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

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Abstract

This paper examines the price-setting behaviour across sectors in the UK and identifies the main determinants of the observed heterogeneity. I first estimate the New Keynesian Phillips Curve (NKPC) at the sector level using heterogeneous panel methods that account for cross-sectional effects. This approach enables the identification of the NKPC parameters with significant and positive slope when using labour costs. The findings also reveal that financial services firms are more forward-looking compared to other services sectors and manufacturing firms. By uncovering the asymmetric degree of forward-lookingness across sectors, I further investigate the main drivers, taking into account their cost and market structure. Notably, the results reveal that the level of concentration and the share of imports positively influence the relevance of expectations in firms' price-setting decisions. This suggests that expectations play a larger role in the price-setting decisions of firms facing less competition.

JEL: C21, C23, E31, E70

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1 Introduction

The New Keynesian Phillips Curve (NKPC) is a crucial component of many modern macroeconomic models. This relationship was microfounded by Gali and Gertler, 1999 (hereafter referred to as GG) and Woodford, 2003. The NKPC explains how past inflation, expected future inflation, and a measure of real marginal cost or output gap collectively shape the current inflation rate. Traditionally, estimations of the NKPC have been conducted at the aggregate level, assuming homogeneneity across firms and sectors. However, when there is heterogeneity across sectors in the available data, imposing homogeneity can introduce an aggregation bias, resulting in inconsistent findings [Pesaran and Smith, 1995; Barkbu et al., 2005].

Using more disaggregated data helps mitigate the simultaneity bias that arises when estimating aggregate NKPCs. As discussed in McLeay and Tenreyro, 2019, identifying the Phillips Curve presents challenges due to the monetary policy's role in offsetting potential demand shocks that could otherwise aid in its identification. However, the central bank is unable to offset regional or sectoral shocks using a national interest rate. Notably, McLeay and Tenreyro, 2019 and Hazell et al., 2022 have shown evidence of statistically and economically significant slopes by employing regional data. Can the identification of the NKPC be further enhanced by using sectoral data? Can the NKPC framework uncover heterogeneity across sectors? If so, which sectors demonstrate a more pronounced role for expectations? What are the main drivers of these sectoral asymmetries? Addressing these questions not only contributes to the academic literature but also holds implications for policymaking, as monetary policy can impact 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 relevance of sector-level heterogeneity. I also found evidence that highlights the greater role of expected inflation in the price-setting behaviour of financial services firms.

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 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 with larger share of imports relative to their supply give more weight to their expectations when setting prices.

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].

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

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

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

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 of the aggregate Phillips curve framework for policy analysis (DelNegro et al., 2020, Hazell

[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.

et al., 2022) and suggested to use dissagregate data, either regional or sectoral, as a way of addressing the identification issues.

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 controlling for oil inflation and real import prices, 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 labour 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 characterised 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 labour-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 6.

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/realised 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 those 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 a proxy 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.

In another study, Coibion and Gorodnichenko, 2015 stress the importance of using direct measures of firms' expectations for optimal analysis. Not having firms' expectations available, they provide evidence that even household data serves as a more accurate proxy for firms' expectations than professional forecasters and financial markets.

Importantly, the original microfoundation of the NKPC states that rational expectations are crucial. This condition has been examined by Adam and Padula, 2011, who argue that nonrational expectations can be incorporated into the NKPC 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[3] 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 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 compared to aggregate economic conditions. This aligns with the findings of Andrade et al., 2020, 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.

3.2.3 Dynamic panel mean group estimation

The mean group estimation procedure employed in this study primarily follows the approach proposed by Chudik and Pesaran, 2015 using the common correlated effects (CCE) estimator. This methodology takes into account heterogeneous coefficients, endogeneity, and the inclusion of covariates to address the potential effects of unobserved common factors, which reflect cross-sectional linkages or common macroeconomic shocks.

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.

I employ various empirical approaches to estimate the NKPC based on equation 2.

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

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

[3] See also Coibion, Gorodnichenko, and Kamdar, 2018 for the derivation of the NKPC with survey-based expectations.

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).

The common correlated effects (CCEs) are approximated by taking the cross-section averages of the dependent variable and the individual-specific regressors, as initially proposed by Pesaran, 2006. This method was extended by 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. For instance, Byrne et al., 2013 justify the use of CCEs to adjust for the possibility that shocks to inflation or marginal costs may be cross-sectionally correlated.

Ignoring the heterogeneity across sectors in dynamic panels and estimating a pooled (homogeneous) model can lead to inconsistent and potentially misleading coefficient estimates, as argued by 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.

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

3.2.4 Dealing with endogeneity by using IVs

To obtain an accurate estimation of the NKPC slope in the presence of simultaneous variables, I must employ a valid instrument that aligns with the changes in demand reflected in the slack measure, while being unrelated to cost-push shocks. Also, it is plausible that inflation expectations are simultaneously determined along with the current inflation rates. By conducting a first-stage regression, the resulting fitted value effectively removes the endogenous effect of monetary policy response to cost-push shocks from the slack variable and the potential simulateneity of expectations. These purged variables can then be utilized to uncover the true parameters of the NKPC.

Therefore, I will employ lagged variables as instruments to deal with the potential endogeneity between the explanatory variables and the errors.

[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

3.3 Slack measure: output gap or marginal cost

The slack measure of the NKPC 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 NKPC whereas in different ways in the sectoral-NKPC.

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 NKPC 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 sector-level NKPC by Woodford, 2003 contains both relative prices and aggregate output gap[5] 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, as shown in Equation 2.

I will employ various measures of output gap, real activity and labour costs for empirical comparison.

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

4 Data and descriptives

4.1 Survey of firms' expectations

The Confederation of British Industry (CBI) suite of business surveys comprises four surveys[6] 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.

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[7]. 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 utilized 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

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

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

examines data from all four CBI surveys, allowing for a comprehensive assessment of heterogeneity across sectors and capturing broader cross-sectional effects. For a more detailed understanding of the CBI survey, please refer to Lee et al., 2020.

4.1.1 Inflation expectations question

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

Respondents are asked to report their expectations and perceptions about price movements by selecting from one of the ten buckets within the range -10% to 10% (ITS)[8] whereas for DTS, FSS and SSS[9] are -5% to 5%. Additionally, in the four surveys they can answer zero or enter 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[10] 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 33,836. Also, I identified as outliers those expectations reports that are either very far from the other firms' reports in the same sector or are very far from the same firm's reports through time. This is explained in detail in Appendix D. Using this conservative method, only 363 observations are identified as outliers and thereby removed.

The respondents in the CBI dataset encompass 65 sectors classified at the 2-digit SIC level. However, for my analysis, I focus on 45 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 noticeable discrepancy in sectoral inflation expectations among sectors in line with the assumptions I am imposing to the sector-specific parameters

[8] 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%

[9] 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%

[10] Bank of England/Ipsos Inflation Attitudes Survey

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.

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

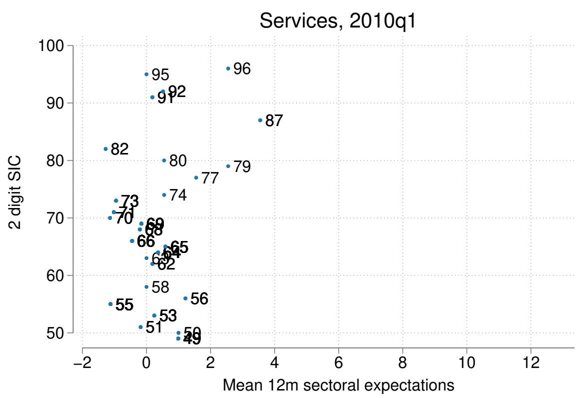


Figure 2

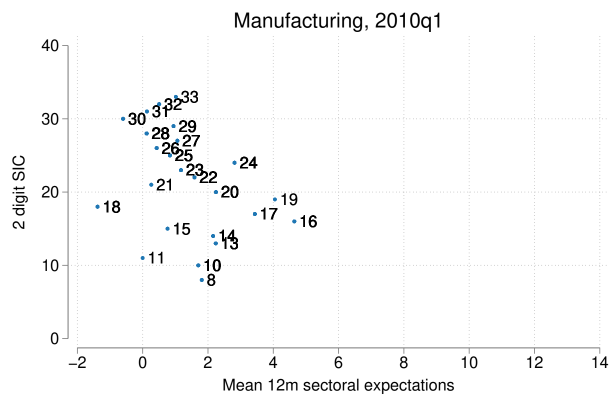


Figure 3

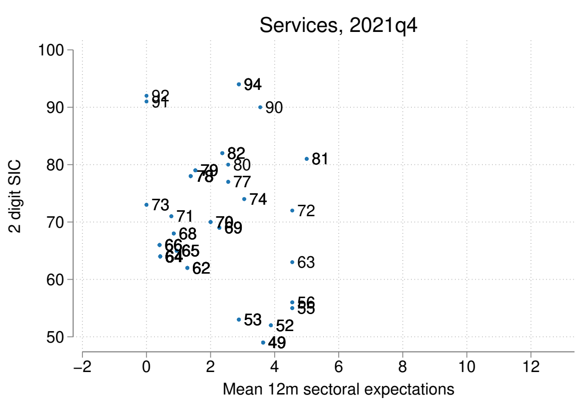
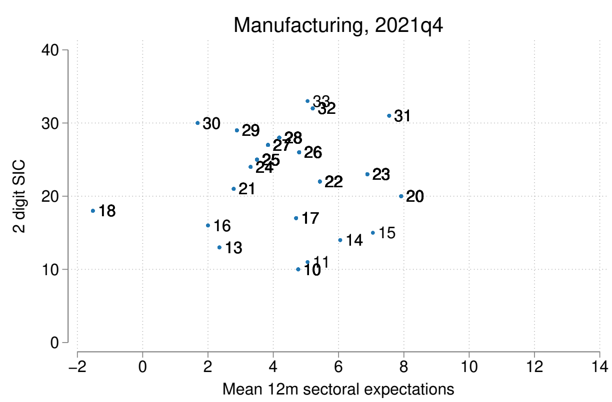


Figure 4



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.

Table 2: Number of firms in each of the sectors used in the panel

	2009-2014	2015-2020	2021-2022
Manufacturing firms			
Fabricated metal	52	46	20
Machinery and equip.	61	38	9
Rubber and plastic	30	27	12
Electrical equipment	21	24	12
Computer; electronic	23	19	5
Non-metallic mineral	19	16	7
Food products	19	14	5
Basic metals	17	13	7
Chemicals	15	12	5
Paper and paper	15	11	4
Textiles	13	11	3
Motor vehicles	11	13	5
Other Manuf.	12	9	2
Wood	10	8	2
Furniture	8	8	2
Other vehicles	8	6	2
Printing and Media	7	7	2
Wearing apparel	7	6	1
Beverages	5	8	1
Footwear, luggage	5	5	2
Pharmaceutical	4	4	3
Other mining	5	3	1
Distributive firms			
Retail (non vehicles)	55	39	21
Wholesale (non vehicles)	38	35	15
WS & retail of vehicles	9	7	2

	2009-2014	2015-2020	2021-2022
Services firms			
Fin service act	30	35	13
Act. aux to fin serv.	20	16	3
Legal and accounting	16	13	3
Insurance and pension	19	12	4
Land transport	13	10	2
Accommodation	11	7	2
Real estate	6	6	3
Postal and courier	6	5	1
Architect. and engin.	8	4	2
Advertis. and mkt res	7	4	0
Mangmnt. Consult.	5	5	2
Employment acts.	6	4	2
Sporting activities	5	4	2
Computer program.	4	4	1
Restaurants & food	3	5	2
Recreational,cultural	4	3	1
Private security	2	4	3
Water transport	3	3	1
Travel agents	3	5	0
Cleaning	4	2	1
Renting and leasing	2	4	2
Travel agency	2	3	2
Other service activities	1	2	0
Medical, optical	2	2	1

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 NKPC analysis.

4.2 Actual inflation rates vs. perceived change in prices

There are at least two sources of prices that I can utilize to analyze sector-level price setting: the actual inflation rates reported by the Office for National Statistics (ONS) and the reports from CBI firms regarding past changes in sectoral prices. While neither source is perfect, I will explain why the CBI reports may be less biased or more suitable for the analysis of sectoral NKPC.

One issue 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[11]) by SIC code for industrial sectors. For non-industrial sectors, the Consumers Price Indices (CPI) and Services Producer Prices Indices (SPPI) could be used. However, further details on the mapping between these indices and the specific sectors can be found in Appendix C.

The second issue arises from the fact that the CBI elicits firms' expectations regarding "changes in the general level of output prices in the UK markets that your firm competes

[11]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.

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.

Using the perceived change in sectoral prices from the CBI survey is a good proxy for the actual inflation rates. As shown in figures 5 and 6, the average of CBI inflation reports follows quite closely the average of 2-digit SIC inflation rates[12].

Figure 5

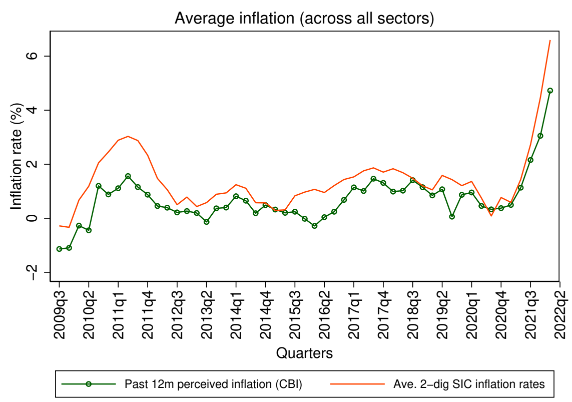
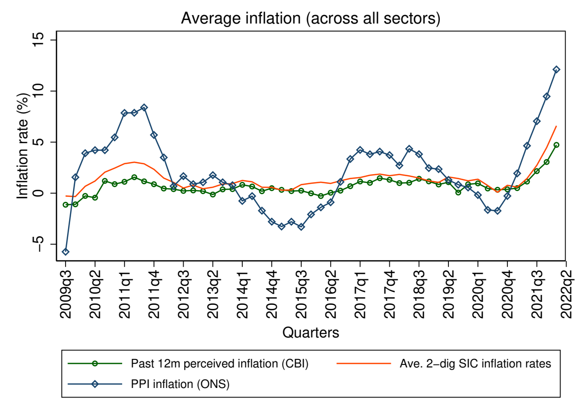


Figure 6



4.3 Slack measures

The measure of real activity in the NKPC literature are usually proxied by either the output gap or some measure of real marginal costs.

For the sectoral labour costs, I tried two measures: the CBI self-reported changes in salary costs and a measure of the unit labour cost (ULC) provided by the ONS. The former is shown in figure 7 and it yields the expected statistical and economic estimates as predicted by the NKPC theory (see the regressions section). The alternative measure, the ULC, measures the nominal cost of labour input per unit of real (inflation-adjusted) economic output. It is the ratio of total nominal employment costs relative to output (divided by real gross value added (GVA)). The ULC data is not available at the 2-digit SIC level. The ONS provides 20 industry categories at the 2 digits SIC grouped as follows: 05to39, 45to98, 01to03, 05to09, 10to33, 35, 36to39, 41to43, 45to47, 49to53, 54to56, 58to63, 64to66, 68, 69to75, 77to82, 84,

[12]This average is built using all inflation indices from the mapping of 4-digit SIC sectors and PPI, CPI, SPPI data as explained in Appendix C.

85, 86to88, 90to93, 94to96, 97to98. I mapped these categories to the closest 2-digit SIC in the dataset. Yet, this measure is not statistically significant in the NKPC estimation. See in Figure 9 an average measure of these series using the corresponding sectors from the sample.

Obtaining sector-level output gaps is not an easy task given the lack of activity data at the sector level and quarterly frequency. Additionally, even at the national level, the way of calculating the output gap is largely debated in the literature. None of the output gap measures tried yield significant coefficients. Some of the measures of output gap used were constructed using the methodology proposed by Garratt et al., 2008. For the data I used two alternatives: the Gross Domestic Product (GDP) index and the Index of Production (IoP). See Figure 10 for the former.

The other measure I used as proxy for the slack measure is the UK output gap calculated and provided by the Bank of England[13]. See the time series in Figure 8.

Figure 7

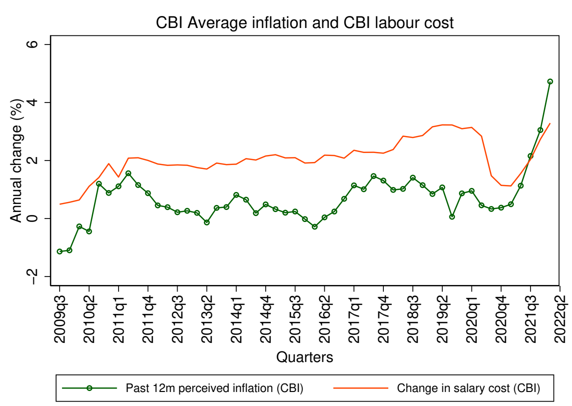
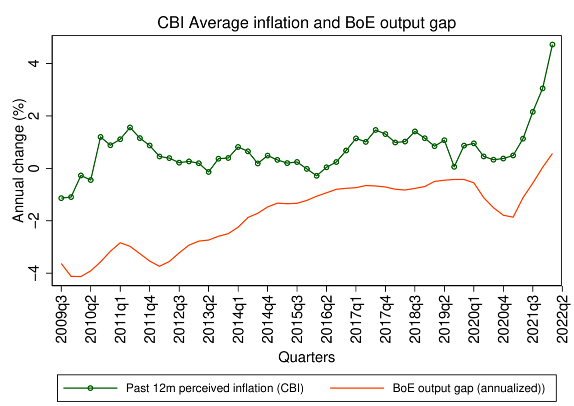


Figure 8



4.4 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

[13]This data was provided by the colleagues at the Bank of England and is publicly available in the BoE monetary policy reports

Figure 9

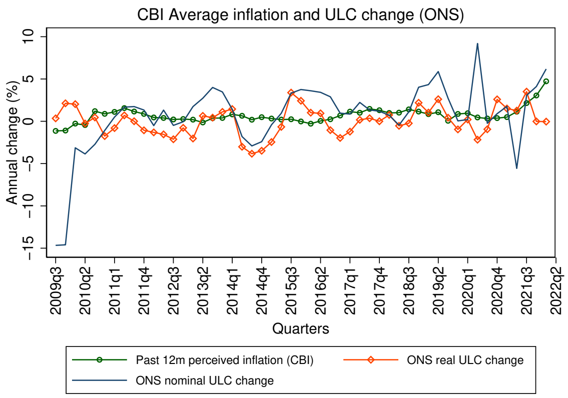
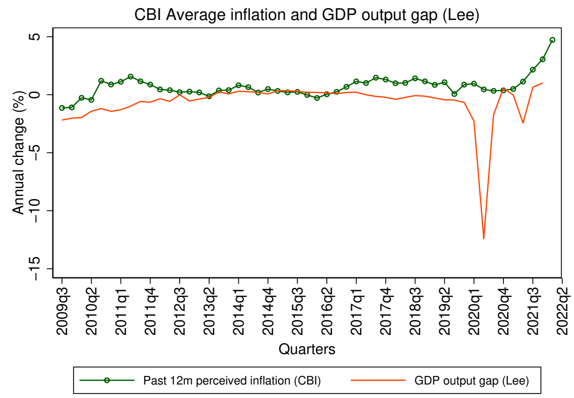


Figure 10



Labour share is also used in the estimations, calculated as suggested by the ONS[14]: real ULC = ULC/GVAdeflator[15].

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[16], 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).

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

To identify the industrial structure, previous studies like Domberger, 1979 utilized the five-firm concentration ratios and estimated the Herfindahl-Hirschman Index (HHI) using employment data. However, I am not aware of any ongoing production of these indices for UK firms. Therefore, I constructed the HHI using turnover data from FAME BvD[17], as described in Brezina et al., 2016 and Naldi and Flamini, 2018.

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

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

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

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

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

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.

4.5 Other relevant aspects about the data

In the estimations of the NKPC 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 NKPC: empirical estimation

The sector-level NKPC is estimated for 49 sectors, and the expectations variable is calculated as the sector-weighted average of firms' reports using the number of employees as weights. One advantage of this approach is that it yields a balanced sample without any outliers from individual firms. Furthermore, the NKPC has been microfounded at the sector level, providing greater theoretical structure to the estimations. However, a disadvantage of using sector-level variables is the loss of firm-level information

5.1 Previous evidence in the UK

The validity of the NKPC in UK data has been confirmed by Batini et al., 2005 using system-based expectations. To the best of my knowledge, the sector-level NKPC has not yet been estimated using survey-based expectations.

Incorporating some of the variables proposed by Batini et al., 2005 into the estimation of the aggregate NKPC reveals that oil price inflation and labour share are significant in some specifications. In Section 6, I also examine whether these variables are more relevant in explaining the price-setting behaviour of certain sectors over others. For instance, it may be expected that manufacturing firms would be more sensitive to changes in oil prices, whereas labour-intensive sectors such as services firms may be more sensitive to labour share and salary costs.

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. In Table 6, I present the results from 2SLS estimations for the aggregate NKPC through models 1 and 2, and compare them with mean group estimations using dynamic panel techniques.

The slack measure, which is the change in salary cost, is only statistically and economically significant when estimated through panel data models. Specifically, in models 4, 6 and 8, the estimated coefficient is positive and statistically significant. However, in the case of the time series analysis using aggregate data (models 1 and 2), the slack measure is not significant.

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

Remarkably, exploiting the sector-level micro data and estimating a dynamic panel for the NKPC appears to yield superior results. To address the potential endogeneity of inflation expectations and the slack variable, I use the Stata command xtdcce2 developed by Ditzen, 2021. This toolkit estimates dynamic panel data models with common correlated effects (CCE) and allows for instrumental variable estimation to deal with potential endogeneity issues.

In models 3-8, I estimate the NKPC using sectoral data, with sectoral inflation as the dependent variable. Models 3 and 4 assume homogeneous slopes for all sectors, while models 5-8 assume heterogeneous slopes and include CCEs. Upon comparing various model specifications, the Root Mean Squared Errors (RMSE)[18] indicate that allowing for heterogeneous coefficients across sectors and partialling out the unobservable common correlated effects (CCE) lead to lower average residual magnitudes. Specifically, models 7 and 8 exhibit lower RMSEs compared to models 3 and 4.

These results suggest that only models 4, 6 and 8 have estimated parameters with the expected sign and size for the three target variables: lagged inflation, expected inflation and the slack measure. Therefore, I choose model 8 as the best specification. Furthermore, these estimates are also consistent with the theory. On average, γ^f is larger than γ^b, suggesting that sectors set prices in a more forward- than backward- looking way. These findings are aligned with other evidence in the UK, although it is not exactly comparable due to the effect of the control variables in my specification. 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).

These results suggest that allowing for heterogeneous coefficients and partialling out the CCEs proxied by the cross-sectional averages leads to better results. See estimations results using other slack measures in Appendix B.

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 estimation for financial services is $\gamma^f : 0.99$, followed by retail and wholesaling $\gamma^f : 0.74$, manufacturing $\gamma^f : 0.67$ and the other services firms $\gamma^f : 0.63$. See details in Figure 11.

Model 8 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.

[18] 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.

Table 3: Estimations

	(1) **TS-2SLS**	(2) **TS-2SLS**	(3) **Pooled FE**	(4) **Pooled FE**	(5) **MG-CCE & no IV**	(6) **MG-CCE & no IV**	(7) **MG-CCE & IV**	(8) **MG-CCE & IV**
	Dependent variable: CBI sectoral inflation							
Inf. Expectations	0.75***	0.81***	0.82***	0.71***	0.62***	0.62***	0.58***	0.70***
	(0.17)	(0.17)	(0.15)	(0.17)	(0.04)	(0.04)	(0.08)	(0.06)
Lagged inflation	0.48***	0.37*	0.34***	0.34***	0.05**	0.09***	0.04	0.09***
	(0.16)	(0.20)	(0.10)	(0.08)	(0.02)	(0.02)	(0.03)	(0.03)
Output gap (BoE)	0.00		0.20		0.09		-0.02	
	(0.06)		(0.15)		(0.13)		(0.15)	
Salary cost		0.15		0.36**		0.20***		0.27***
		(0.13)		(0.15)		(0.05)		(0.10)
Het/Hom coeff	Homog	Homog	Homog	Homog	Heterog	Heterog	Heterog	Heterog
FE / CCE			FE	FE	CCE	CCE	CCE	CCE
IV	Yes	Yes	Yes	Yes	No	No	Yes	Yes
Observations	48	48	2,392	2,392	2,519	2,519	2,390	2,390
RMSE	0.325	0.327	1.958	1.900	1.513	1.579	1.588	1.530
N. of groups			49	49	49	49	49	49
CD test					0.257	0.214	0.205	0.938

Note: S.E. in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. Variables in Cols 1-2 are calculated using averages across all sectors. Columns 3-8 have sector-level variables. For 3-8: Expectations are calculated as weighted averages among all firms for each sector. For 1-8: The endogenous variables (slack and expectations) are instrumented out with: lags (1, 2, 3) of expectations, lags (2, 3) of the dependent variable and lags (1, 2) of the slack. CCEs are proxied with oil inflation, average inflation (and its lag), average expectations (and its lag), real import prices (and its lag) and average wage. The CCEs 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 2009q1-2022q2.

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.

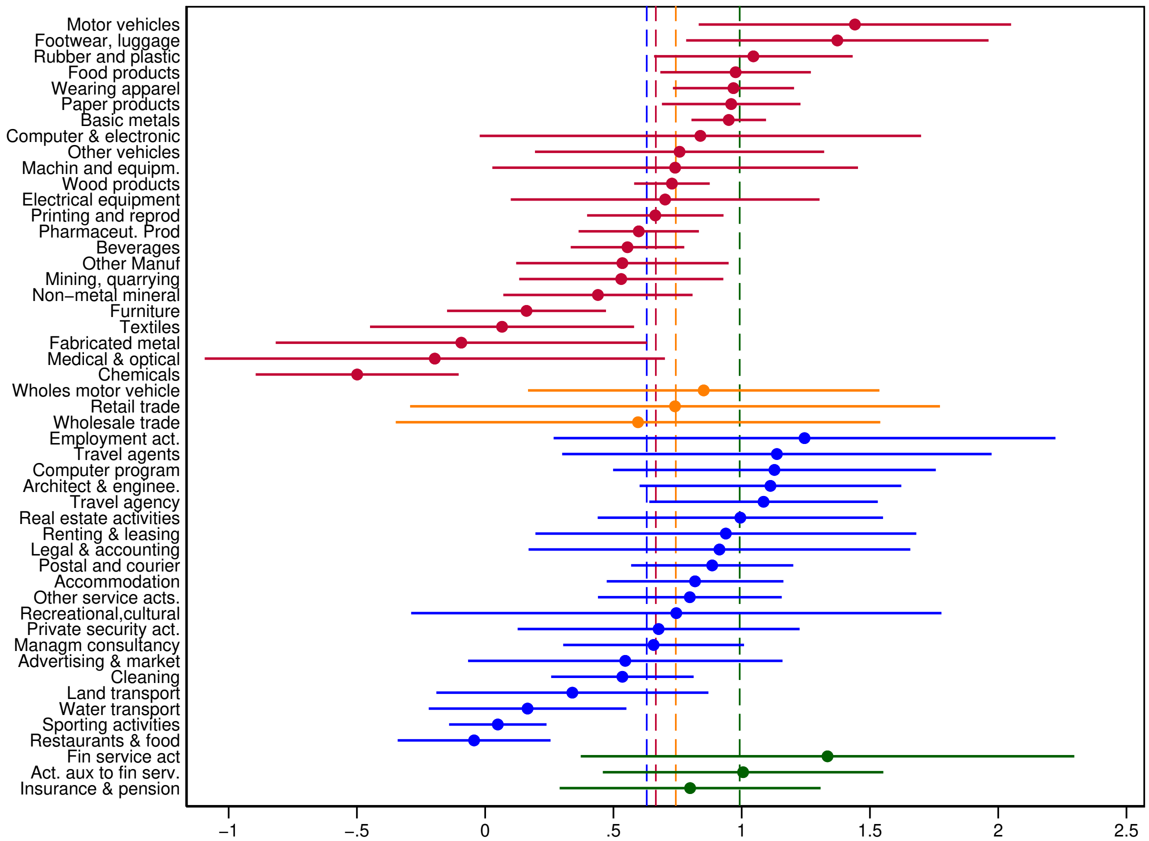
6.1 Estimated parameters weighted by their standard error

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 of the estimates, I use a similar approach to the so called weighted least squares (WLS)[19]. Given that the standard errors are obtained from the OLS estimation of the NKPC (see section 5), these are used to adjust the imprecise parameters. The weights are obtained by first calculating the inverse of the standard errors, and then, these weights are rescaled to sum up to one.

$$w_k = 1/s.e_k$$

[19]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.

Figure 11: Role of expectations by sector



Note: Estimations of individual expectations coefficients from model 8 (Table 6, through dynamic panels with CCE and IV). These coefficients are net from the effect of the 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 Distributive, Blue for services and Green for Financial Services.

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

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

The weighted regression is expressed as follows

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

By adjusting the dependent variable and regressors by the precision of the estimates I am 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.

Table 4: Correlation table

	Gamma_f	HHI	Concentr. Ratio	Petrol over costs	Energy over costs	Imports over costs	Imports over supply	Labour share	ULC vari-ability
Gamma_f	1.00								
HHI	**0.60**	1.00							
Concentr. Ratio	**0.68**	**0.95**	1.00						
Petrol/costs	0.40	**0.52**	**0.57**	1.00					
Energy/costs	0.45	0.42	**0.56**	0.44	1.00				
Imports/costs	**0.54**	**0.64**	**0.58**	0.35	0.25	1.00			
Imports/supply	**0.61**	**0.62**	**0.67**	**0.55**	**0.53**	**0.69**	1.00		
Labour share	**0.55**	**0.60**	**0.74**	**0.54**	**0.64**	0.33	**0.52**	1.00	
ULC variability	-0.02	0.14	0.17	0.16	0.33	-0.12	-0.13	**0.52**	1.00

Note: The table shows correlations between the variables used in the regressions. Correlations of at least 0.5 are highlighted in bold. Data used for correlations corresponds to 2021q4.

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 and 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.

In column 3 I drop variables that show high correlation with other explanatory variables and are/or are not significant. This specification yields positive and statistically significant effect of HHI and the share of imports on the degree of forward lookingness.

For robustness, in columns 4-6 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 1-3.

These results are in favour of the hypothesis that firms facing less competition (higher degree of concentration) will update prices less frequently (higher stickiness). One way to explain this could be by considering the low demand elasticity of highly-concentrated sectors. When a firm faces only a few competitors, the demand elasticity is low. However, in a highly competitive sector, setting a price slightly below others can result in reduced sales or even no sales. Thus, firms in sectors with a low degree of concentration (high competition) tend to simply follow their competitors' prices, attaching little importance to their own expectations.

In sectors characterised by both high degrees of concentration and price stickiness, firms often opt 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.

The positive correlation between the role of expectations and the share of imports could be attributed to the exposure to foreign currency. Sectors that heavily rely on imported goods are likely to face increased volatility due to exchange rate fluctuations. Consequently, these sectors may need to rely more on their own forecasts when making pricing decisions.

Table 5: Regressions estimations

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: sector-level forward-lookingness					
	Market concentration					
HHI	0.023***	0.015**	0.014**			
	(0.005)	(0.006)	(0.006)			
5-firm CR				0.869***	0.690***	0.597***
				(0.155)	(0.214)	(0.170)
	Controls					
Imports/supply		0.605	0.902**		0.495	0.707**
		(0.467)	(0.400)		(0.372)	(0.339)
Energy/costs		0.055			0.029	
		(0.048)			(0.050)	
Petrol/costs		-0.002			-0.008	
		(0.025)			(0.026)	
ULC variability		-0.006			-0.006	
		(0.010)			(0.010)	
Constant	0.009***	0.008***	0.007***	0.006***	0.006***	0.005***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Observations	49	47	48	49	47	48
R-squared	0.351	0.474	0.448	0.438	0.511	0.489

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 49 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.

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

The sector-level New Keynesian 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

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

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.

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

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

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, labour 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 firms optimising 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 $Y_{k,t,t+j}(i)$ is real output produced in $t+k$ by firms that changed their prices at t and $\Psi(Y_{k,t,t+j}(i))$ are the total nominal costs of supplying good k.

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 (A.4) and working on the algebra, I get the following expression:

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

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

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. We assume that in equilibrium each supplier in the same sector always chooses the same price. Also, in steady state $P_{k,t,t+j}(i) = P_{k,t}(i), P_{k,t,t+j}(i) = P^*_{k,t}(i)$, $P_k(i) = P^*_{k,t}(i)$, $P_{t+j} = P_t$, $Y_{k,t,t+j}(i) = Y_{k,t}(i)$, $S_{k,t,t+j}(i) = S_k = \eta/(\eta-1)$

A first order Taylor expansion around the steady states gives

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

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

Next, I will present the derivation of the equation that determines price setting at the sector level. According to Imbs et al., 2011, they propose that when there are no specific shocks affecting individual firms, all firms capable of adjusting their prices at time t will choose the same optimal price. This assumption guarantees a symmetric equilibrium across firms within each sector. Consequently, for simplicity, firms' indices i will be omitted from the succeeding steps.

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:

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

Also, 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 Gali and Gertler, 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:

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

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

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:

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

8.2 Appendix B: Other regression estimations

Table 6: Estimations

	(1) MG-CCE and IV	(2) MG-CCE and IV	(3) MG-CCE and IV	(4) MG-CCE and IV	(5) MG-CCE and IV	(6) MG-CCE and IV
	Dependent variable: CBI sectoral inflation					
Inflation Expectations	0.71***	0.62***	0.71***	0.77***	0.70***	0.70***
	(0.07)	(0.09)	(0.07)	(0.08)	(0.07)	(0.06)
Lagged inflation	0.06**	0.06*	0.07**	0.06**	0.07**	0.09***
	(0.02)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)
GDP gap (Lee)	-0.07					
	(0.07)					
IOPP gap (Lee)		0.00				
		(0.04)				
Output gap (Melolinna)			0.02			
			(0.14)			
ULC change (by SIC)				0.06**		
				(0.03)		
Real ULC change (by SIC)					0.03	
					(0.06)	
Change in salary cost						0.27***
						(0.10)
Heterog/Homog coeff	Heterog	Heterog	Heterog	Heterog	Heterog	Heterog
FE / CCE	CCE	CCE	CCE	CCE	CCE	CCE
IV	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,299	1,903	2,390	2,390	2,390	2,390
Number of groups	49	49	49	49	49	49
RMSE	1.472	1.296	1.698	1.683	1.591	1.530
CD test	0.648	0.252	0.538	0.097	0.532	0.938

Note: S.E. in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. Columns 1-6 have sector-level variables. Expectations are calculated as weighted averages among all firms for each sector. The endogenous variables (slack and expectations) are instrumented out with: lags (1, 2, 3) of expectations, lags (2, 3) of the dep.var. and lags (1, 2) of the slack. CCEs are proxied with oil inflation, ave. inflation (and its lag), ave. expec. (and its lag), import prices (and its lag) and ave. wage. The CCEs are partialled out. RMSE is the square root of the average of squared errors and is defined in terms of the dep. var. CD test: null hypothesis of weak CSD. Data 2009q1-2022q2

8.3 Appendix C: Price mapping

Table 7: 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	

Figure 12

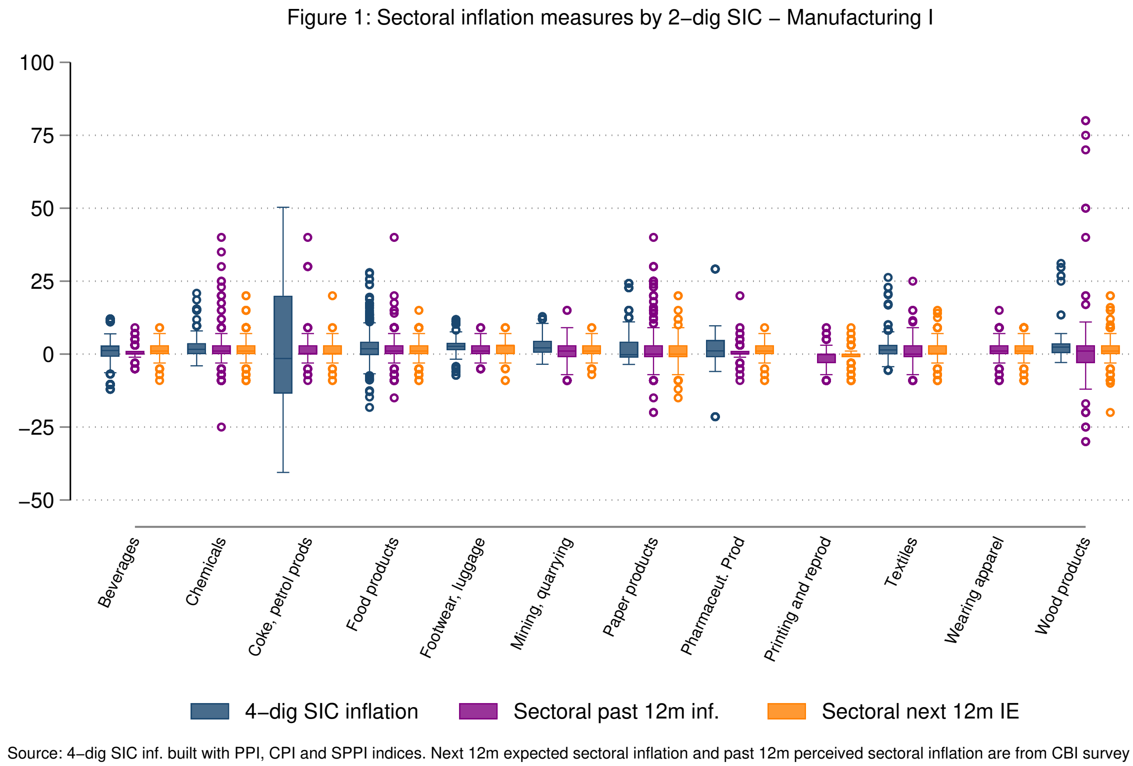


Figure 13

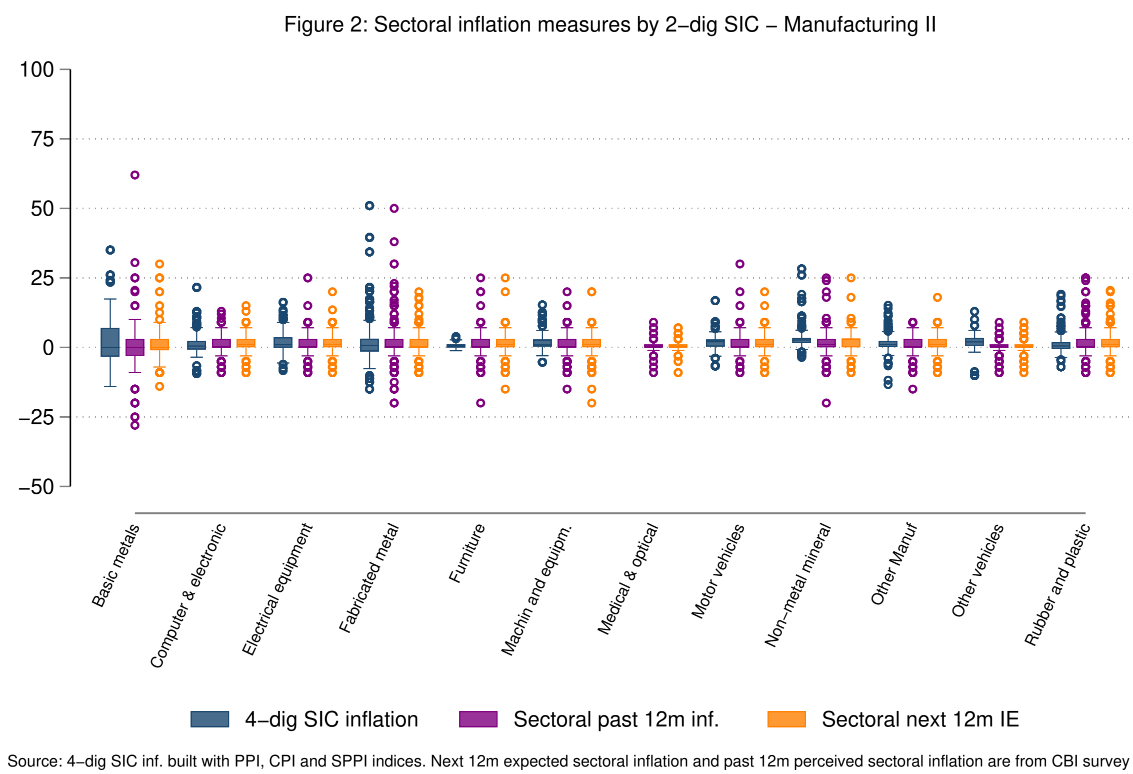


Figure 14

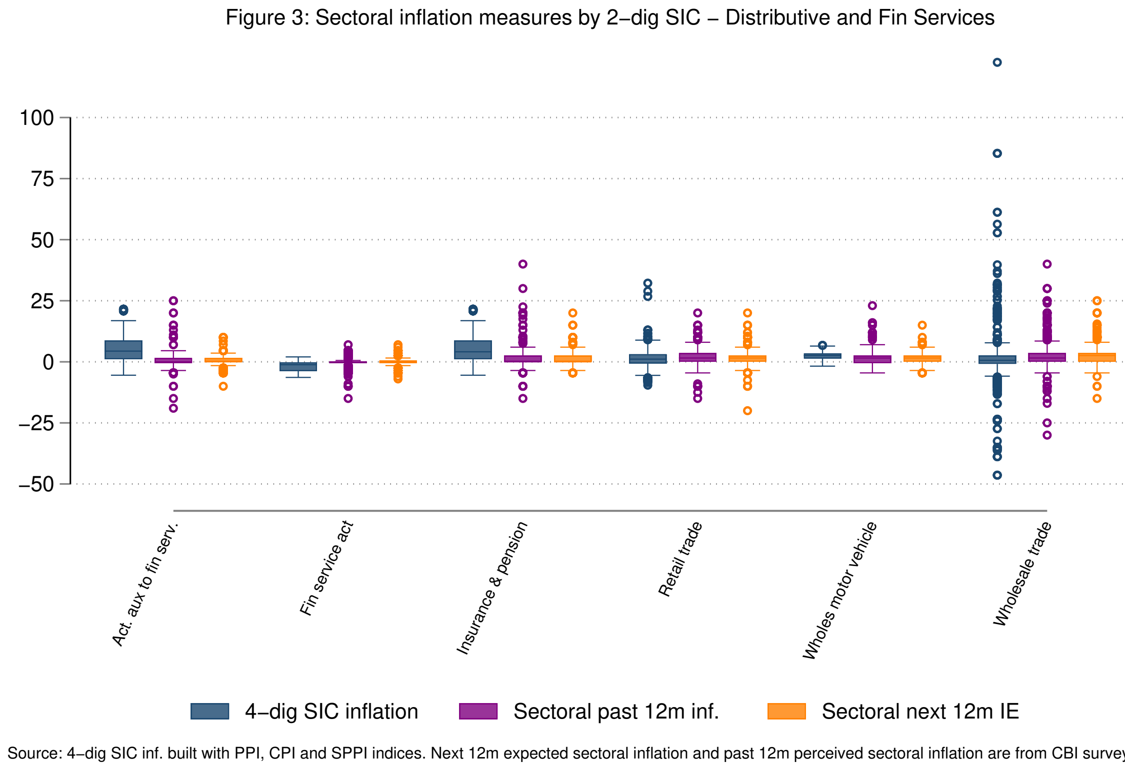


Figure 15

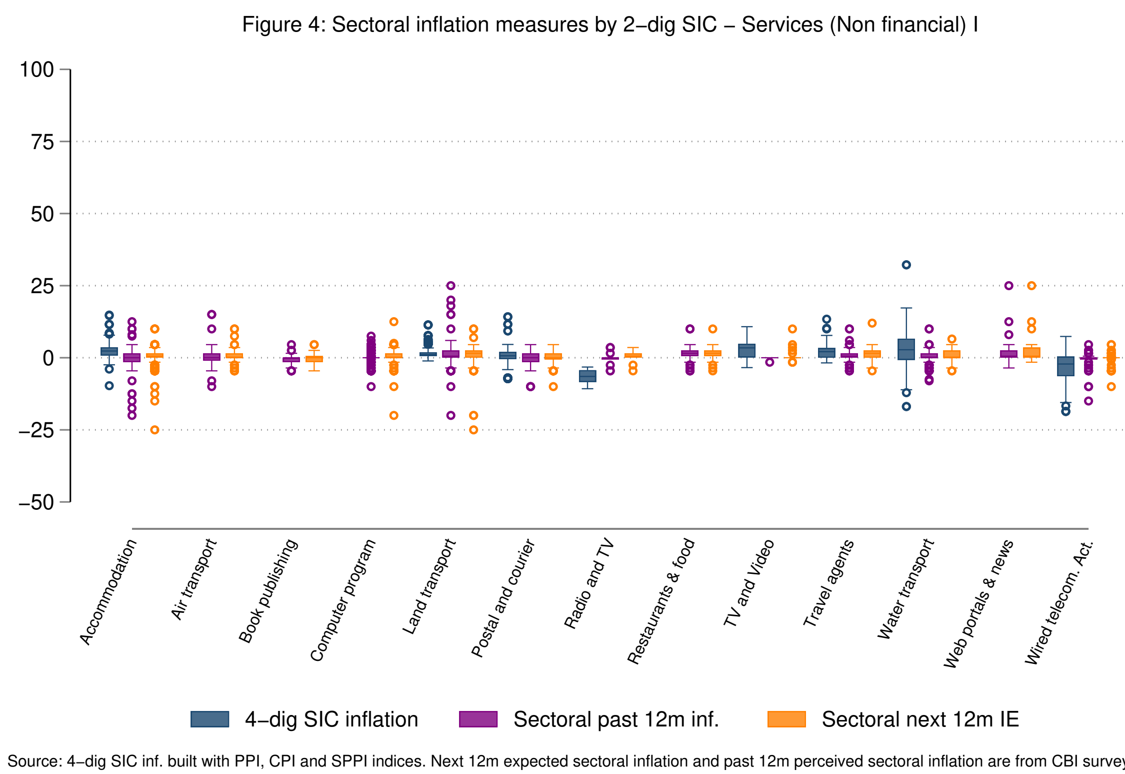


Figure 16

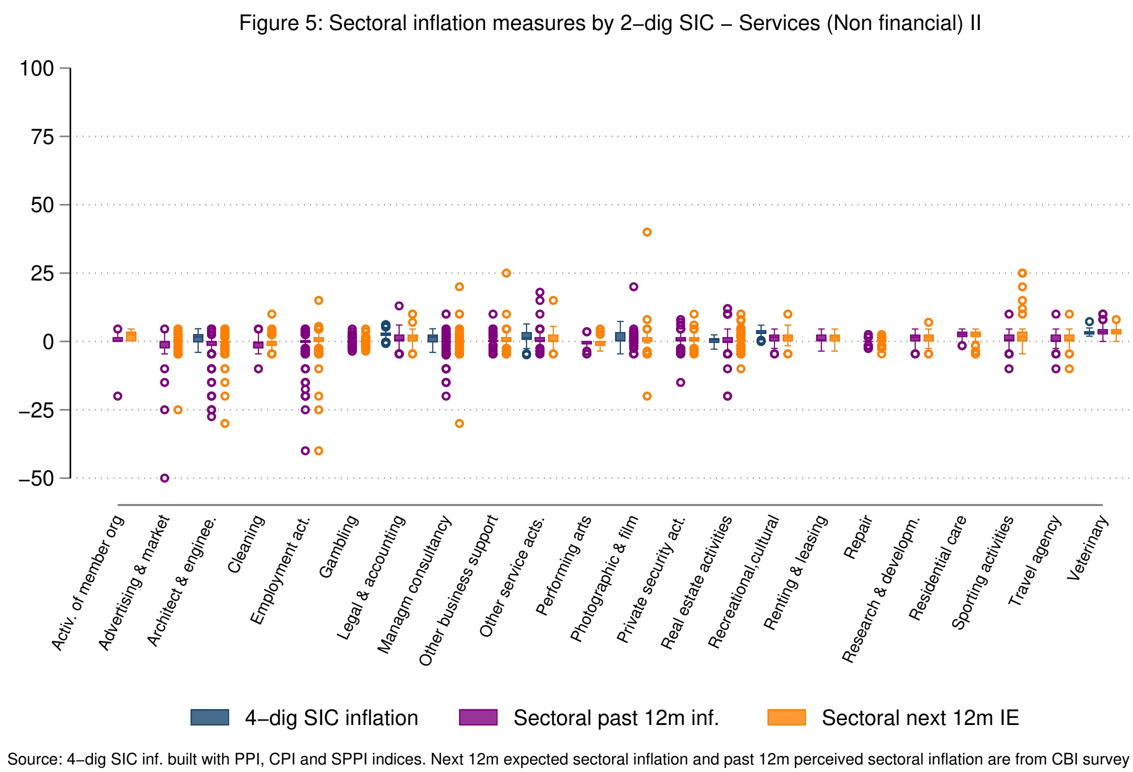


Figure 5: Sectoral inflation measures by 2−dig SIC − Services (Non financial) II
100
75
50
25
0
−25
−50
Activ. of member org
Advertising & market
Architect & enginee.
Cleaning
Employment act.
Gambling
Legal & accounting
Managm consultancy
Other business support
Other service acts.
Performing arts
Photographic & film
Private security act.
Real estate activities
Recreational,cultural
Renting & leasing
Repair
Research & developm.
Residential care
Sporting activities
Travel agency
Veterinary
4−dig SIC inflation
Sectoral past 12m inf.
Sectoral next 12m IE
Source: 4−dig SIC inf. built with PPI, CPI and SPPI indices. Next 12m expected sectoral inflation and past 12m perceived sectoral inflation are from CBI survey

8.4 Appendix D: Outliers detection scheme

Table 8 summarises the number of outliers removed from the sample based on the inflation expectations questions: changes in general prices in the past 12 months and expected changes in general prices in the next 12 months. The outliers are defined using two schemes: (1) values greater than percentile 75 + 8*IQR[20], or (2) values lower than percentile 25 - 8*IQR. The IQR is calculated in two ways i) across firms within the same 2-digit SIC or ii) over time within each firm.

Table 8: Summary of outliers

2-dig SIC	CBI Past 12m sectoral inflation	CBI Next 12m expected sectoral inflation	N. of outliers	2-dig SIC	CBI Past 12m sectoral inflation	CBI Next 12m expected sectoral inflation	N. of outliers
64	1,885	1,874	71	**15**	268	267	2
25	2,717	2,708	38	**45**	420	417	2
46	2,167	2,095	29	**77**	154	151	2
28	2,618	2,600	25	**63**	71	63	1
26	1,136	1,132	22	**75**	149	148	1
22	1,532	1,526	18	**93**	241	236	1
66	890	888	18	**21**	232	230	1
27	1,243	1,235	12	**73**	296	291	1
47	2,447	2,409	12	**91**	206	195	1
20	752	744	11	**18**	363	363	-
24	798	794	11	**11**	278	275	-
32	578	573	9	**8**	203	199	-
55	468	462	7	**19**	86	86	-
30	353	351	6	**61**	53	52	-
65	762	757	6	**33**	113	111	-
68	369	366	5	**95**	42	43	-
78	321	310	5	**81**	161	159	-
10	865	861	4	**96**	131	121	-
17	694	688	4	**51**	92	92	-
53	304	301	4	**87**	79	81	-
82	153	150	4	**50**	161	159	-
14	338	334	3	**80**	186	179	-
49	642	629	3	**74**	115	113	-
69	771	757	3	**56**	214	214	-
71	354	345	3	**92**	94	93	-
13	624	618	3	**58**	94	93	-
16	468	464	3	**72**	67	62	-
23	917	913	2	**52**	182	179	-
31	420	420	2	**90**	24	17	-
62	283	289	2	**60**	13	13	-
70	346	336	2	**59**	31	32	-
79	140	137	2	**94**	19	13	-
29	643	640	2				
Full sample (including outliers):			33,836				
Total number of outliers:			363				

[20] Interquartile range

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