mark-up pricing. While Domberger shows evidence supporting the first hypothesis, it is important to mention that the sample studied (1963-1974) is characterized by a rising inflation period and, hence, mostly upward price movements. Also, his sample comprises mainly industrial sectors whereas my sample includes services and distributive sectors as well, showing a wider spectrum of market structures.

2.3.1 Forward-looking parameter is positively related to price stickiness

From the microfoundation of the NKPC we know that γ^f is a combination of β (discount factor), α (price stickiness; the share of firms that do not update prices in t) and ϕ (which ultimately depends on α, β, ω). β is usually assumed close to 1. Intuitively, the larger the price stickiness (larger α) in sector k, the more firms without the chance to update prices every t and will give more weight (larger γ^f) to expected future markups. That is because firms will have to stick to the same price for a longer time. As a result, γ^f is positively related to the rigidity in prices.

This argument is in line with Werning, 2022 who argues that firms set their price initially above their ideal price, but over time their price ends up below their ideal price. Then, the greater the expected inflation, the greater must be the price over the currently ideal price. Hence, firms in sectors that face lower frequency of price changes will overshoot inflation proportionally more to compensate. The larger α (share of firms that do not have the chance to update prices), the higher pass-through from expectations of future inflation to current inflation.

2.3.2 Forward-looking parameter and the Herfindahl-Hirschman Index

Bils and Klenow, 2004 find 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.

To study this relationship I calculate the Herfindahl-Hirschman Index for each sector given that it's not officially calculated in the UK.

2.3.3 Other determinants of the cross-sector heterogeneity in the forward-lookingness

Competition: Besides the indices of degree of concentration already mentioned, Vermeulen et al., 2007 also studies the impact of external competition through an indicator of "import penetration" derived from input–output tables. Alvarez and Hernando, 2007 obtain that the degree of import penetration has a significant positive but weak effect on the frequency of price changes. These authors measure import penetration as total imports over total resources (production plus total imports), using the Input–Output tables.

Inflation variability: Dhyne et al., 2006 show that the overall frequency are significantly higher in sectors in which the variability of inflation is higher. Then we may expect that firms move quicker when they face more volatility in inflation as a way of staying closer to the optimal price.

Cost structure: Vermeulen et al., 2007 and Alvarez and Hernando, 2007 show that firms in labor-intensive sectors adjust prices less frequently ($\uparrow \alpha$), potentially because wages adjust less frequently than other input prices. Both mentioned works also show that firms with higher share of energy and intermediate inputs in total costs is positively correlated with the frequency of price changes, because prices of raw materials change very frequently.

I will test these potential drivers of forward-lookingness in section .

3 Sectoral NKPC: an empirical investigation

In the empirical analysis that follows, I adopt a partial equilibrium approach to estimate the NKPC as in IJP. These authors use French data to estimate the NKPC for each sector k, where the magnitude of backward-looking behaviour and price stickiness are sector-specific.

In the first part of this section I briefly describe the main identification issues encountered and discussed in the literature related to the estimation of the NKPC. For a comprehensive review, see Mavroeidis et al., 2014 and Abbas et al., 2016. In the second part I explain how I address some of the issues using direct measures of expectations, sectoral data, and panel methods, among other aspects. In the third part I discuss the tradeoff between using the marginal cost and the output gap as a proxy for the slack measure.

3.1 Identification and estimation challenges

Over the last decade, the empirical performance of the NKPC has been largely debated. Some of the main identification problems raised in the literature are: the assumption about homogeneity across sectors, the choice of the slack variable, the use of actual/realized inflation as a proxy for expected future inflation, and the approach used to deal with the endogeneity problem.

The NKPC has typically been estimated at the aggregate level, assuming homogeneity across firms and sectors. Nonetheless, if there is heterogeneity across sectors in the data and homogeneity is imposed, the results will have an aggregation bias as explained before. Imbs et al., 2011 and Byrne et al., 2013 estimated the sectoral NKPC and obtained lower persistence of inflation and significantly large coefficients on real marginal costs, as compared to the aggregate level, thereby confirming the empirical importance of sector-level heterogeneity.

As an example against the use of actual inflation as a proxy for inflation expectations, Roberts, 1995 compared the estimation of the economy-wide NKPC by using survey data and actual inflation. He found that only the former yield the correctly signed (positive) and statistically significant slope. These estimates were statistically insignificant when actual future inflation is used as a proxy for inflation expectations.

Simulateneity problem: the estimation of the NKPC also faces the simultaneity problem of distinguishing demand and supply shocks, as argued by Hazell et al., 2022. They explain that supply shocks comove both inflation and unemployment positively. If the variation used to identify the slope of the NKPC is contaminated by such shocks, the estimated slope will be biased.

The flat slope might be driven by the endogenous response of the monetary policy: Another simultaneity problem faced when estimating the aggregate NKPC is the disconnect between inflation and the real activity generated by a forcefull response of the monetary policy to inflation. As explained in McLeay and Tenreyro, 2019, the slope of the NKPC is the result of the interaction between the Aggregate Supply (AS) and the Aggregate Demand (AD). The AS captures the positive relationship between inflation and real activity. The AD relationship tells us that the central bank aims to offset demand shocks with the monetary policy. Being successful in its goal, the AD would offset the AS and we would only see a negative slope, reflecting the endogenous response of the monetary policy to inflationary pressures: when inflation is rising, the central bank tightens slowing down the economy. This argument would explain the empirical evidence on flat Phillips Curves when using aggregate data. As a way of addressing this problem, some researchers showed that cross-sectional data (either regional or sectoral) can help overcome this simultaneity issue. See McLeay and Tenreyro, 2019 for an example with regional data.

3.2 Solutions proposed to the described challenges

3.2.1 Using disaggregate data

If there is heterogeneity across sectors in the data and homogeneity is imposed, the results will have an aggregation bias. Estimations show potentially misleading and inconsistent results such as large inflation inertia and low significance of real marginal costs. Imbs et al., 2011 and Byrne et al., 2013 estimated the sectoral NKPC and obtained lower persistence of inflation and significantly large coefficients on real marginal costs, as compared to the aggregate level, thereby confirming the empirical importance of sector-level heterogeneity.

Using disaggregate data not only captures better inflation dynamics but it has also helped to reveal some interesting policy implications. Sheedy, 2007 shows that inflation persistence is lower with heterogeneity in price stickiness across sectors than without it. Carvalho, 2006 argues that the presence of heterogeneity in the frequency of price changes across sectors leads to differences in the speed of reaction to a shock. Monetary policy shocks are larger and more persistent in heterogeneous economies.

3.2.2 Survey-based expectations

The importance of future prices raises the issue of how to deal with expectations about prices. The most common approach to estimate the forward-looking component of the NKPC has been using system-built expectations, either IVs or rational-expectations (GG, Leith and Malley, 2007, Maćkowiak et al., 2009, Imbs et al., 2011, Byrne et al., 2013) mainly due to the lack of available data on firms' expectations.

Byrne et al., 2013 and Nason and Smith, 2005 claim that these methods have been under scrutiny and criticism regarding the problem of weak instruments, and suggest as a solution to use surveys of disaggregate expectations. Similarly, Coibion, Gorodnichenko, and Kumar, 2018 state: "The survey-based NKPC addresses one of the weaknesses of the RE-based NKPC 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 proxies for inflation expectations in the NKPC was introduced by Roberts, 1995. The latter as well as Adam and Padula, 2011 used survey-based expectations from professional forecasters and consumers to estimate the NKPC model and obtained significant and theoretically-consistent results. Nonetheless, the survey-based specification of the NKPC is not microfounded unless the forecasts are rational, as argued by Mavroeidis et al., 2014[3]

[3] See Mavroeidis et al., 2014 for a detailed review of the role of expectations that integrates across the different papers and specifications in the literature.

Coibion and Gorodnichenko, 2015 relate the malfunctioning Phillips Curve in the US partly to using professional forecasters and financial markets data as proxies of firms' inflation expectations. They prove that households data are better proxies of firms' expectations but emphasize that it would be rather optimal to use direct measures of firms' expectations.

It is also important to recognize that surveys are not perfect either, given that are subjective measures and rely on the precision of the questionnaire and the interpretation of the respondent. For instance, in the case of the survey used in this work, firms are being asked about prices in the sector they compete in. The questionnaire does not specify which sector the respondent should refer to. Therefore, there could be some bias either in terms of the activities involved in the referred sector or in terms of the scope of the industry. I attempt to reduce this bias by estimating a "perception error" which will be explained below and included in the estimations.

One interesting aspect of the survey that I am using is that firms are being asked about inflation in their sector. A priori, one would expect firms to pay more attention and be better informed about prices in their sector than about aggregate economic conditions. For instance, Andrade et al., 2020 show that French firms respond much more rapidly to industry-specific shocks than aggregate shocks, so they choose to be more informed about disaggregate.

3.2.3 Dynamic panel mean group estimation

The estimation procedure for mean group estimations mainly follows Chudik and Pesaran, 2015 with common correlated effects (CCE) estimator. This methodology accounts for heterogeneous coefficients, endogeneity and the use of covariates to deal with the effects of potential unobserved common factors reflecting cross-sectional linkages or common macroeconomic shocks.

Ignoring the heterogeneity across sectors in dynamic panels and estimating a pooled (homogeneous) model give inconsistent and potentially highly misleading estimates of the coefficients (as argued in Pesaran and Smith, 1995). Some evidence of the importance of sector-level heterogeneity can be found in Byrne et al., 2013.

Further motivation for adding unobserved common factors lies in the ability of capturing unobserved information about the inflation process through a dimensionality-reducing device, as suggested in Eberhardt, 2022. The CCE are proxied by cross-section averages of the dependent variable and the individual specific regressors (as firstly proposed in Pesaran, 2006). For instance, Byrne et al., 2013 argue their use of CCE to adjust for the possibility that shocks to inflation or marginal costs may be cross-sectionally correlated.

I estimate the NKPC using a variety of empirical implementations for equation 2

$$\pi_{k,t} = \alpha_k + \gamma_k^f F_{k,t}\{\pi_{k,t+1}\} + \gamma_k^b \pi_{k,t-1} + \gamma_k^s \chi_t + u_{k,t} \tag{4}$$

$$u_{k,t} = g_k f_t + \varepsilon_{k,t}^{\pi} \tag{5}$$

where α_k are the sector fixed-effects, g_k is the heterogeneous factor loading and f_t are the unobserved common factors, which are approximated by z_t (the cross-sectional means). Ignoring the heterogeneity across sectors in dynamic panels and estimating a pooled (homogeneous) model give inconsistent and potentially highly misleading estimates of the coefficients (as argued in Pesaran and Smith, 1995).

$$\begin{aligned}\pi_{k,t} =& \gamma_k^f F_{k,t}\{\pi_{k,t+1}\} + \gamma_k^b \pi_{k,t-1} + \gamma_k^s \chi_t + u_{k,t} \\ & \gamma^f F_{k,t}\{\pi_{k,t+1}\} + \gamma^b \pi_{k,t-1} + \gamma^s \chi_t + \varepsilon_{k,t}\end{aligned}$$

As long as $\gamma_k^f \neq \gamma^f$, $\gamma_k^b \neq \gamma^b$ or $\gamma_k^s \neq \gamma^s$, then the errors $\varepsilon_{k,t}$ will be correlated with the explanatory variables.

$$\varepsilon_{k,t} = \left[u_{k,t} + (\gamma_k^f - \gamma^f) F_{k,t}\{\pi_{k,t+1}\} + (\gamma_k^b - \gamma^b) \pi_{k,t-1} + (\gamma_k^s - \gamma^s) \chi_{k,t}\right]$$

See evidence of the importance of sector-level heterogeneity in Byrne et al., 2013.

The common correlated effects (CCE) estimator is a panel data technique that can be used to control for omitted variables that are common to all sectors in the panel. It aims to capture unobserved heterogeneous information about the inflation process through time-varying covariates. These are combined with sector-specific "factor loadings" aiming to capture the various sector-specific shocks using a much smaller number of variables. This way, this approach reduces the dimensionality of the data and helps to avoid overfitting by focusing on the most important factors that influence the outcomes of interest, as suggested in Eberhardt, 2022. The Common Correlated Effects (CCE) are proxied by cross-section averages of the dependent variable and the individual specific regressors. This method was proposed in Chudik and Pesaran, 2015[4] to estimate dynamic heterogeneous panel data models with weakly exogenous regressors. By not accounting for the different impact that the shocks might have across sectors, that effect will enter into the residuals, hence losing efficiency. Byrne et al., 2013 argue their use of CCE to adjust for the possibility that shocks to inflation or marginal costs may be cross-sectionally correlated.

[4]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

3.2.4 Dealing with endogeneity by using IVs

Having direct measures of expectations attenuates the problem of using a weak instrument. Yet, instrumental variables need to be used to deal with the endogeneity between the explanatory variables and the errors. Therefore, all models will have the endogenous variables estimated with instrumental variables by using 2SLS.

3.3 Slack measure: output gap or marginal cost

Sbordone, 2002 uses data on the average level of unit labor 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 labor cost. She also proves that the real marginal cost of the firms that are allowed to charge a new price is the same as the average level of real marginal cost for firms in general. This implies that real marginal costs vary across firms only if optimal pricing does.

$$s_{ik,t,t+j} = \left(\frac{P^*_{ik,t}}{P_{k,t+j}} \right)^{-\eta\, a_k/(1-a_k)} s^{avg}_{k,t+j}$$

In the absence of any firm-specific shock, all firms that are allowed to re-optimize their price at date t select the same optimal price, which ensures a symmetric equilibrium across firms in each sector (k).

Regarding marginal costs vs. average costs, Sbordone, 2002 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 labor hours, which is used to compute unit labor costs. In her paper, she proposes some ways to account for these potential biases.

4 Data and descriptives

4.1 Survey of firms' expectations

The CBI suite of business surveys comprises four surveys[5] completed by firms operating in the UK. It gathers information from thousands of firms on inflation expectations at the sector level, both retrospectively and in expectation, along with other firm-level outcomes such as output, investment, capacity, and inventories. The same firms are being targeted on a quarterly basis but their completion is voluntary.

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

Table 1: Summary of CBI survey data

	Ave. Number of firms/reports			**Representation of sector (*)**
	2009-2014	2015-2020	2021	
ITS	373	353	175	2.71%
DTS	107	92	68	2.54%
SSS	128	143	69	1.98%
FSS	71	74	46	1.92%
All	**679**	**663**	**358**	

(*) Calculated using turnover data reported by firms through the CBI surveys and sector-level statistics from the ONS

Although the CBI survey began in 1958, the quantitative question on past and expected future price movements started being collected in 2008[6]. 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 my knowledge, there is only one work previous to this one that has exploited the CBI data on inflation expectations. The difference is that Boneva et al., 2020 only used the ITS survey comprising the manufacturing firms whereas this work aggregates and studies the four surveys. This way, I could describe the degree of heterogeneity across all sectors while capturing broader cross-sectional effects. For a detailed description of the CBI survey also see Lee et al., 2020.

4.2 Inflation expectations question

The key questions about prices in the four surveys are framed identically. The question about future expectations is "What has been the percentage change over the past 12 months in the general level of output prices in the UK markets that your firm competes in, and what is expected to occur over the next 12 months and the following 12 months?". And the question about past inflation is "What has been the percentage change over the past 12 months in your firm's own average output price for goods sold into UK markets and what is expected to occur over the next 12 months?

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

Respondents are asked to report their expectations and perceptions about price movements by selecting from one of the ten buckets[7] within the range -10% to 10%, by answering zero or by entering a point estimate manually. The covered range has been of great advantage for the rising inflation in the period 2020-2022, compared to the households survey[8] which had the highest bucket at 5%.

I construct a continuous variable by assigning the midpoint of each price change bin. The full dataset with the sample from 2009q2 to 2022q3 contains 41,300 observations. By keeping only inputs with sector and firm ID information, plus a non-empty report on price movements, the panel is reduced to 36,300. Also, since the NKPC estimations require the CBI data to be mapped to ONS price data, and the latter is not available for the entire time span and for all sectors, the sample is cut down to 29,400. CBI respondents belong to 65 sectors at the 2-digit SIC, but I am able to study 38 of them with actual inflation data for the entire time span.

4.2.1 ONS and CBI data mapping

For the NKPC analysis I combine ONS data with CBI inflation expectations data. In the case of inflation rates, both ONS actual data and CBI expectations data are referred to annual changes but the time span does not match perfectly. Therefore, I approximated the mapping in the following way. Taking the PPI inflation March edition as an example, this report comprises changes in prices through the last 12 months (including March). I map the March PPI report to expectations elicited between the end of March and beginning of April. The intuition is that the latest changes in prices (through March) may be determined by expectations elicited over that month. Adding three lags of expectations as instruments in the regression analysis allows to capture the fact that previous quarters' expectations have also determined the annual inflation rate released in March.

4.2.2 Stylised facts from CBI survey data

The CBI data shows evidence of noticeable discrepancy in sectoral inflation expectations among sectors in line with the assumptions I am imposing to the sector-specific parameters of the NKPC. Figure 1 shows that sectoral inflation expectations for services firms were centered between -2% and 4% in 2010, with sectors 79, 87, 93 and 96 close to the upper bound. More recently the entire distribution of services expectations has shifted to the right. Figure 3 shows that inflation expectations for services firms are centered between 0% and 6%. The new upper bound is flanked by sectors 55, 56, 63, 72, and 81.

[7]Specifically, the buckets 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%

[8]Bank of England/Ipsos Inflation Attitudes Survey

By comparing expectations between services and manufacturing firms (Figure 3 and Figure 4), the data suggests that services firms have shown minimal response to the shocks endured by the UK over the past decade (Brexit, the pandemic, Ukraine war, and the resulting unstable inflation) compared to the response from manufacturing firms. This highlights the importance of adopting a heterogeneous approach in the estimation of the NKPC.

Figure 1

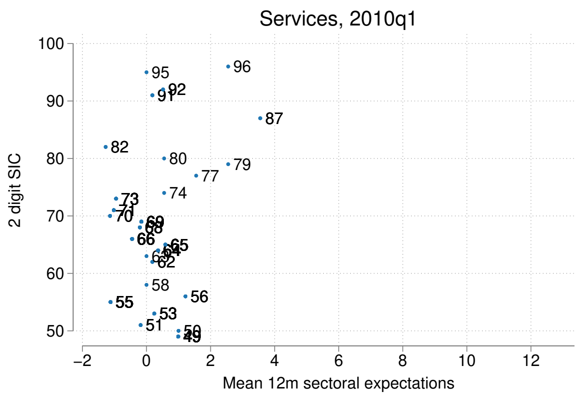


Figure 2

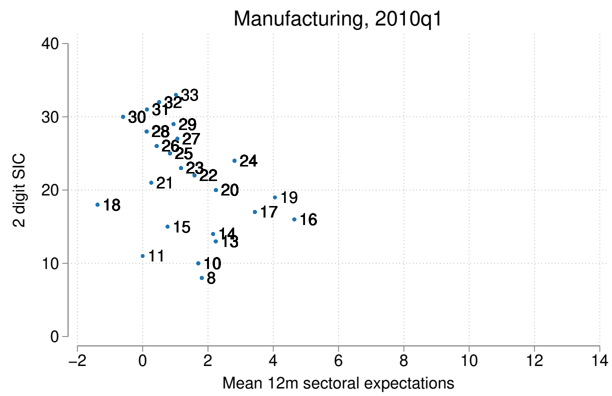


Figure 3

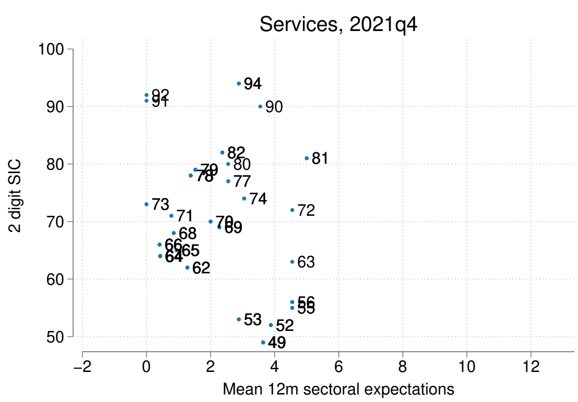
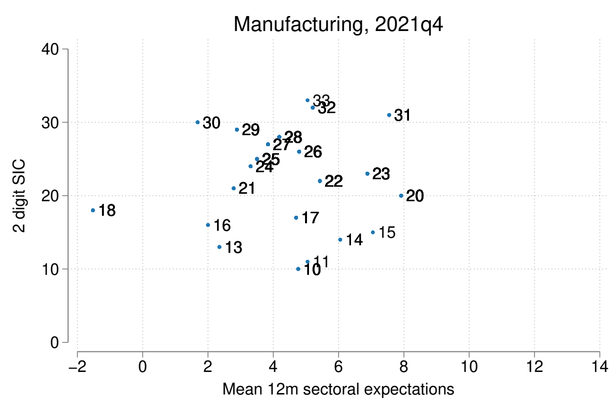


Figure 4



4.3 Perception error

Using survey data raises the problem of not knowing whether firms are forming expectations differently due to a different index, cost structure, or they are just not paying attention to available information. In addition, 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. Given that I average out firms' expectations to study sectoral

Table 2: **Average number of firms in each of the sectors used in the panel**

	2009-2014	2015-2020	2021		2009-2014	2015-2020	2021
Manufacturing firms				**Services firms**			
Fabricated metal products	52	52	33	Act. auxiliary to fin serv	21	17	9
Machinery and equipment	61	42	19	Legal and account. acts	16	14	5
Wholesale trade	38	41	31	Insurance and pension	20	13	6
Fin service act	32	42	31	Land transport	13	12	5
Rubber and plastic prods	31	28	18	Accommodation	11	8	2
Electrical equipment	22	25	18	Act. of head offices, etc	5	7	5
Computer; electronic, etc	24	20	11	Real estate activities	7	7	5
Other non-metallic mineral	19	17	8	Architect. and engin. acts	8	6	2
Food products	19	15	9	Postal and courier acts	7	6	3
Basic metals	18	13	8	Aux transport activ	3	5	2
Chemicals	15	14	9	Recreational, cultural	4	4	1
Paper and paper products	15	12	5	Other service acts	1	3	1
Motor vehicles and trailers	11	14	7	Water transport	3	3	1
Textiles	13	12	4				
Other Manufacturing	12	11	5				
Wood and wood products	10	9	4	**Distributive firms**			
Furniture	8	8	3	Retail trade; except of motor	55	43	31
Other vehicles	8	6	3	Wholesale, retail trade	9	8	6
Beverages	5	8	1				
Footwear, luggage	5	6	2				
Basic pharmaceutical prods	4	4	4				
Other mining, quarrying	5	3	1				
Coke, petrol, nuclear prods	3	2	0				

NKPC (at 2-digit SIC) I need these expectations (at the 4-digit SIC) to refer to the closest similar sector (at the 2-sigit SIC) as possible.

To account for this problem, I first calculate a "perception error" (PE) as the difference between the contemporaneous report by the firm about "inflation in the markets they compete in" and the inflation rate (ONS) based on the SIC reported by them.

Other works that investigated some type of measurement error (or bias) concerning readily available information, were Coibion, Gorodnichenko, and Kumar, 2018 for firms inflation expectations in New Zealand and Inatsugu et al., 2019 for Japan. Similar evidence was provided in the case of households' expectations by Afrouzi et al., 2015, Cavallo et al., 2014, Murasawa, 2020, among others.

Let us define firm-level perception error as: $PE_{i,t} = \pi_{k_4,t} - E_{i,t}\pi_{k_4,t}$ where k_4 refers to 4-digit SIC.

Actual inflation rates ($\pi_{k_4,t}$) are provided by the ONS at 4-digit SIC through either the PPI, SPPI or CPI series.

Then, "purged expectations" is calculated as: $\tilde{E}_{i,t}\pi_{k_4,t+4} = E_{i,t}\pi_{k_4,t+4} + PE_{i,t}$

The PE aims to account for the bias in the expectations term, yet remaining agnostic about its nature. When the PE is incorporated into the NKPC specifications, the estimated parameters become more consistent with the literature. To see this difference, estimations are conducted using the three cases: i) with the original expectations, ii) with the perception error as an explanatory variable, and iii) with purged expectations. Results (see corresponding section) suggest that adding the perception error or using purged expectations yield results more consistent with the theory and other empirical evidence.

4.3.1 Simplified framework to explain how the PE works

Let us express the sector-level NKPC for sector A and assume there are only 2 firms in this sector. One perceives itself as a low cost firm and the other perceives itself as a high cost firm (both with respect to the sector A reference). These are named firm LC and firm HC.

Ignoring the lagged inflation and the slack measure, the NKPC for sector A without adjusting for the perception error could be expressed as:

$$\pi_{A,t} = \frac{1}{2}\left[\sum_{i} \gamma_i^f \, E_{i,t}\pi_{A,t+1}\right]$$

where i is either LC or HC and π_A is the inflation rate for sector A.

Remember from the definition that $PE_{i,t} = \pi_{A,t} - E_{i,t}\pi_{A,t}$ and that by purging the perception error from the firms' expectations, we get purged expectations for each firm as $\tilde{E}_{i,t}\pi_{A,t+1} = E_{i,t}\pi_{A,t+1} + PE_{i,t}$.

By combining the above terms, we can re-express the NKPC for sector A as:

$$\begin{aligned}
\pi_{A,t} =& \frac{1}{2}\,\gamma_{LC}^f\Big(E_{LC,t}\pi_{A,t+1} + PE_{LC,t}\Big) + \frac{1}{2}\,\gamma_{HC}^f\Big(E_{HC,t}\pi_{A,t+1} + PE_{HC,t}\Big)\\
=& \frac{1}{2}\,\gamma_{LC}^f\Big(E_{LC,t}\pi_{A,t+1} + (\pi_{A,t} - E_{LC,t}\pi_{A,t})\Big) + \frac{1}{2}\,\gamma_{HC}^f\Big(E_{HC,t}\pi_{A,t+1} + (\pi_{A,t} + E_{HC,t}\pi_{A,t})\Big)
\end{aligned}$$

4.4 Sector-level prices

Data of inflation at the sector-level is used to match with the sector-level expectations elicited through the CBI survey. The Office for National Statistics (ONS) makes available disaggregated producers price indices (PPI; by SIC code) for industrial sectors. For non-industrial sectors, Consumers Price Indices (CPI; by COICOP) and Services Producer Prices Indices (SPPI) are used.

For the PPI I use the output prices 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.

[More details about the price indices matching in Appendix C].

4.5 Slack measures

The unit labour cost (ULC) is provided by the ONS but not at the 2-digit SIC level[9]. ULCs measure the nominal cost of labour input per unit of real (inflation-adjusted) economic output. They are the ratio of total nominal employment costs relative to output (divided by real gross value added (GVA)).

For the output gap I try several measures for the estimation of the NKPC. One measure is based on the methodology proposed by Garratt et al., 2008 using both the Gross Domestic Product (GDP) index and the Index of Production (IoP). Another measure is the Bank of England calculation of the output gap, published in the monetary policy reports.

Figure 5

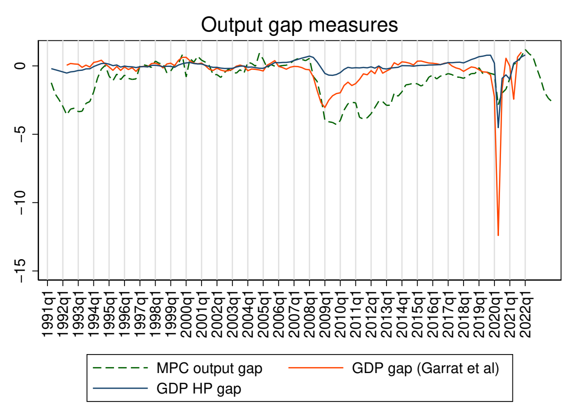
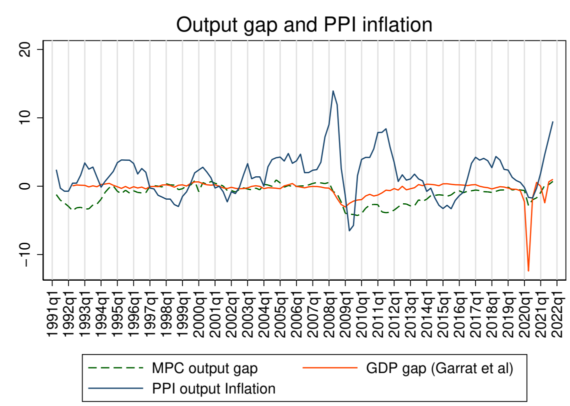


Figure 6



4.6 Other data

The real oil price inflation is the change in oil price adjusted by bilateral FX change. This measure is based on Roberts, 1995, calculated as DCOILBRENTEU - DEXUSUK. DCOILBRENTEU is the FRED series for Crude Oil Prices: Brent - Europe, Percent Change, Quarterly (average of the quarter), Not Seasonally Adjusted. DEXUSUK is the FRED series for U.S. Dollars to U.K. Pound Sterling Spot Exchange Rate, Percent Change, Quarterly (End of period), Not Seasonally Adjusted

Labour share is also tried, calculated as suggested by the ONS[10]: real ULC = ULC/GVAdeflator[11].

[9] The ONS provides 20 industry categories at the 2 digits SIC grouped as follows: 05to39, 45to98, 01to03, 05to09, 10to33, 35, 36to39, 41to43, 45to47, 49to53, 54to56, 58to63, 64to66, 68, 69to75, 77to82, 84, 85, 86to88, 90to93, 94to96, 97to98

[10] https://www.ons.gov.uk/economy/economicoutputandproductivity/productivitymeasures/bulletins/labourcostsandlabourincomeuk/latest

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

Figure 7

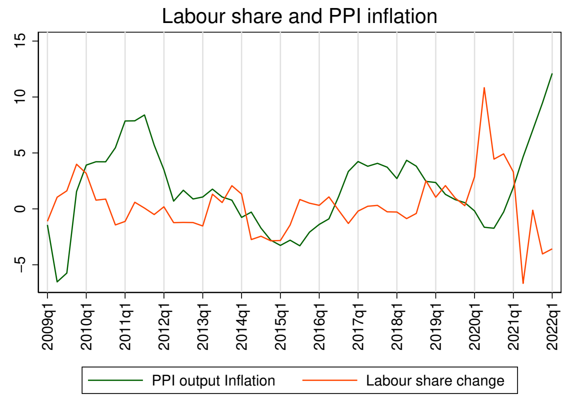
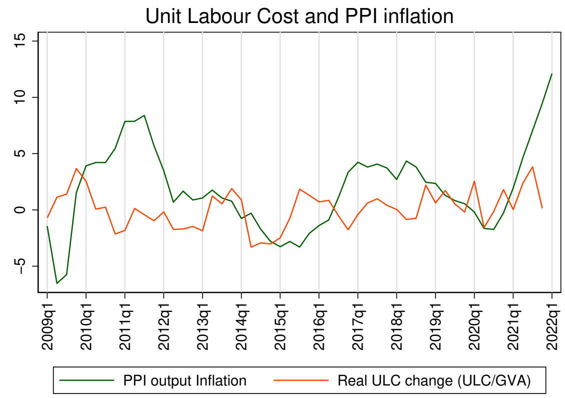


Figure 8



Another measure for the labour share, as suggested by BJN: ln[((HAEA*A)/ABML)*100], where A = (E + SE)/E. E is given by BCAJ[12], 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, where IKBI is total imports (current prices), and IKBL is total imports (constant prices).

4.6.1 Market concentration (Herfindahl-Hirschman Index and Concentrarion ratio)

To identify the industrial structure Domberger, 1979 uses the five-firm concentration ratios and estimates of the HHI calculated using employment data. I am not aware that the production of these indices have continued. Therefore, I built the HHI following Brezina et al., 2016 and Naldi and Flamini, 2018, using turnover data from FAME BvD[13].

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

The HHI for each sector is equal to $\sum_{i=1}^{n} (s_i)^2$ (summing up all firms i in each sector). HHI< 0.1 suggests an unconcentrated industry, 0.1 <HHI< 0.2 moderately concentrated and HHI> 0.2 highly concentrated.

the ONS

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

[13] Bureau van Dijk provides information on companies and unincorporated businesses throughout the UK and Ireland

4.7 Other relevant aspects about the data

In the estimations of the NKPC I set the data as annual changes with quarterly frequency. The latter is usually supported by researchers given that it allows to calculate price adjustments lower than the year, as evidence shows. Regarding modelling annual changes, this is to avoid having to adjust the survey data by seasonality. Also, adjusting the 4-quarter ahead expectations to 1-quarter ahead expectations would require some assumptions regarding the revisions.

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 macro data as annual growth rates, hence holding consistency.

5 Sectoral NKPC: empirical estimation

The sector-level NKPC is estimated for 38 sectors The expectations variable is calculated as the average of firms' reports within each sector. One advantage of averaging out expectations by sector is that I get a balanced sample, and that there are no outliers from individual firms. Also, the NKPC has been microfounded at the sector level, providing more theoretical structure to the estimations. On the other hand, one disadvantage of using sector-level variables is that I lose firm-level information.

5.1 Previous evidence in the UK

The NKPC has been confirmed to be valid in UK data by Batini et al., 2005 using system-based expectations. To my knowledge, the NKPC has not been estimated at the sector level with survey-based expectations.

Incorporating some of the variables proposed by Batini et al., 2005 to the estimation of the aggregate NKPC reveals that the oil price inflation and the labour share are significant in some specifications. I also assess whether these variables are more relevant in explaining sector-level inflation. One would expect that prices in manufacturing firms be more affected by oil price changes, whereas labour share and salary costs might play a key role in labour-intensive sectors, i.e. services firms.

5.2 Are the NKPC parameters identified with aggregate data?

The starting point for my analysis is the estimation of Equation 1 in a time series setting.

I estimate the coefficients from Equation 1, as well as some slight modifications proposed in Equation 3. The aggregate NKPC time series are estimated through Two-Stage Least Squares (2SLS) given the potential endogeneity of inflation expectations and the slack variable. Results from 2SLS estimations for the aggregate NKPC are compared with mean group estimations using dynamic panel techniques.

Regarding the potential perception error issue explained above, expectations seem to perform better when purged by the perception error. The coefficient on the purged expectations is significant and around 0.7 whereas the estimate on lagged inflation is around 0.35. Also aligned with GG's prediction, the sum of lagged inflation and purged expectations is about 1, without imposing the restriction.

The slack measure seem not to be properly identified through the aggregate specification, regardless of the variable chosen. While the BoE measure of output gap is significant, the sign is not the expected one (i.e. is negative). The measure of output gap calculated as in Garratt et al., 2008 is positive but not significant.

By comparing across different specifications, the Root Mean Squared Errors (RMSE) suggest that the models with perception error or purged expectations have a lower average magnitude of the residuals. The RMSE is calculated as the square root of the average of squared errors and is defined in terms of the dependent variable.

5.3 Are the NKPC parameters identified with cross-sectional data?

Interestingly, exploiting the micro data at the sector level by estimating a dynamic panel for the NKPC seems to yield better results. For the panel estimations I use the Stata command xtdcce2 developed by Ditzen, 2021 allows to use instrumental variables (IV) to deal with potential endogeneity of inflation expectations and the slack variable.

While the panel estimations show similar results than the aggregate time series estimations with respect to sizes and signs of the lagged and expected inflation, estimates on the slack variable are now consistent with the theory (see GG) (e.g. model 6 in Table 3; see more specifications in Appendix B). Models 1 and 2 are estimated using average measures of inflation and inflation expectations, calculated as simple mean among the sectors in the sample. The slack measure (output gap) in model 1 is statistically significant but negative, against the economic theory. In model 2 expectations are adjusted by the perception error, reducing the RMSE considerably, while also losing the significance for the output gap. The estimated parameter of expectations in model 1 is significant but nonsensical in economic terms. The estimated parameter of purged expectations in model 2 is more economically significant but less so statistically. In models 3-6 I estimate the NKPC using sectoral data. Model 3 assumes homogeneous slopes for all sectors, obtaining a statistically significant slope for the output gap but not aligned with the economic theory. Models 4-6 assume heterogeneous slopes among sectors and add CCEs. While model 4 and 6 show statistically and economically significant coefficient for expectations, only model 6 has the expected coefficient for the output gap.

By comparing model 5 and 6, both with heterogeneous slopes and CCEs, the RMSE drops from 2.7 to 1.5 when accounting for the perception error by using purged expectations. Therefore, the best specification seem to be model 6.

Estimates of the slope are positive and significant for models 6, consistent with the theory and estimations by Gali and Gertler, 1999 (GG) and Gali et al., 2001. Model 6 also shows that, on average, γ^f is larger than γ^b, suggesting that sectors set prices in a more forward- than backward- looking way. Furthermore, results indicate that accounting for bias via PE, dynamic panel, IV and CCE improve the estimations.

Model 6 is also aligned with other evidence in the UK. Meeks and Monti, 2022: $\gamma^b : 0.2$; $\gamma^f : 0.8^{***}$ & Byrne et al., 2013: $\gamma^b : 0.1^{***}$ $\gamma^f : 0.9^{***}$ & Batini et al., 2005: $\gamma^b 0.3^{***}$; $\gamma^b : 0.7^{***}$) and recent findings in the US (Meeks and Monti, 2022: $\gamma^b : 0.1$ $\gamma^f : 1.6^{***}$ McLeay and Tenreyro, 2019: $\gamma^b : 0.1^{***}$ $\gamma^f : 0.22$). Moreover, Boneva et al., 2020 estimated firm-level pricing equations using CBI expectations about own prices and obtained $\gamma^f : 0.2 - 0.3$ (γ^b not explicitly reported).

5.4 Can we unmask the heterogeneity in the price setting behaviour across sectors?

The sector-level estimations reveal a broad heterogeneity across sectors, with services firms, on average, more backward-looking than manufacturing. The average estimations for services are: $\gamma^b : 0.17$, $\gamma^f : 0.81$ while for the manufacturing firms: $\gamma^b : 0.08$, $\gamma^f : 0.93$. See details in Figure 9.

Model 6 is then used in the next section to estimate the γ_k (for each sector). By using these parameters, I investigate the determinants of these asymmetries across sectors.

Table 3

	TS-IV	TS-IV	Pooled MG FE & IV	MG Panel-CCE	MG Panel-CCE&IV	MG Panel-CCE&IV
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	*Mean Inflation*	*Mean Inflation*	*Sectoral Inflation*	*Sectoral Inflation*	*Sectoral Inflation*	*Sectoral Inflation*
Expectations	2.52***				0.06	
	(0.67)				(0.25)	
Purged expectations		0.42	-0.09	0.69***		0.76***
		(0.35)	(0.49)	(0.04)		(0.05)
Lagged inflation	0.29	0.68*	0.96***	0.22***	0.64***	0.22***
	(0.22)	(0.36)	(0.35)	(0.03)	(0.05)	(0.05)
BoE output gap	-0.51*	0.46	3.85**	-0.00	-0.12	0.42**
	(0.30)	(0.37)	(1.86)	(0.05)	(0.25)	(0.20)
Constant	-1.88**	0.47		0.13	-0.13	0.51**
	(0.75)	(0.62)		(0.11)	(0.55)	(0.24)
Heterog./Homog. coeff.	Homog.	Homog.	Homog.	Heterog.	Heterog.	Heterog.
FE / CCE			FE	CCE	CCE	CCE
IV	Yes	Yes	Yes	No	Yes	Yes
Observations	45	45	1,715	1,715	1,632	1,627
Number of groups			38	38	38	38
RMSE	1.016	0.555	0.987	0.987	2.728	1.469
CD test			0.764	0.764	0.001	0.222

Note: Standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. Variables in Column 1-2 are calculated using unweighted averages among all sectors for each quarter. Columns 3-6 have sector-level variables. For 3-6: Expectations, perception error and purged expectations are calculated as unweighted averages among all firms for each sector and quarter. For 1-6: The endogenous variables are the slack measure and the expectations, which are instrumented out with: lags (1, 2, 3) of expectations and lags (2, 3) of the dependent variable. CCEs are proxied with oil inflation and the mean inflation across sectors (and its lag) and the mean expectations across sectors. The CCE are partialled out. RMSE is the square root of the average of squared errors and is defined in terms of the dependent variable. CD test: null hypothesis of weak cross-sectional dependence. Data 2010q1-2021q4

6 Determinants of the sectoral heterogeneity in price setting

Having unmasked the degree of forward-lookingness for each sector in section 5, the next goal is to investigate its main sources. In this section I use the estimated sector-specific parameters of forward-lookingness from the NKPC to understand how responsive they are to the market structure and other industry-characteristics. In order to do so I need to first adjust the estimates by their estimation precision.

6.1 Estimated parameters weighted by their standard error

Some of the parameters estimated for the sector-specific forward-looking coefficients of the NKPC are not significant. To account for the various degrees of precision or imprecision

Figure 9

Note: Estimations of individual purged expectations coefficients from model 6 (Table 3, through dynamic panels with CCE and IV. These coefficients are net from the effect of the common factor effects. Intervals show 95% confidence. Intervals calculated as the mean +/- s.e *1.96 and the labels indicate the mean coefficient. The endogenous variables are the slack measure and the expectations, which are instrumented out with: lags (1, 2, 3) of expectations and lags (2, 3) of the dependent variable. CCEs are proxied with oil inflation and the mean inflation across sectors (and its lag) and the mean expectations across sectors. The CCE are partialled out. The dashed vertical lines are the averages; only showing sectors with significant forward looking coefficients.

of the estimates, I use a similar approach to the so called weighted least squares (WLS)[14]. Given that the standard errors are obtained in the OLS estimation of the NKPC (see section 5), these are used to adjust the imprecise parameters. The weighted estimators are obtained

[14]See Domberger, 1979 for an application that deals with the presence of serial correlation revealed in the OLS results and Stock and Watson, 2019 (section 18) for further reference.

by first dividing the dependent variable (γ_k^f) and regressors (X_k^i) by the standard errors.

$$\gamma_k^f / s.e_k$$

$$X_k^i / s.e_k$$

Specifically, divide both sides of the regression equation by $s.e_k$ to obtain

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

In other words, by dividing the dependent variable and regressors by the inverse of the standard error we are giving more weight to the less biased estimated sectors.

6.2 Regression estimation results

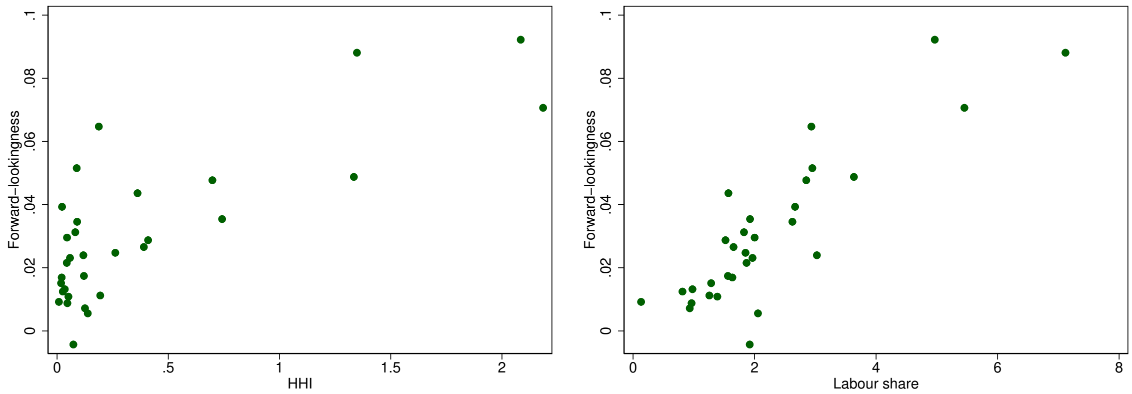
Table 4 presents correlations that compare the degree of forward-lookingness with some industry-characteristics. Among them, the main interest is to study the relationship with the degree of concentration, but I will control for other characteristics that might play a role in determining the weight of expectations in price setting. Specifically, I run a sequence of cross-sectional regressions, adding controls one at a time.

Table 4: Correlation table

	Gamma_f	HHI	Concentr. Ratio	Coal over costs	Petrol over costs	Energy over costs	Imports over supply	Imports over costs	Labour share	Inf. variability
Gamma_f	1.00									
HHI	**0.37**	1.00								
Concentr. Ratio	**0.41**	**0.95**	1.00							
Coal/costs	**0.33**	0.10	0.21	1.00						
Petrol/costs	0.23	0.26	0.27	**0.31**	1.00					
Energy/costs	-0.16	0.00	0.05	0.25	0.03	1.00				
Imports/supply	0.30	-0.01	0.10	0.25	-0.18	0.08	1.00			
Imports/costs	**0.38**	0.02	0.11	**0.49**	-0.19	0.03	**0.72**	1.00		
Labour share	0.28	0.22	0.26	-0.06	**0.42**	-0.19	0.03	-0.13	1.00	
Inf. variability	**0.38**	0.30	**0.34**	**0.76**	0.28	0.18	**0.36**	**0.48**	0.02	1.00

Note: The table shows correlations of at least 0.3 in bold. Data used corresponds to 2019q1 to 2019q4 where quarterly data is available, otherwise, the 2019 average is used.

Given the relatively limited existing work on what determines the degree of forward-lookingness, the precise regression specification is unclear. Column 1 of Table 5 presents the regression of the degree of forward-lookingness (γ^f) on the degree of concentration measured by the HHI. The results indicate a positive relationship as suggested in Table 5 and scatter plots, plus being highly statistically significant. Column 2 adds all potentially relevant controls, based on determinants of the frequency in price changes found in the literature. While including these controls adds predictive power (R-squared), it also reduces the T-ratio of the HHI coefficient, and hence, the quality of its estimation.



(a) **(b)**

Both scatterplots show weighted variables (by the inverse of the s.e. of γ^f parameters), as used in the regressions. Data used for scatterplots corresponds to 2019q4, equivalent to the data used in the regressions.

In column 3 I drop variables that show correlation above 0.3 with other explanatory variables. Specifically, inflation variability is correlated to HHI and imports, while petrol is largely correlated to labour share. This specification yields positive and statistically significant effect of HHI on γ^f. In column 4 I drop energy due to being insignificant in the previous specifications. Results in columns 3 and 4 show that the positive sign of HHI is robust to the addition of controls while keeping track of the correlation among explanatory variables. That is, HHI has a positive and significant effect on the degree of forward lookingness.

For further robustness, in columns 5-8 I run the same regressions using an alternative market concentration index (the five-firm concentration ratio) and the results are very similar to those in columns 1-4.

When studying the effect of inflation variability[15], similar to Dhyne et al., 2006, combined with labour share, both are positive and statistically significant. However, the R-squared is 0.79, smaller than the one obtained in specifications which include some measure of market concentration. Lastly, I also tested imports over supply (similar to Alvarez and Hernando, 2007) but it is never significant in any specification. Instead, I use imports over costs which seems to perform better within the controls. Coal over costs, exports over turnover and exports over demand were also tested but they are never close to significant.

[15] These results are not shown here but are available upon request. This specification tests the effect of inflation variability and labour share on the degree of forward-lookingness. The concentration index is not included as an explanatory variable due to large correlation with the inflation variability.

Table 5

Dep Var: Forward looking coefficient	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Market concentration				
HHI	0.031***	0.009	0.010*	0.009*				
	(0.005)	(0.006)	(0.005)	(0.005)				
5-firm CR					0.920***	0.299	0.336*	0.248
					(0.201)	(0.180)	(0.173)	(0.155)
				Controls				
Labour share		0.010***	0.010***	0.010***		0.010***	0.010***	0.010***
		(0.004)	(0.002)	(0.002)		(0.003)	(0.002)	(0.002)
Imports/costs		0.149	0.189***	0.189***		0.133	0.179***	0.183***
		(0.093)	(0.044)	(0.044)		(0.083)	(0.041)	(0.042)
Energy/costs		-0.020	-0.022			-0.032	-0.034	
		(0.021)	(0.022)			(0.026)	(0.027)	
Inf. variability		0.015				0.018		
		(0.031)				(0.030)		
Petrol/costs		-0.014				-0.016		
		(0.023)				(0.021)		
Constant	0.019***	-0.001	0.000	-0.001	0.014***	-0.001	-0.001	-0.002
	(0.003)	(0.004)	(0.003)	(0.002)	(0.004)	(0.004)	(0.003)	(0.002)
Observations	31	31	31	31	31	31	31	31
R-squared	0.605	0.856	0.851	0.848	0.643	0.857	0.849	0.842

Note: OLS regressions, robust s.e. in parentheses
All variables are weighted by the inverse of the s.d. from the NKPC γ^f estimated parameters
*** p< 0.01, ** p< 0.05, * $p < 0.1$

7 Conclusions

Using survey-data of firms' expectations allows to identify the NKPC 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 NKPC. Also, exploiting the micro data at the sector level by estimating a dynamic panel for the NKPC seems to yield better results than ignoring the cross-sectional effects.

I estimate industry-level NKPCs for 38 sectors and find: positive and significant coefficients on lagged inflation, expected inflation and on the slack variable, consistent with the theory. Results also show that, on average, γ^f is larger than γ^b, suggesting that sectors set prices in a more forward- than backward- looking way.

I also investigate the main determinants of price setting by sectors and find a positive effect of the degree of concentration on the NKPC forward-looking parameters. This suggests that expectations play a larger role in the firms' price setting behaviour when their sector is more concentrated. Also, labour share and inflation variability play an important role in driving producer price setting.

The results of the paper speak to recent policy debates on the relevance of inflation expectations in the firms' price setting behaviour and the heterogeneity across sectors.

8 Appendix

8.1 Appendix A: Sectoral NKPC derivation by Imbs et al., 2011

As it is usual in models of monopolistic competition, it is assumed that each supplier understands that its sales depend upon the price charged for its good, according to the demand function

$$Y_{k,t}(i) = Y_{k,t}\left(\frac{P_{k,t}(i)}{P_{k,t}}\right)^{-\eta} \qquad \text{(A.1)}$$

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

$Y_{k,t}$ is defined through the Dixit and Stiglitz CES aggregator:

$$Y_{k,t} = \left[\int_0^1 Y_{k,t}(i)^{\frac{\eta-1}{\eta}}\, di\right]^{\frac{\eta}{\eta-1}} \qquad \text{(A.2)}$$

Each firm produces a differentiated good with a production function

$$Y_{k,t}(i) = A_{k,t}\, f(h_{k,t}(i)) \qquad \text{(A.3)}$$

where $A_{k,t}$ is a time-varying sector-specific exogenous technology factor. Labor is the only factor of production and $h_{k,t}(i)$ denotes hours worked.

Price setting decisions are governed by the Calvo, 1983 mechanism. A fraction $0 < \alpha_k < 1$ of firms keep their prices unchanged each period, whereas new prices are chosen for the other $1 - \alpha_k$ of the firms. Each supplier that chooses a new price for its goods in period t faces exactly the same decision problem. In equilibrium, all prices that are chosen in period t have the common optimal price $P_{k,t}(i)^*$. The remaining fraction α_k of prices charged in period t are simply a subset of the prices charged in period $t-1$.

The firms optimizing in t will choose $P_{k,t}(i)^*$ that solves:

$$\max_{P_{k,t}(i)^*} E_t \sum_{j=0}^{\infty} (\alpha_k\beta)^j \left[Y_{k,t,t+j}(i)\, P^*_{k,t}(i) - \Psi\left(Y_{k,t,t+j}(i)\right)\right] \qquad \text{(A.4)}$$

where $\Psi(Y_{k,t,t+j}(i))$ are the total nominal costs of supplying good k

$$\sum_{j=0}^{\infty} (\alpha_k\beta)^j\, E_t\left[Y_{k,t,t+j}(i)\left(P^*_{k,t}(i) - \frac{\eta}{\eta-1} S_{k,t,t+j}(i) P_{k,t+j}(i)\right)\right] = 0 \qquad \text{(A.5)}$$

where real marginal cost is $S_{k,t,t+j}(i) = \Psi'(Y_{k,t,t+j}(i))/P_{k,t+j}(i)$

The sector is assumed to be a collection of suppliers that always change their prices at the same time and hire inputs in common factor markets as well. Because in equilibrium each supplier in the same sector always chooses the same price. Also, in steady state $P_{t+j}(i) = P_t(i)$, $P_{k,t+j}(i) = P^*_{k,t}(i)$, $P_{t+j} = P_t$, $Y_{k,t,t+j}(i) = Y_{k,t}(i)$, $S_{k,t,t+j}(i) = S_k = \eta/(\eta-1)$

A Taylor expansion around the steady state gives

$$\hat{p}^*_{k,t}(i) = (1-\alpha_k\beta)\sum_{j=0}^{\infty}(\alpha_k\beta)^j E_t\left[\hat{s}_{k,t,t+j}(i) + \hat{p}^k_{t+j}(i)\right] \qquad \text{(A.6)}$$

where $\hat{s}_{k,t,t+j}(i) = s_{k,t,t+j}(i) - S_k$ and $\hat{p}_{k,t+j}(i) = p_{k,t+j}(i) - \hat{p}_k(i)$

In order to replace the real marginal costs at the firm level $S_{k,t+j}(i)$ with the measure we observe in the data, the sector average across firms, $S^{avg}_{k,t+j}$, they use the relation proposed by Sbordone, 2002 [see section 2.1.1 from Imbs et al., 2011 for details] which states that:

$$S_{k,t,t+j}(i) = \left(\frac{P^*_{k,t}(i)}{P_{k,t+j}}\right)^{-\eta\, a_k/(1-a_k)} S^{avg}_{k,t+j}$$

which implies that real marginal costs vary across firms only if optimal pricing does. Assuming there are no firm-specific shocks, all firms will optimally set prices at the same level, ensuring a symmetric equilibrium across firms in each sector. Firm indices (i) are therefore omitted from now on.

Next, they argue that in the presence of price rigidities, the sectoral (log) price level in t is calculated as:

$$\hat{p}_{k,t} = \alpha_k\,\hat{p}_{k,t-1} + (1-\alpha_k)\,\hat{p}^*_{k,t} \qquad \text{(A.7)}$$

There's a proportion of firms ω among the $(1-\alpha)$ that are updating prices who will do so in a purely backward-looking manner. This is similar to GG (1999), in the sense that the price in t for backward-looking firms depends only on information dated $t-1$ or earlier.

Then, newly set prices will be defined as:

$$\hat{p}^*_{k,t} = \omega_k\,\hat{p}^b_{k,t} + (1-\omega_k)\,\hat{p}^f_{k,t} \qquad \text{(A.8)}$$

where p^b_k refers to prices set by backward-looking firms, who adjust for inflation the prices they set the last time they could, i.e.:

$$\hat{p}^b_{t,k} = \hat{p}^*_{k,t-1} + \hat{\pi}_{k,t-1} \qquad \text{(A.9)}$$

and $p^f_{t,k}$ refers to prices set by forward-looking firms according to (A.6).

Combining (A.6) to (A.9), they get the following linearized hybrid sectoral Phillips Curve:

$$\hat{\pi}_{k,t} = \frac{\omega_k}{\phi_k}\,\hat{\pi}_{k,t-1} + \frac{\beta\alpha_k}{\phi_k}\,E_t\hat{\pi}_{k,t+1} + \frac{(1-\omega_k)(1-\alpha_k)(1-\beta\alpha_k)}{\phi_k}\,h_k\,\hat{s}^{avg}_{k,t} \tag{A.10}$$

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

Lastly, $\varepsilon^{\pi}_{k,t}$ 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:

$$\hat{\pi}_{k,t} = \gamma^b_k\,\hat{\pi}_{k,t-1} + \gamma^f_k\,E_t\hat{\pi}_{k,t+1} + \gamma^s_k\,\hat{s}^{avg}_{k,t} + \varepsilon^{\pi}_{k,t} \tag{A.11}$$

8.2 Appendix B: Estimations

Table 6: Aggregate data - Time Series 2SLS

Dependent variable: Mean Inflation	(1)	(2)	(3)	(4)	(5)	(6)
Expectations	1.62***	2.52***	0.86***	0.68		
	(0.27)	(0.67)	(0.23)	(1.36)		
Perception error			0.96***	1.00		
			(0.34)	(0.76)		
Purged expectations					0.81***	0.42
					(0.11)	(0.35)
Lagged inflation	0.60***	0.29	0.16	0.20	0.29***	0.68*
	(0.10)	(0.22)	(0.18)	(0.13)	(0.09)	(0.36)
Unit labour cost by SIC	0.74		-0.37		1.16	
	(1.02)		(1.16)		(1.27)	
BoE output gap		-0.51*		0.10		0.46
		(0.30)		(0.47)		(0.37)
Constant	-0.87***	-1.88**	-0.24	-0.07	-0.44***	0.47
	(0.29)	(0.75)	(0.30)	(1.34)	(0.17)	(0.62)
Observations	45	45	45	45	45	45
Number of groups						
RMSE	0.732	1.016	0.441	0.384	0.405	0.555
CD test						

Note: Standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. All variables are calculated as unweighted averages among all sectors for each quarter. The endogenous variables are the slack measure and the expectations, which are instrumented out with: lags (1, 2, 3) of expectations and lags (2, 3) of the dependent variable. RMSE is the square root of the average of squared errors and is defined in terms of the dependent variable. Data 2010q1-2021q4

Table 7: Sectoral data - Pooled estimation with Fixed Effects and IV

Dependent variable: Sectoral Inflation	(7)	(8)	(9)	(10)	(11)	(12)
Expectations	1.86***	0.53	1.82***	1.80***		
	(0.58)	(0.83)	(0.34)	(0.58)		
Perception error			0.63***	0.62**		
			(0.17)	(0.24)		
Purged expectations					0.49***	-0.09
					(0.19)	(0.49)
Lagged inflation	0.74***	0.84***	0.31***	0.32	0.47***	0.96***
	(0.05)	(0.10)	(0.11)	(0.20)	(0.13)	(0.35)
Unit labour cost by SIC	-0.30		-0.01		1.23	
	(1.88)		(1.39)		(1.86)	
BoE output gap		2.55		0.05		3.85**
		(1.85)		(1.18)		(1.86)
Constant						
Observations	1,718	1,718	1,715	1,715	1,715	1,715
Number of groups	38	38	38	38	38	38
RMSE	2.251	2.261	1.011	1.009	1.016	0.987
CD test	0.000	0.000	0.000	0.000	0.545	0.764

Note: Standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. Expectations, perception error and purged expectations are calculated as unweighted averages among all firms for each sector and quarter. Constants are included in the estimation but not reported by the Stata command xtvireg2. RMSE is the square root of the average of squared errors and is defined in terms of the dependent variable. CD test: null hypothesis of weak cross-sectional dependence. Data 2010q1-2021q4

Table 8: Sectoral data - Mean Group Estimations with CCE and no IV

Dep var: Sectoral Inflation	(13)	(14)	(15)	(16)	(17)	(18)
Expectations	0.13*	0.14**	0.50***	0.50***		
	(0.07)	(0.07)	(0.04)	(0.04)		
Perception error			0.71***	0.71***		
			(0.04)	(0.03)		
Purged expectations					0.70***	0.69***
					(0.04)	(0.04)
Lagged inflation	0.65***	0.62***	0.25***	0.23***	0.23***	0.22***
	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)
Unit labour cost by SIC	0.25		-0.02		0.09	
	(0.17)		(0.07)		(0.07)	
BoE output gap		-0.08		0.05		-0.00
		(0.08)		(0.05)		(0.05)
Constant	0.03	-0.05	-0.02	0.10	0.11	0.13
	(0.21)	(0.31)	(0.12)	(0.13)	(0.12)	(0.11)
Observations	1,718	1,718	1,715	1,715	1,715	1,715
Number of groups	38	38	38	38	38	38
RMSE	2.251	2.261	1.011	1.009	1.016	0.987
CD test	0.000	0.000	0.000	0.000	0.545	0.764

Note: Standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. Expectations, perception error and purged expectations are calculated as unweighted averages among all firms for each sector and quarter. CCEs are proxied with oil inflation and the mean inflation across sectors (and its lag) and the mean expectations across sectors. The CCE are partialled out. RMSE is the square root of the average of squared errors and is defined in terms of the dependent variable. CD test: null hypothesis of weak cross-sectional dependence. Data 2010q1-2021q4

Table 9: Sectoral data - Mean Group Estimations with IV and CCE

Dep var: Sectoral Inflation	(19)	(20)	(21)	(22)	(23)	(24)
Expectations	-0.33	0.06	0.48***	0.36***		
	(0.27)	(0.25)	(0.12)	(0.13)		
Perception error			0.71***	0.75***		
			(0.06)	(0.06)		
Purged expectations					0.74***	0.76***
					(0.05)	(0.05)
Lagged inflation	0.57***	0.64***	0.25***	0.19***	0.22***	0.22***
	(0.06)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)
Unit labour cost by SIC	2.68		0.27		-0.59	
	(2.10)		(0.70)		(0.95)	
BoE output gap		-0.12		0.20		0.42**
		(0.25)		(0.15)		(0.20)
Constant	0.22	-0.13	-0.05	0.50	0.04	0.51**
	(0.37)	(0.55)	(0.15)	(0.37)	(0.10)	(0.24)
Observations	1,632	1,632	1,630	1,630	1,627	1,627
Number of groups	38	38	38	38	38	38
RMSE	3.303	2.728	1.386	1.416	1.293	1.469
CD test	0.002	0.001	0.000	0.000	0.983	0.222

Note: Standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. Expectations, perception error and purged expectations are calculated as unweighted averages among all firms for each sector and quarter. The endogenous variables are the slack measure and the expectations, which are instrumented out with: lags (1, 2, 3) of expectations and lags (2, 3) of the dependent variable. CCEs are proxied with oil inflation and the mean inflation across sectors (and its lag) and the mean expectations across sectors. The CCE are partialled out. RMSE is the square root of the average of squared errors and is defined in terms of the dependent variable. CD test: null hypothesis of weak cross-sectional dependence. Data 2010q1-2021q4

8.3 Appendix C: Price mapping

Figure 11

SIC 2 digit from the CBI sample	SIC 2 digit description	Available price indices		
		PPI by 4 digit SIC	SPPI at 4 digit SIC	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 and related products	x		
16	Manuf. of wood and of products of wood and cork	x		
17	Manuf. of paper and paper products	x		
18	Printing and reproduction of recorded media	x		
19	Manuf. of coke and refined petroleum products	x		
20	Manuf. of chemicals and chemical products	x		
21	Manuf. of basic pharma. products and preparations	x		
22	Manuf. of rubber and plastic products	x		
23	Manuf. of other non-metallic mineral products	x		
24	Manuf. of basic metals	x		
25	Manuf. of fabricated metal products	x		
26	Manuf. of computer, electronic and optical products	x		
27	Manuf. of electrical equipment	x		
28	Manuf. of machinery and equipment n.e.c.	x		
29	Manuf. of motor vehicles, trailers and semi-trailers	x		
30	Manuf. of other transport equipment	x		
31	Manuf. of furniture	x		
32	Other manufacturing	x		
33	Repair and installation of machinery and equipment	x		
45	Wholesale and retail trade and repair of motor vehicles		x	
46	Wholesale trade, except of motor vehicles and motorcycles			Various CPI indices at 5 digit COICOP
47	Retail trade, except of motor vehicles and motorcycles			Various CPI indices at 5 digit COICOP
49	Land transport and transport via pipelines		x	Index 0731: Passenger transport by railway
50	Water transport		x	Index 0734: Psger transport by sea and inland waterway

Figure 12

51	Air transport		x	Index 0733: Passenger transport by air
52	Warehousing and support activities for transportation		x	
53	Postal and courier activities		x	Index 081: Postal Services
55	Accommodation		x	Index 112: Accommodation services
56	Food and beverage service activities		x	Index 1111: Restaurants & Cafes
58	Publishing activities		x	
59	Motion picture, video and television programme production		x	Index 0914: Recording media
60	Programming and broadcasting activities			Index 0911: Reception and reprod. of sound and pictures
61	Telecommunications		x	Index 082/3: Telephone and telefax equip. and serv.
62	Computer programming, consultancy and related activities		x	
63	Information service activities			
64	Financial service activities, except insurance and pension		x	Index 126: Financial services
65	Insurance, reinsurance and pension funding			Index 125: Insurance
66	Activities auxiliary to financial services and insurance act.			Index 1262: Other financial services (nec)
68	Real estate activities		x	
69	Legal and accounting activities		x	Index 12702: Legal services and accountancy
70	Activities of head offices; management consultancy act.		x	
71	Architectural and engineering activities; technical testing		x	
72	Scientific research and development			
73	Advertising and market research		x	
74	Other professional, scientific and technical activities		x	
75	Veterinary activities			Index 09350: Veterinary and other services for pets
77	Rental and leasing activities		x	
78	Employment activities		x	
79	Travel agency, tour operator and other related activities			
80	Security and investigation activities		x	
81	Services to buildings and landscape activities		x	
82	Office administrative, office support and other business …		x	
87	Residential care activities			Index 12402: Residences for elderly/disabled persons
90	Creative, arts and entertainment activities			Index 094: Recreational and cultural services
91	Libraries, archives, museums and other cultural activities			Index 0942: Cultural services
92	Gambling and betting activities			
93	Sports activities and amusement and recreation activities			Index 0941: Recreational and sporting services
94	Activities of membership organisations			
95	Repair of computers and personal and household goods			Index 0533: Repair and household appliances
96	Other personal service activities		x	

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