Monetary policy in a low inflation regime: evidence from the Euro Area

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Dissertation written under the supervision of Professor Joana Silva

Dissertation submitted in partial fulfilment of requirements for the MSc in Economics – Major in Macroeconomic Policy, at Universidade Católica Portuguesa and for the MSc in Economics and Finance at Università degli Studi di Napoli Federico II

April 2023

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Abstract

This thesis examines the transmission of monetary policy in a low inflation environment, discussing the policy implications of sluggish and persistent inflation in a European Union framework and addressing possible causes behind cross-sectional heterogeneities at the sector-specific level. Exploring a disaggregated panel dataset of monthly HICPs for Germany, this thesis shows that the principal component of sectoral prices, a proxy for "pure-inflation", successfully tracks the transmission of macroeconomic shocks in the economy. The proportion of sectors affected though is limited as the law of motion of inflation in a low regime is denoted by a self-stabilising pattern, which limits monetary authorities' margins of action. However, when positive and negative shocks are treated asymmetrically, the difference in impact is striking: the proportion of sectors affected by pure positive (contractionary) shocks are more than three times the proportion affected by negative (expansionary) shocks, stressing the key role of the existing inflation environment. Overall, the broad sectoral categories that respond meaningfully to monetary intervention are those endowed with cyclical properties and, by definition, more sensitive to policy-induced fluctuations of aggregate demand.

Keywords: Monetary policy, Inflation persistence, Cyclically sensitive sectors, Low-inflation regime, High-inflation regime, Synchronous price movement, Pure inflation, Sectoral prices.

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Abril 2023

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Resumo

Esta tese examina a transmissão da política monetária num ambiente de baixa inflação, discutindo as implicações políticas da inflação lenta e persistente num quadro da União Europeia e abordando possíveis causas por detrás de heterogenidades transversais a nível sectorial específico. Explorando um conjunto de dados de painel desagregado de IHPC mensais para a Alemanha, esta tese mostra que a principal componente dos preços sectoriais, um proxy para a ”inflação pura”, acompanha com sucesso a transmissão de choques macroeconómicos na economia. A proporção de sectores afectados, embora limitada, uma vez que a lei do movimento da inflação num regime baixo é denotada por um padrão auto-estabilizador, que limita as margens de acção das autoridades monetárias. Contudo, quando os choques positivos e negativos são tratados assimetricamente, a diferença no impacto é impressionante: a proporção de sectores afectados por choques puramente positivos (contraccionistas) é mais do triplo da proporção afectada por choques negativos (expansionistas), salientando o papel fundamental do ambiente de inflação existente. Globalmente, as grandes categorias sectoriais que respondem de forma significativa à intervenção monetária são as dotadas de propriedades cíclicas e, por definição, mais sensíveis às flutuações da procura agregada induzidas pelas políticas.

Palavras-chave: Política monetária, Persistência da inflação, Sectores ciclicamente sensíveis, Regime de inflação baixa, Regime de inflação alta, Movimento sincrónico dos preços, Inflação pura, Preços sectoriais.

Acknowledgments

I thank sincerely Professor Joana Silva for her guidance over the last year, and for her instructive feedback.

I am indebted to Martim Leitão for his genuine help and to the PROSPER team, Católica Lisbon Center of Economics for Prosperity, for giving me the tools to build my coding skills.

I kindly thank all my colleagues and friends at the Bank for International Settlements, for their understanding, support and small teachings they enriched my experience with everyday.

A special thank goes to Egon Zakrajšek, for the time he dedicated to this project and for his unreserved support. Working under his supervision has been a privilege, as he made every step of this process a precious learning experience, and as I could find in him a role model and a mentor.

Finally, I thank my parents and my brother, for their unconditional love and wholehearted support.

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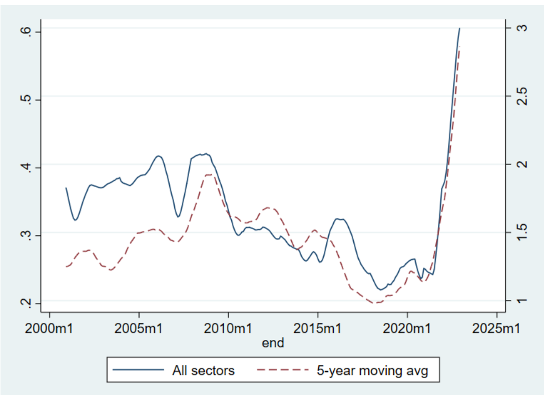
1 Introduction

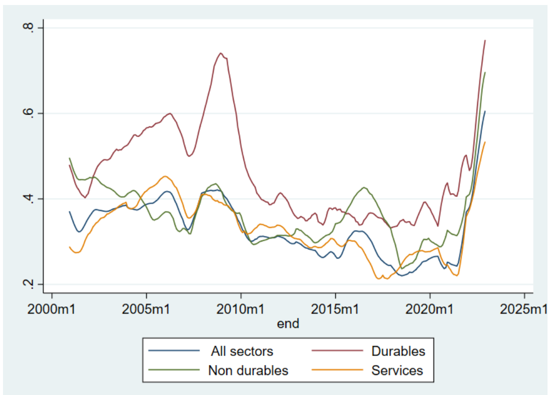
After two decades of low inflation, with central banks struggling to promote expansion and lead inflation back to target, it is puzzling how, in the aftermath of the Covid-19 crisis, the scenario has muted dramatically. Inflation has picked promoting a spiral of worldwide tightening from major central banks. Investigating the components of inflation at the most disaggregated level, sector by sector, could help tracing the dynamics which determine the transition from one framework to the other and, more importantly, can shed light on the most compelling implications for monetary policy authorities.

Following Borio et al. (2021) and Borio (2021), in this thesis I start exploring these dynamics in a European framework by considering the behaviour of 101 price indexes of sectors in the HICP basket in Germany from January 1999 to December 2019. From this level of disaggregation of the 12-month log-price changes, I retrieve an indicator of the co-movement of sectoral prices and trace the time-varying variance explained by the first principal component on a rolling window of 5 years. As can be observed in the left-hand panel of Figure 1a, the explanatory power of the principal component is remarkably low, around 30% as much as the level of headline inflation, especially in the years following the Great Financial Crisis. Accordingly, the latest estimates covering the Covid and post-Covid years, are characterized by a significant spike in the proportion of time-varying variance explained by the principal component, hitting twice the magnitude as in the previous stage.

Figure 1: Time-varying fraction of total price change variation due to the common component



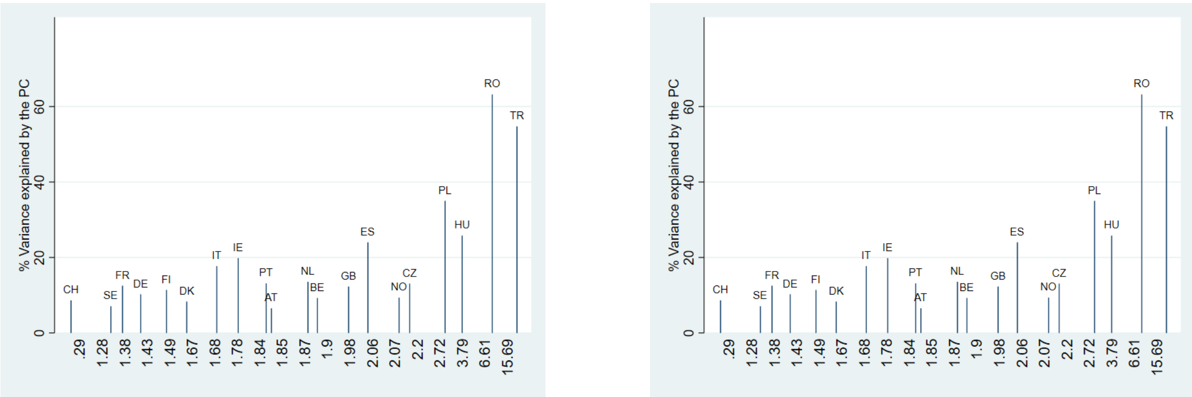
(a) All sectors and trend inflation



(b) Partition in durables, non-durables and services

This is evidence that the patterns of headline inflation and the role played by the principal component in overall volatility of prices are closely interrelated. When looking to broad sectoral inflation rates, such as durables, non-durables and services, the same observations stands, meaning that the phenomenon we are documenting is somewhat pervasive. A similar conclusion emerges additionally when looking at a cross-section of Euro Area countries. In Figure 1b, I plot the fraction of sectoral prices variance explained by the first principal component against average trend inflation from January 1999 to December 2019 for a basket of Euro Area countries.

Figure 2: Total price change variance due to the common component in the cross section of EA countries



(a) 3-month inflation

(b) 12-month inflation

Notes: The x-axis represents average inflation over the sample period (Jan 1999 – Dec 2019), the y-axis the % of sectoral prices variance due to the first principal component

The higher trend inflation, meaning the closer a country is to a high-inflation regime, proportionally the higher is the variance explained by the common component. The need for distinguishing across two regimes[1], denoted by low and high inflation levels respectively, hinges on different behaviors of inflation in these two opposite frameworks.

In a low-inflation regime the harmonized index of consumer prices, conventional measure of inflation at an aggregate level, mostly embeds sector-specific price changes that, by definition, are very scarcely correlated to each other. It comes as no surprise that, in this regime, the role of the component common to the different sectors is very limited and marginal. Therefore, the wage-price spiral dynamics at the core of textbook inflationary processes are weak and not significantly connected. The resulting frameworks is characterized by stagnating and persistent low inflation, precisely what most central banks have been struggling with for many years after the Great Financial Crisis.

[1]For an extensive discussion on the topic see Borio et al. (2023)

When transitioning to a high-inflation regime, the scenario is completely reversed: the role of the common component is staggering and dominating, becoming more representative of price changes across its different sectoral declinations. Inflation in more volatile and steered by critical prices, as energy and food, and the passthrough of exchange rates fluctuations to prices is more pronounced. Since the link between prices and wages is stronger, inflation becomes now self-reinforcing.

Can a two-regime view of inflation explain the effectiveness of monetary policy? Recent publications shadowing Borio (2022)[2] have shown that in a low and stable inflation regime, the first principal component of sectoral price changes – a concept closely related to a synchronous increase across all sectoral prices (i.e., “pure” inflation) – responds significantly to unanticipated changes in the stance of monetary policy. The common component of sectoral price changes however accounts for a relatively small fraction of the variability of aggregate inflation. In combination, these findings suggest that the ability of monetary policy to affect inflation in such an environment may be quite limited. That is, monetary policy affects as small subset of sectoral prices and thus unusually large and persistent adjustments in the stance of policy may be required to bring inflation back to narrowly defined targets. It also raises a question of what are the sectors in which prices respond to monetary policy?

Evidence based largely on disaggregated US price data indicates that in a low and stable inflation regime, measured headline inflation is to a large extent an average of the “noisy” component of sectoral price changes. Given that monetary policy affects inflation through its influence on aggregate demand, it stands to reason that these idiosyncratic sectoral price fluctuations do not respond to changes in the stance of monetary policy. This conjecture is in line with the contribution of Boivin et al. (2009), who examine the impact of monetary policy shocks by means of a factor-augmented auto-regression (FAVAR) model. The results of their study highlight that roughly only 15 percent of sectoral prices fluctuations is explained by macroeconomic shocks, whereas the remaining 85 percent is due to sector specific shocks. Though disaggregated sectoral prices are much more volatile than assumed in macroeconomic model, the limited reaction to macroeconomic variables explains their sluggish response detected at an aggregate level.

The aim of this thesis is to analyse the effectiveness of monetary policy in the Euro Area, a jurisdiction characterized by common monetary policy and persistent differences in the structure

[2]See e.g. Borio et al. (2022); Borio et al. (2023); Borio et al. (2023)

of product and labour markets, as well as availability of harmonised disaggregated price data. Essential to my analysis is the ability to identify unanticipated changes in the stance of monetary policy in the euro area. To that purpose, I rely on "shocks," that is, unanticipated changes in the stance of monetary policy, inferred from high-frequency financial asset prices. As a vast literature shows, these monetary policy surprises are exogenous by construction because they correspond to changes in the prices of relevant interest rate derivatives in narrow windows bracketing policy announcement.Moreover, they capture a well-identified "shock" to the entire near-term path of policy rates and thus capture unanticipated changes in forward guidance, a powerful channel through which monetary policy seeks to stabilise the macroeconomy.

An important distinction needs to be made between pure monetary policy shocks and central bank information shocks, in the sense of Jarociński and Karadi (2020). Since the announcements of the policy authority conveys the central bank's assessment of the economic outlook, it is crucial for the monetary policy shocks to be purged from this component to avoid otherwise biased estimates of monetary non-neutrality. To this respect, I pick the updated pure monetary policy shocks series computed by Jarociński (2022) and ensure that the information component is cleared out. Armed with these well-identified shocks, we can utilize the standard local projections methodology to trace out the impact of these shocks on aggregate or sectoral prices.

As shown in the influential work of Montiel Olea and Plagborg-Møller (2021) and Plagborg-Møller and Wolf (2021), impulse response functions derived from a structural VAR and those derived from local projections coincide, when the same set of identifying restrictions is used to identify the structural shocks. Not only local projections estimate the same coefficient as VARs in population, lag-augmented local projections are also endowed with more robustness to persistence in the data and longer horizons, two features extremely common in macroeconomic outcomes. This makes local projections a powerful and flexible method to trace out the causal impact of monetary policy on inflation outcomes.

For Germany, I compile a balanced panel of prices at a sector level. I begin the analysis by ascertaining the number of common factors in sector-level price changes using the methodology of Bai and Ng (2002). The outcome of the procedure is indeed that only one underlying factor explains common variability across sectoral prices. Hence, I proceed with a principal component analysis on the sector level data to extract the first factor. Observing the eigenvalues associated to the firs factor I can estimate the proportion of variation explained by the common component of price changes separately for sector-specific, idiosyncratic ones. I can then rescale the first principal component – the proxy for "pure" inflation – to observed inflation and can estimate how monetary policy affects its dynamics.

My hypothesis is that, though the portion of the overall inflation variance attributable to the first principal component may be minimal, it is still responsive to changes in the stance of monetary policy, a dynamic consistent with the US evidence. This can help explain why when one looks at disaggregated sectoral prices data and run local projections on actual sectoral prices, there is very limited traction of monetary policy across sectors. Eventually, those sectors that respond are cyclically sensitive, namely they are sectors sensitive to policy-induced fluctuations in aggregate demand, in sense intended by Stock and Watson (2020).

The remainder of the thesis is organised as follows. Section 2 covers the related literature, indulging on the main contributions on inflation persistence and the use of high-frequency financial data to achieve identification of monetary policy shocks. Section 3 describes the sectoral prices dataset examined in the present analysis. In Section 4, I delve deeper into the methodology adopted whereas in Section 5 I present the empirical background. I discuss the key results in Section 6. Section 7 concludes.

2 Literature Review

This thesis contributes to the strands of literature studying the policy implications of inflation persistence by providing a Euro-Area based empirical counterpart to results which are mostly grounded in a US framework. The most established methodology for the estimation of the synchronous price movement relies on dynamic factor models. This thesis complements this literature showing that proxies of the unobserved common component of inflation, combined with a sensible use of local projections, can be used as valid alternative tools to detect the works of "pure inflation" in sector-specific price dynamics.

Bryan and Cecchetti (1993), the first in the literature to use dynamic factor models to distinguish between absolute and relative prices, point to two major issues behind the use of the Consumer Price Index (CPI) as main measure of core inflation. The first accrues to the presence of noise deriving from non-monetary, sector specific, events. Secondly, the CPI measure of inflation is prone to two different sources of bias: the weighting bias and the measurement bias. The weighting bias relates to the covariation of the relative price change and the set of accurately defined sector-specific weights: when a sectoral price increases, consumer theory demands that both the weight of the specific sector and the weighted composition of the remaining goods in the basket balance up to the point that the expenditure level is unchanged. Weighting the new quantities by the original weights introduces a positive margin which biases the measure of inflation. The existence of a bias makes the CPI index, as any fixed-weight price index, an imperfect long-run target for policy.

Analysing a disaggregated sectoral prices panel made of 36 series, Bryan and Cecchetti (1993) estimate a unique dynamic factor describing inflation through a maximum likelihood estimation procedure. This new component is thus immune to any form of weighting bias. By computing the difference between the trend in the dynamic factor index and measured CPI inflation, the authors gauge a weighting bias in the amount of roughly 0.6 percentage points per year. This preliminary result in the literature though comes at the cost of a strong identification assumption: namely that relative prices are all independent across goods.

Conversely, Altissimo et al. (2009) estimate a dynamic factor model to investigate inflation persistence in the Euro-Area: however, what is inflation persistence and why is it relevant? A nice analogy advanced by Fuhrer (2010) compares the concept behind inflation persistence to the concept of inertia in physics. As he phrases it, "Inertia may be defined as the resistance of a body to changing its velocity (direction and rate of speed) unless acted upon by an external force." What economists usually mean by any economic variable being persistent is that said variable shows a sluggish tendency to move if not triggered by a proper economic force on the outside. Inflation is persistent whenever it remains somewhat constant and self-stabilising unless promoted by policy intervention.

Altissimo et al. (2009) find that there is only a unique dynamic first principal component explaining most of the common variability in sectoral prices data. This component is the main cause of persistence in aggregate inflation measures. Sectoral prices, if taken individually, display high volatility and most of their variation is promoted by sector specific shocks, rather than macroeconomic shocks. The low persistence of inflation at the sectoral level is in stark opposition to the smoothness and persistence observed in the aggregate. To justify the empirically observable differences between micro and macro inflation dynamics, they investigate three different aggregation procedures: exact, asymptotic and naïve.

The persistence obtained in each of these aggregation exercises mimics precisely the persistence observed in the aggregate CPI measure. The high persistence mostly feeds through the common component in disaggregated inflation, particularly pronounced in some sub-indexes belonging to the service sector (such as housing in Germany). The persistence that shows in aggregate inflation measures is thus heritage of the persistence from the common macroeconomic components of the individual series, with a more pronounced impact accruing to those sectors that exhibit a somewhat higher level of persistence.

Boivin et al. (2009) deliver similar conclusions, relying on the empirical framework of Factor-Augmented Vector Autoregression models outlined by Bernanke et al. (2005). The estimation of unobserved macroeconomic factors driving the data is the more accurate the more comprehensive is the set of macroeconomic indicators and disaggregate data used. This framework, as it is conceived, is particularly adequate when the presumed data-generating process acknowledges a common component on one side and a series-specific component on the other, and this happens to be the case. It also achieves better identification of policy shocks than standard VARs because it exploits the same set of information which drives the decision process of both monetary policy authorities and financial market participants in the first place.

The authors compile an extended panel of 653 monthly series, accounting for both disaggregated sectoral price series and broad macroeconomic indicators. Such indicators involve measures of industrial production, interest rates, employment and financial distress in order to maximise the information set available for the analysis. They then estimate a small number of principal components and, relating those to observed individual price series, can decompose inflation rates into three specific kinds of fluctuations: idiosyncratic, sector-specific and macroeconomic fluctuations. The baseline results point to the evidence that only 15% of monthly individual sectoral price fluctuations are promoted by macroeconomic shocks: 85% of the variation is indeed sourced by sector specific shocks.

To enforce the idea that it is the common component which channels through more persistence in aggregate measures, they find that sectoral prices respond very differently following a sector-specific shock or a macroeconomic shock. Whereas idiosyncratic fluctuations induce no persistence, since price changes are very short-lived, aggregate macroeconomic shocks affecting the common component inherent individual sectoral prices sort a persistent and sluggish effect. Since the role of the common component in explaining the variation of each sectoral price individually is uneven across sectors, it stands to reason that the propagation of a common shock such as monetary policy shocks is heterogenous. The high persistence observed in the service sector is due to role exerted by the principal component in determining its fluctuations, which is dominating in this case vis-à-vis the idiosyncratic component. This evidence, combined with the noticeable weight associated to service sectors in the aggregate price index, can explain in good amount the high level of persistence observed in aggregate data.

A contribution complementary to this pioneering study is the research of Reis and Watson (2010). The empirical framework relies analogously on dynamic factor models to identify the different components of inflation. In contrast to Boivin et al. (2009) however, these authors rely exclusively on disaggregated price data to generate the underlying information set of the analysis, since they are not after the computation of impulse responses and the link of real variables on inflation conditional on well-identified monetary shocks. What they are after is the computation of unconditional estimates between the two. Looking at quarterly changes in consumption goods' prices in the United States since 1959, they identify three components of inflation and advance a simple model to evaluate the correlations of each component relative to other macroeconomic variables.

Adopting the PCE deflator as observed measure of aggregate inflation, they find that roughly 15 percent of the variability in observed inflation accrues to fluctuations "pure inflation", whereas almost 76 percent is due to the relative price index component, with the remaining part explained by the idiosyncratic factor. So overall, roughly 90 % of the variability in observed inflation accrues to aggregate shocks. The main finding here is that, failing to control for relative price inflation can lead to flawed conclusions in the evaluations of theoretical models built to explain inflation.

Deeper in their analysis, it emerges that even the most conventional measures of relative price inflation, such as the relative inflation of nondurables, food and energy, are not well suited to capture most of the relative inflation component in price data. The most striking result eventually is that the quantitative significance of the relation implied by the Phillips curve comes less when accounting for the two relative price factors. It means that changes in relative goods' prices account for the correlation observed between real quantity variables and nominal inflation: this leads to the conclusion that the distinction between absolute and relative prices is a matter of crucial importance in economics.

In this thesis, following Borio et al. (2021), I will adopt a more straight-forward approach and assume that sector-specific price changes are simply idiosyncratic movements in sectoral prices and thus, by definition, are uncorrelated with the common component of inflation. Stock and Watson (2002) are the pioneers in the literature as they first attempted to forecast one series exploiting a large number of predictor series. Their contribution formally proves that factor analysis as simple as principal component produces forecasts which are first-order asymptotically efficient.

This methodology provides a succinct solution to the high-dimensionality problem often encountered in macroeconomic forecasting, since it requires only a large number of predictor series to enhance an accurate estimation of the common factor. Then the relationship between the variable that has to be forecasted and the factors can be estimated through a simple linear regression. Indeed, provided that the number of predictors is large enough, these factors can be computed under roughly general assumptions and are consistent with idiosyncratic errors which are both serially and cross-sectionally correlated.

The results of this thesis are also related to the high-frequency financial literature, since the methodology relies on the use of high-frequency financial data to extract exogenous monetary policy shocks. Gürkaynak et al. (2004) are first in the literature using intraday high-frequency data to investigate the effects of monetary policy actions and statements on asset prices on multiple dimensions. Furthermore, they carefully advance the possibility to use derivatives prices to measure the surprise component in monetary policy announcements.

The authors compile a brand-new dataset incorporating changes in asset prices in a thirty-minute window around monetary policy Federal Open Market Committee (FOMC) meeting. By tracing the changes in a narrow time-window around the announcement, changes are exclusively determined by the monetary authority announcement since relevant news are unlikely to have occurred in such a short window of time. In doing so, the authors obviate to two major causes of bias otherwise very common when estimating the effects of policy on stocks at lower frequencies: reverse causality and omitted variable bias.

With quarterly or daily data, it is not feasible to control for the fact that monetary policy may be responding to signals coming from stocks market; or asset prices and monetary surprises may both be responding to some macroeconomic shock hidden in the error term. By considering high-frequency intra-day shocks they can ensure that the direction of causality is unique and well-defined and that estimates are consistent.

This paper also acknowledges the need to use derivatives to compute pure monetary policy surprises. Using raw changes in the federal funds rate target would be wrong because changes in policy that are correctly anticipated by market participants do not sort any effect on asset prices. The novelty of this contribution it is then to use price changes in federal funds futures to detect the component of the announcement unanticipated by market participants, namely pure, exogenous, monetary policy surprises.

Federal funds futures are traded on the Chicago Board of Trade exchange since 1988 and they have their settlement price usually matched by the federal funds rate effectively realised in the same calendar month. Thus, daily changes in the current-month futures rate mirrors any revision in market participants' expectations for the federal funds rate over the rest of the month, before they get eventually priced. In this setting, Gürkaynak et al. (2004) estimate that a 25-basis point tightening causes a drop in S&P500 of roughly 1 percent, with the level of statistical significance of the estimated coefficients imporving remarkably when moving from daily data to higher frequencies.

Gürkaynak et al. (2004) as well acknowledge the plural dimensionality of monetary policy. Since the monetary policy statement implies also release of central bank information concerning further horizons of the yield, it stands to reason that asset prices must react to more than one factor. Starting from the same matrix of data including federal funds futures and euro dollar futures with one year or less to expiration, they first investigate its range running a Cragg-Donald test. This allows to assess the number of statistically significant unobserved factors expected in the data, which amounts to two in this first preliminary study. Thus, they run a principal component analysis to extract the first two factors which explain the maximal fraction of variance observed in the data. Both correlate with the current month federal fund rates so cannot be already compared to the Target and Path factor. What needs to be done is rotating the original factors up to the point that the two new rotated factors are orthogonal to each other. Indeed, at this point the one factor that correlates with current-month federal fund rates may be interpreted as the Target factor, whereas the other embraces all additional component of monetary policy which sort effects at longer horizons in the yield curve, without moving current rates. This last factor may as well be interpreted as Path factor, basically standing for the conventional forward guidance.

As innovative as the contribution of Gürkaynak et al. (2004) was at the time it was published, the idea that monetary policy can be summarised in two components becomes flawed when one considers the introduction of unconventional monetary policy tools from the Great Financial Crisis onwards. Nonethless, the validity of their methodology stands as it has been similarly employed in the more recent work of Swanson (2021). Here, the author extends the methods of Gürkaynak et al. (2004) in order to identify large-scale asset purchase component (LSAP) next to the Target factor and Forward Guidance. With forward guidance being more effective at short-medium maturities, and LSAPs being more impactful at five or ten-year maturities, Swanson (2021) finds these as valid instruments to stimulate real economy in a world in close proximity to the Zero Lower Bound, where real activity is here measured by changes in private-sector interest rates as corporate bond yields for example.

Altavilla et al. (2019) is the milestone of high-frequency financial shocks in the Euro-Area. The contribution of this paper to the literature is twofold: on one side, it provides the first ad-hoc event-study database (EA-MPD) tailored for the Euro Area Monetary Policy, featuring price changes for a broad class of assets at different maturities; on the other, it incorporates a comprehensive quantitative assessment of ECB's monetary policy, encompassing the last two decades. Since 2001, the ECB Governing Council takes policy decision once a month, whereas from January 2015, the frequency of policy meetings has moved to a six-week cycle. For each communication window, either press release or press conference, each cell of the EA-MPD database reports price changes for each class of assets from the pre-event quote to the post-event quote.

In compliance with the high-frequency literature, the price changes estimated are orthogonal to the information set of market participants because computed in a narrow window around the policy announcements. The underlying rationale presumes that policy decisions, mirroring the authorities' stance towards the current economic outlook, are most likely already embed in market participants' expectations. However, market participants are oblivious of what policymakers will eventually decide to do. It stands to reason then that the price change in financial assets sensitive to monetary policy, in a narrow window around the policy announcement, captures the component of pure innovation brought by the announcement: pure monetary policy surprises.

Altavilla et al. (2019) additionally argue that raw price changes in Overnight Index Swap rates at different maturities are not sufficient alone to exhaust the full spectrum of nuances of the Euro Area Monetary Policy. In this exercise, the Cragg-Donald test delivers only one statistically significant factor in the press release window in both pre- and post-QE periods; in the conference window instead it acknowledges two statistically significant factors in the pre-QE subsample and three factors afterwards.

As in Gürkaynak et al. (2004), the raw factors are interpretable once the factor rotation procedure leads to orthogonality. There are two dimensions additional to Target and Forward Guidance: Timing and Quantitative Easing. The Timing factor captures shift in markets' expectations concerning coming-up meetings, without affecting long-run maturities. Whereas, the QE factor explains most of the volatility as unconventional monetary policy unfolds in the post-QE sample, by construction. Once measured monetary policy surprises as described, causality is established and the effect of policy on assets can be computed via OLS. Indeed, this factor estimation methodology provides a more attractive narrative of how communication surprises, rather than assets responses, changed overtime, with Forward Guidance being dominant before 2014 and Quantitative Easing afterwards.

Altavilla et al. (2019) also acknowledge the role of information shocks in monetary policy announcements, i.e. when markets react to the information content of the policy decision. In the literature, this type of shocks are defined as Delphic in Campbell et al. (2012) and information shocks in Miranda-Agrippino and Ricco (2021) and Jarociński and Karadi (2020). The novelty of their contribution in the literature of high-frequency financial market surprises is the distinction across pure monetary policy shocks and central bank information shocks.

Standard macroeconomic theory suggests that, following a monetary tightening, stock depreciate for two valid reasons: on one side, future expected dividends drop in the event of a recession induced by the policy; on the other, higher rates increase the discount factor which has the effect of pushing downwards the present value of said dividends. However, a negative co-movement between interest rates and stock prices is not always observed. If it is the case that to tighter conditions stock prices evaluation increase, it means that markets are not reacting to news to monetary policy in a strict sense, but rather to the information content conveyed by the monetary policy authority through its decision. The main identifying assumption behind this approach is that each month the monetary policy shock is a combination of these two components, with non-zero shares each usually. This means that failing to purge the pure monetary policy shock from the information component, compromises a proper estimation of monetary non-neutrality in the economy.

This thesis will rely on the identification proposed by Jarociński and Karadi (2020), which use changes in the high-frequency 2-year maturity Overnight Index Swap rates. The authors of this paper have made available the series of ECB shocks up to December 2021, suiting the time-period required for this analysis perfectly. From this series I generate two additional orthogonal variables: positive monetary policy shocks and negative monetary policy shocks. I need to distinguish across the two since, later on in this thesis, I delve deeper into possible asymmetries across the two kinds of shocks and their effects on the sectoral prices.

3 Data

The raw data used are monthly harmonised consumer price indexes (HICPs) for Germany, available at the Eurostat Bulk Download Repository. All HICP values are associated to a COICOP code identifying the level of aggregation, from level 1 up to level 4. All data have been transformed to induce consistency in the final panel. Price indexes with less than 36 months of data are dropped from the final panel data set. Any price indexes with gaps in the time-series dimensions are dropped accordingly. Then, all price indexes in the final panel data set are seasonally adjusted using the X12 seasonal-adjustment procedure. The annual expenditure weights in the final panel data set are re-normalized to equal one in each year. Finally, at level 3 and level 4 of disaggregation, log-differences of prices indexes are winsorised at the 0.25 and 99.75 percentiles.

The criterion I adopt to select the most appropriate level of disaggregation aims at maximising the number of cross-sectional observations within the longest panel dimension available. I pick then the third level of disaggregation, which incorporates 101 items in total from January 1996 to December 2019. However, the Ahrens-Pincus Index[3] for this dataset is 0.77. When estimating the first principal component as described in section 4.1, I proceed manually re-balancing the panel by keeping only sector with continued observations starting January 1999 until December 2019. In doing so, the total number of sectors in the analysis is 74.

[3]Closer to 1 indicates balanced panel. See e.g.Ahrens and Pincus (1981)

Table 1: Summary statistics

Total number of observations	27293
Total number of cross-sectional units	101
Avg. number of cross-sectional units per time period	84.24
Total number of time periods	324
Average tenure	270.23
Ahrens-Pincus Index	0.77

Table 2: Panel data summary

Minimum	Pctl-25	Median	Pctl-75	Maximum
A. *Distribution of the tenure in the panel*				
96	277	324	324	324
B. *Distribution of cross-sectional units across time*				
74	78	78	101	101

Finally, in order to obtain more efficient estimates of monetary policy effects on sectoral prices, I collect additional macroeconomic variables: unemployment rate, Brent Crude Oil Spot price and US dollar bilateral exchange rate. This final dataset is the starting point for all subsequent computations.

4 Empirical Strategy

4.1 Principal component analysis

I start by detecting the number of factors underlying this data. The factor estimation procedure based on the first information criterion of Bai and Ng (2002) identifies only one common factor as expected. This means that there is only one dimension which embodies that synchronous co-movement common to all sectors: this component is precisely what we call "pure inflation". I de- annualize the one-month log-price change and reshape the panel into a time-series of sectors. Thus, I can run a principal component analysis to estimate the first factor. The factor is obtained as a weighted sum of standardized versions of the 74 variables representing the sector-specific monthly log price changes. By default, this factor is normalized to have mean 0 and standard deviation 1. To be interpreted in percent, it needs to be rescaled. To do so, I retrieve a de-annualized seasonally adjusted series of headline 1-month CPI inflation for Germany and regress it on the standardised factor. By picking only the fitted values of this simple regression, I have obtained a re-scaled series of the common factor describing pure inflation in our data and interpretable in percentage units.

4.2 Lag-augmented local projections

The econometric approach I adopt in the results section are lag-augmented local projections. Replicating the exercise of Borio et al. (2022), I first consider the impact of high-frequency monetary policy shocks on the common component of inflation, which I have estimated as discussed in the previous sub-section. I compute standard local projections for cumulative changes of the principal component at horizons h=0,...,48 months:

$$PC_{i,t+h} - PC_{i,t-1} = \alpha_{i,h} + \beta_{i,h} MP_{m,t} + \sum_{s=1}^{11} \rho_{i,h,s} \Delta p_{i,t-s} + \lambda_{i,h} x_{t-1} + \epsilon_{i,t+h} \tag{1}$$

where $MP_{m,t}$ is the monetary policy shock in month t, $\rho_{i,h,s}$ are lags of the dependent variable, and x_{t-1} is a vector of aggregate controls: 12-month change in the unemployment rate, the 1-month log difference in brent crude oil spot price and the 1-month log difference of US dollar bilateral exchange rate. This set of controls accounts for macroeconomic conditions which concur to sector-specific price dynamics, inflating the standard errors of the estimated coefficients.

Then, I consider the price impact of high-frequency monetary policy shocks on each of the 100 narrowly defined sectors over different horizons during the period January 1999–December 2019 and compute standard local projections for each sector i at horizon h=0,...,48 months:

$$p_{i,t+h} - p_{i,t-1} = \alpha_{i,h} + \beta_{i,h} MP_{m,t} + \sum_{s=1}^{11} \rho_{i,h,s} \Delta p_{i,t-s} + \lambda_{i,h} x_{t-1} + \epsilon_{i,t+h} \tag{2}$$

where $p_{i,t+h}$ is the log price level for sector i in month t+h, $MP_{m,t}$ is the monetary policy shock in month t, $\rho_{i,h,s}$ are lags of the dependent variable, and x_{t-1} is a vector of aggregate controls as before.

Starting from Jordà (2005), local projections (LPs) have become an increasingly established econometric tool in modern dynamic macroeconomic studies, alternative to the more popular Structural Vector Autoregression (SVARs). Indeed, the recent contribution of Plagborg-Møller and Wolf (2021) provides evidence that linear local projections and VARs estimate the same impulse responses in population: specifically, all implementations of local projections in the literature can be obtained through an appropriately recursive VAR and viceversa (see for example Ramey (2016)). Since the two methods are equivalent in population, none of he two is expected to dominate the other in terms of mean squared error in finite samples.

In a second contribution authored by Montiel Olea and Plagborg-Møller (2021), lag-augmented local projections prove to be robust to two very common features of macroeconomic analyses, namely high persistence in the data and consistency of impulse responses at longer horizons. The authors formally prove that the confidence interval produced by this procedure in lag-augmented local projections showcase well-behaved asymptotic properties at increasing degrees of persistence in the data. In addition to more robust inference, they require less intensive computational effort. Usually, in the local projection literature it is frequent to adopt heteroscedasticity and autocorrelation consistent/robust (HAC/HAR) standard errors to account for serial autocorrelation of the residuals. However, computing standard errors in the sense of Newey and West (1986) prolongs by far the estimation process.

Another key take-away of this paper is indeed that Eicker–Huber–White heteroscedasticity-robust standard errors are just sufficient for lag-augmented local projections. Under the weak assumption that the innovations are strictly stationary and mean independent relative to past and future innovations, it stands to reason that, although regression residuals are serially correlated, the regression scores of interest are serially uncorrelated. Thus, heteroskedasticity robust standard errors suffice. Back to the choice between VARs and LPs, it is true that conventional VARs are more efficient and provide smaller standard errors in most of the cases. However, this choice undergoes the possibility of an estimation process prone to less consistency at longer horizons.

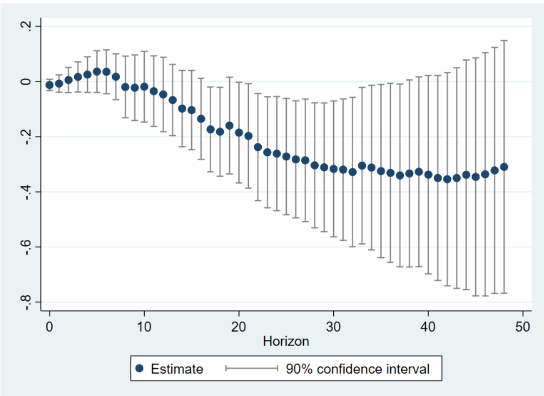
As highlighted by the two authors in this relevant contribution, there are only two cases in which lag-augmented local projections prove to be inferior to their counterparties: VARs should be privileged when the analysis focuses on very short impulse responses, since they prove to be more valid and efficient in this case: secondly, when the horizons chosen for the projections are a sizeable proportion of the sample size. None of these conditions materialises in the present analysis since our impulse responses are relatively long (up to 4 years), though they represent a small fraction of the overall sample size, roughly 20 percent (48 months over 252 in total). Hence, the use of lag-augmented local projections fits the purpose of the exercise conducted in this thesis, providing a compelling trade-off between robustness and efficiency.

5 Results

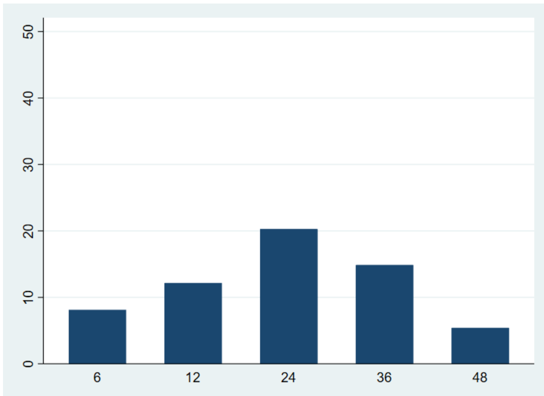
5.1 The role of monetary policy

Estimating equation 1, the principal component of sectoral prices responds meaningfully to monetary policy shocks: as shown in Figure 3a, a 25 basis point contraction of monetary policy causes persistent disinflation mostly affecting the medium-long term horizon. This evidence enforces the idea that monetary policy, which impacts the economy inducing fluctuations in aggregate demand, is channeled through sectoral prices mostly via the common component. The impact of policy on the common component of inflation requires at least a lag of 1-year to materialise fully, with its effects picking within the 2-3 years following the shock. The estimates of the coefficients for horizons above 12 months are displayed in Table 3.

Figure 3: The role of monetary policy



(a) Impulse response of the first principal component following a MP shock



(b) Proportion of sectors with statistically significant idiosyncratic responses

Notes: 3a The common component is constructed as the first principal component of monthly log price change across the 100 sectors. The dots are estimates of the response of the common component to a 25 basis points monetary policy shock in month t. 3b Significant at 10% level.

For each sector, I then compute the idiosyncratic log price change by summing up the residuals from the regression of monthly sector-specific log price changes on the estimated common component. Doing so, I estimate that the proportion of sectors with statistically significant idiosyncratic responses following a monetary policy shock peaks at roughly 20% of the overall basket of sectors. Figure 3b plots the proportions (in percent) in stacked bars at $6, 12, 24, 36$

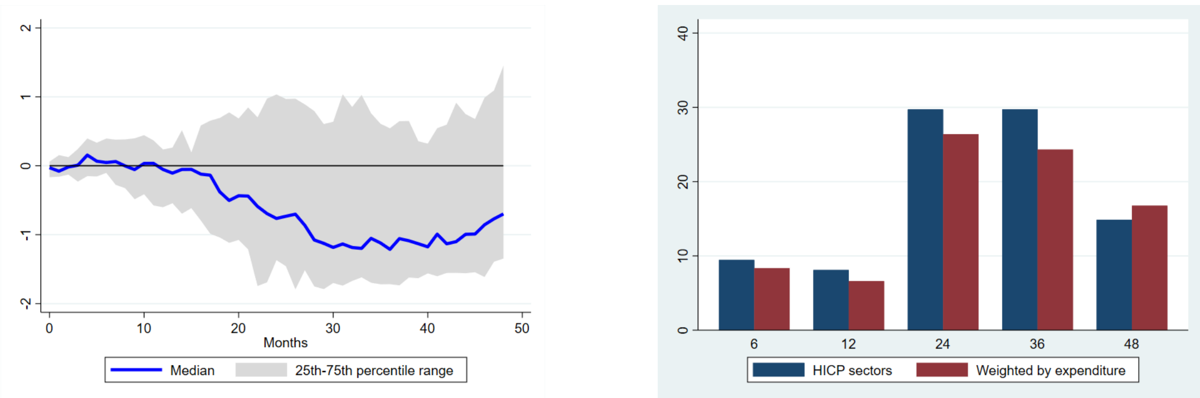
Table 3: Estimated effect of MP shocks on the first principal component

Horizon	PC	St. error
12	-0.047	(0.068)
13	-0.067	(0.066)
14	-0.098	(0.070)
15	-0.103	(0.073)
16	-0.135^{*}	(0.075)
17	-0.173^{**}	(0.078)
18	-0.182^{**}	(0.082)
19	-0.160^{*}	(0.089)
20	-0.185^{**}	(0.093)
21	-0.197^{**}	(0.096)
22	-0.238^{**}	(0.099)
23	-0.257^{**}	(0.102)
24	-0.261^{**}	(0.105)
25	-0.272^{**}	(0.107)
26	-0.282^{***}	(0.108)
27	-0.286^{**}	(0.113)
28	-0.304^{***}	(0.115)
29	-0.311^{***}	(0.118)
30	-0.317^{**}	(0.125)
31	-0.319^{**}	(0.130)
32	-0.328^{**}	(0.137)
33	-0.305^{**}	(0.144)
34	-0.312^{**}	(0.151)
35	-0.325^{**}	(0.159)
36	-0.331^{**}	(0.165)
37	-0.341^{**}	(0.168)
38	-0.333^{*}	(0.172)
39	-0.327^{*}	(0.174)
40	-0.338^{*}	(0.182)
41	-0.350^{*}	(0.188)
42	-0.354^{*}	(0.196)
43	-0.350^{*}	(0.203)
44	-0.338	(0.211)
45	-0.346	(0.219)
46	-0.336	(0.224)
47	-0.322	(0.226)
48	-0.309	(0.232)

NOTE: This table displays the regression results coming out of equation 1. Heteroscedasticity-robust standard errors are displayed in parentheses. *** designates a variable significant at the 1% significance level, ** significant at the 5% significance level, and * significant at the 10% significance level up to 48 months following the shock. Hence, monetary policy operates mostly through the principal component, with very limited margin of action at the sector-specific level. However, as shown previously in Figure 1a, the proportion of variance steered by the principal component is very constrained in a low inflation regime.

How evidence on the principal component is matched by actual sector-specific data? The purpose of equation 2 is to observe the sector-specific response to a monetary policy shock in the pool of 100 sectors gathered in the data. To avoid plotting 100 impulse responses, one for each sector, I compute the weighted median and the weighted 25th and 75th percentiles in Figure 4a, with weights equals to the average expenditure accruing to each sector over the sample period. Hence, the upper and lower bands in Figure 4a do not represent the upper and lower extremities of the confidence intervals, but rather the weighted 75th and 25th percentiles respectively. This configuration allows to make inference on the effects of monetary policy overall the distribution of sectoral prices.

Figure 4: Limited traction of monetary policy



(a) Distribution of sector-specific responses to a monetary policy shock

(b) Proportion of sectors with statistically significant responses to a MP shock

Notes: 4a Weighted percentiles of the response of prices across 100 narrowly defined personal consumption expenditure (HICP) sectors to a monetary policy shock of 25 basis points. The weights are equal to the sector-specific average expenditure shares. 4b Significant at 10% level

Indeed, following a 25 basis points monetary tightening, the distribution of sectoral price responses is skewed to the right, with more than 50% of sectors responding with persistent disinflation as expected. However, the 75th percentile of the distribution (and more) counterintuitively shows positive responses. In contrast with the US framework, the local projections in a Euro Area country such as Germany thus provide evidence of a so-called ‘price puzzle’: it means that multiple additional factors concur in the definition of sector specific price movements where monetary policy is almost ineffective, being merely just a minor component.

However, none of the positive coefficients is statistically significant when performing a one-sided T-test. In the literature there are few contributions supporting remarkable price puzzles. Bils et al. (2003) analyse the 123 components of the CPI and presume two categories of price responses, partitioned in flexible and sticky prices respectively. They find that, following a monetary expansion, flexible prices fall initially and start increasing only later; sticky prices on the other hand need a lag of at least 20 months to display significant responses. Hence the relative price ratio, estimated as the ratio of flexible prices to sticky prices, has a very ambiguous response to monetary expansions. Similarly Balke and Wynne (2007) find evidence of significant price puzzle in disaggregated series and agree with Bils et al. (2003) that estimated price responses to macroeconomic shocks do not reconcile with sticky price models, which after a monetary expansion expect prices to increase at first and then revert back to zero. Both studies rely on small-sized VARs, estimated independently from disaggregated inflation data. They assume disaggregated inflation feed through the economy only via the intermediation of an aggregate inflation index.

The framework that I consider in this thesis crucially relies on the assumption that aggregate co-movements of disaggregated sectoral prices is informative and not inferior to aggregate inflation indeces. This might explain why I do not find statistically significant evidence of price puzzles. Overall, the proportion of statistically significant sectoral price responses following a policy shock is contained– less than 10% at the 90% significance level after 12 months. Also, after 36 months this proportion does not go beyond 30%, enforcing the idea that monetary policy exerts very limited traction across prices in a low inflation regime. Accordingly, the proportion is even smaller if the response of each sector is weighted by its expenditure share over the sample period (Figure 4b).

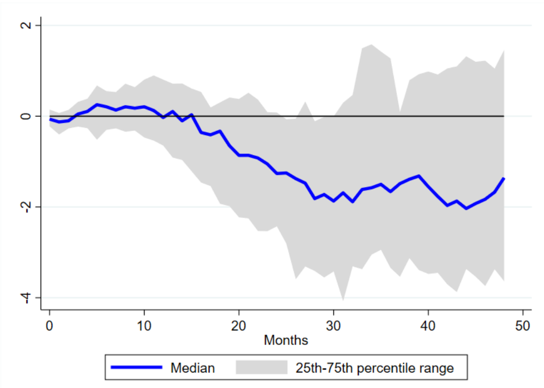
5.2 Positive and negative monetary policy shocks

In the previous specification, positive and negative monetary policy shocks are treated symmetrically. It stands to reason to ask whether results are more pronounced when accounting for monetary tightening and monetary easing separately as two orthogonal shocks. In this section, I run the model established in equation 2 and substitute the symmetric shock in positive and negative changes of the monetary policy stance. For each sector i at horizon h=0,...,48 months, I now compute the following local projections:

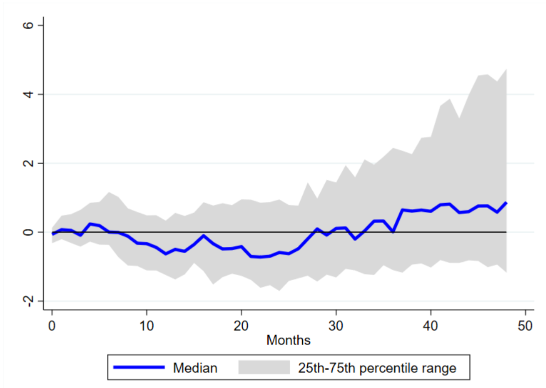
$$p_{i,t+h} - p_{i,t-1} = \alpha_{i,h} + \beta_{1,i,h} MP^{+}_{m,t} + \beta_{2,i,h} MP^{-}_{m,t} + \sum_{s=1}^{11} \rho_{i,h,s} \Delta p_{i,t-s} + \lambda_{i,h} x_{t-1} + \epsilon_{i,t+h} \quad (3)$$

where $MP^{+}_{m,t}$ and $MP^{-}_{m,t}$ stand for contractionary and expansionary shocks respectively. Once again, the interpretation of the impulse responses in Figure 5 requires caution since the upper and lower gray bands do not confine confidence intervals, but rather stand for the weighted 75th and 25th percentiles respectively.

Figure 5: The asymmetric impact of monetary contractions and expansions



(a) Distribution of sector-specific responses to monetary policy tightening



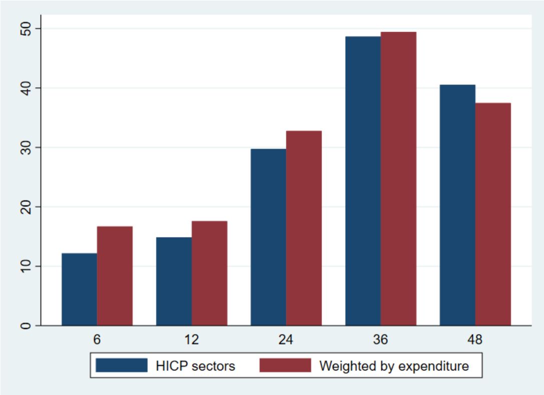
(b) Distribution of sector-specific responses to monetary policy easing

Notes: Weighted percentiles of the response of prices across 100 narrowly defined personal consumption expenditure (HICP) sectors to a monetary policy shock of 25 basis points. The weights are equal to the sector-specific average expenditure shares.

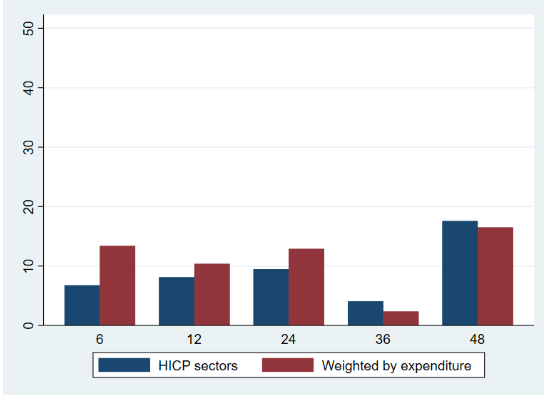
The outcome of the LP procedure encompasses a compelling asymmetry analysis: monetary policy tightening out-weight significantly monetary policy expansions. With tighter conditions following the policy statement, Figure 5a, the distribution lies almost entirely in negative territories, leaving little room for price puzzles if not at very far horizons. With more enhancing conditions introduced by the monetary authority, Figure 5b, the distribution of prices is slightly misplaced in the upper region of the graph, but the median effect is almost null. The reason of this finding lies beneath the following explanation: in a low inflation regime, contractionary monetary policy shocks cannot be but more effective than expansions.

As mentioned in the beginning of this empirical section, in a low inflation regime the monetary policy authority must struggle twice as hard to promote inflation and fight its self-stabilizing

Figure 6: Differential impact on sectoral prices



(a) Proportion of statistically significant price declines following a monetary contraction



(b) Proportion of statistically significant price increases following a monetary expansion

Notes: Significant at 5% level

pattern. Consequently, the proportion of sectors affected by monetary contractions is more than double the proportion affected by monetary easing, as Figure 6 shows. The underlying inflation regime and the effectiveness of monetary policy are closely intertwined by the role exerted by the principal component.

5.3 Cyclically sensitive sectors

Another question I want to address through this empirical exercise is whether sectoral price responses to changes in the policy stance are heterogenous in the cross-section of sectors. In the literature review, it has been extensively discussed how measure of aggregate inflation inherit high persistence from those sectors in which the role of the common component is dominant. Most importantly, the work of Stock and Watson (2020) leverages on empirical evidence proving that different components of inflation are endowed with different cyclical properties. The underlining reasoning is that many prices of the inflation index are internationally determined, so that the observed link between the changes in these components and real economic activity is weak. Other items instead, have their prices set in local markets, so it stands to reason that these components will eventually be more sensitive to national cyclical pressures.

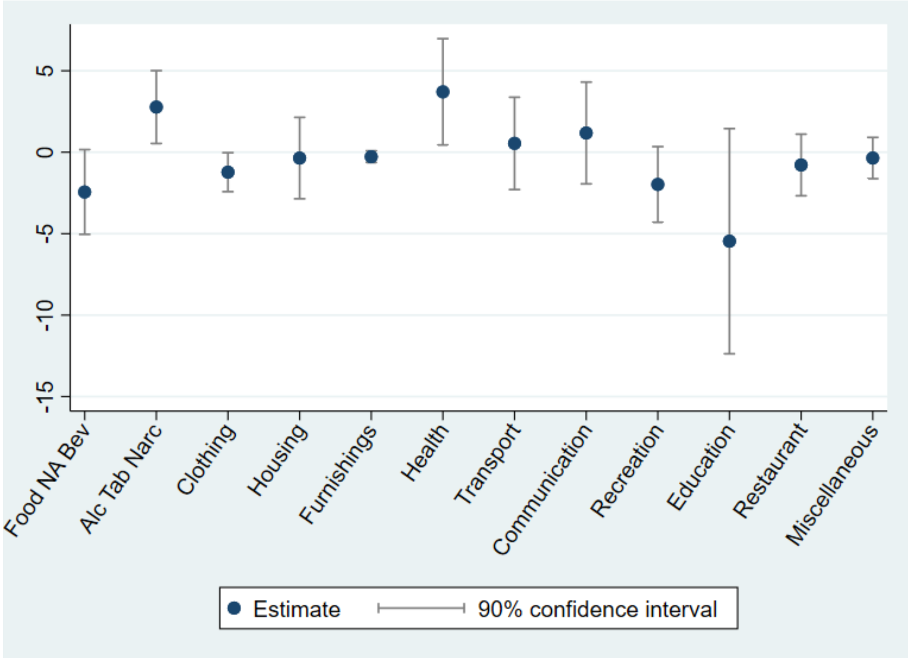
Turning to US data and investigating the co-variation between cyclical inflation and the cyclical activity index, the empirical evidence suggests that those sectors with highest level of correlation to cyclical activity are mostly services that have prices usually determined in local (non-tradable) markets: it is the case of housing services, food and non-alcoholic beverages, accommodation services out of home and recreational services. On the other side, the sectors with the smallest cyclical correlations are heavily influenced by internationally traded goods (for which the major cost is in energy prices) and sectors with regulated or negotiated prices (as it is the case for health and communication services).

For the Euro Area the story is slightly different since the HICP components are different to the US PCE components. The two-tier HICP components do not undergo the convention of differentiating across goods and services, as it is the case for US PCE. HICP components instead are organized by purpose of expenditure and usually contain both goods and services: hence, the transportation sector includes transportation services (train, bus), fuel purchased by households and car purchases. Although the degree of heterogeneity in the co-movement between the cyclical activity index and sectoral inflation is smaller compared to the US case, some sectors indeed display stronger correlation with cyclical activities then others. This is the case for restaurant and hotels, food and non-alcoholic beverages, furnishings and household equipment. Other sectors instead, whose price determination dynamics are not locally set, such as healthcare and communication, display very little correlation with the cyclical component.

For each of the 12 two-tier HICP sectors, I estimate the same model as in equation 2 for 36 horizons. Then, I pick the horizon at 24 months after the shock and observe the point estimates of each sector. As shown in Figure 7, I find that indeed sectors such as food and non-alcoholic beverages, clothing and footwear and furnishings (households' equipment) are endowed with statistically significant price responses. In this exercise I do not manage to exclude energy goods from the housing category, and this might explain why it fails to be significant.

As robustness check, for each of the 12 two-tier HICP sectors, I run the same model as in equation 3 to understand whether differentiating the shock into two asymmetric monetary stimuli can unveil statistical significance for other cyclically sensitive sectors. As displayed in Table 4, all the cyclically sensitive sectors detected by Stock and Watson (2020), except for restaurant and hotels, respond to a monetary contraction with statistically significant price declines at the 5% level. In contrast to Stock and Watson (2020), I find statistically significant responses also in the transport and education sectors. My hypothesis for this to happen is that, as mentioned at the beginning of this discussion on EA results, the HICP classification does not distinguish between goods and services within each category, as it is the case for the US Why should cyclically sensitive sectors respond more than others to monetary policy shocks?

Figure 7: Heterogeneities across 12 two-tier HICP sectors



Notes: The dots show the point estimates of the impulse response of prices at the 24-month horizon following a 25 basis point monetary policy shock

First because, by definition, they respond to economic fluctuations in the national real activity and monetary policy is expected to cause fluctuations in national aggregate demand to sort its effects. Boivin et al. (2009) indeed identify some sector characteristics which might explain the cross-sectional variation in price responses to monetary policy shocks. Industries with inherent high volatility and persistence tend to respond in a more timely and flexible manner to macroeconomic shocks: the conjecture behind this evidence is that firms operating in markets where both common and idiosyncratic components are highly persistent tend to adjust immediately to any shock; firms which expect only macroeconomic disturbances to be persistent might adjust with some delay to observe whether the current shock is transient or not. Also the degree of competition plays a role in explaining heterogenous responses across sectors: firms operating in a competitive framework acknowledge that deviating from the profit maximizing level of prices is costly and are more willing to respond immediately to any kind of shocks. Industries with higher market power display a more sluggish response to the shock instead. Services are non-tradable goods, with prices mostly determined in local markets: possibly, the level of competition in different local markets can explain why services in different sectors display different cyclical characteristics.

Table 4: Cyclically sensitive sectors

Sectors	(1)
Food and NA Beverages	-3.392^{**}
	(1.931)
Clothing and footwear	-1.774^{**}
	(0.807)
Housing and energy goods	-3.025^{**}
	(1.575)
Furnishings	-0.367^{*}
	(0.258)
Transport	-2.562^{*}
	(1.802)
Recreation	-3.450^{***}
	(1.426)
Education	-5.348^{*}
	(3.862)

NOTE: Heteroscedasticity-robust standard errors are displayed in parentheses. *** designates a variable significant at the 1% significance level, ** significant at the 5% significance level, and * significant at the 10% significance level

6 Conclusion

The most relevant contribution of this thesis is that the limited traction of monetary policy detected in studies set in the US analogously applies for one of the major economies in the Euro Area. For Germany, I exploit disaggregated sectoral prices dataset and investigate the effects of monetary policy at sectoral level discussing the muted role of the principal component in the last two decades. Over the last 20 years, the role of the principal component in explaining the variation of sectoral prices is significantly reduced, with clear signals of a turn in scenery approaching. As argued in Borio et al. (2023), this view of two regimes serves to the purpose of highlighting the constraints and possibilities of policymakers in muted environments. Since the self-stabilizing tendency of inflation in the low-regime, monetary policy authorities should allow for more flexibility and tolerate deviations from target since only major movements in the monetary policy stance could produce observable effects. Conversely, when transitioning towards a high inflation regime the intervention of policy makers needs to be as timely as possible to prevent a spiral. The huge effort central bank authorities are currently facing to fasten up the tightening cycle clearly speaks to that.

The work of this thesis echoes the literature on inflation persistence and the methodological difficulties related to a proper measure of core inflation. To keep the analysis more straightforward and intuitive, I proxy the core component of inflation using the first principal component extracted from 100 disaggregated sectoral prices from the HICP index. I estimate the role of this principal component in explaining prices variation in the last two decades and estimate its response to exogenous monetary policy shocks.

As expected, the common component, which is the main cause of the high persistence observed in aggregate indices, is denoted by statistically significant responses to the shocks. Its diminished role in disaggregated sectoral prices though explains why the traction of monetary policy at the sector level is limited and constrained. However, when positive and negative shocks are treated asymmetrically, monetary tightening is way more effective relative to monetary easing, as one might expected in a low and self-stabilising inflation regime. The last dimension of heterogeneity I investigate encompasses the cross-section of two-tier HICP components and I find that the sectors more responsive to monetary policy shocks, in particular to monetary policy tightening, are indeed the cyclically sensitive sectors in the sense of Stock and Watson (2020).

For future research, I believe it could be fruitful to investigate whether the multiple dimensions of monetary policy identified by Altavilla et al. (2019) sort different or better-identified effects on disaggregated sectoral prices. Also, there is room for improvement in understanding whether the cyclically sensitive sectors are as well characterized by a more prominent role of the common component and at the same time display the features outlined by Boivin et al. (2009). Finally, the exercise discussed here could be replicated for the other major economies in the Euro Area which, subject to the same shocks, may yield very different results.

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A Appendix

Table A1: Local projections of sectoral prices weighted percentiles

Horizon	Median	25th percentile	75th percentile
0	−0.028	−0.166	0.060
1	−0.079	−0.158	0.154
2	−0.017	−0.128	0.125
3	0.008	−0.230	0.244
4	0.155	−0.149	0.396
5	0.066	−0.154	0.334
6	0.047	−0.103	0.395
7	0.061	−0.277	0.379
8	−0.002	−0.325	0.383
9	−0.055	−0.485	0.398
10	0.034	−0.413	0.444
11	0.035	−0.575	0.368
12	−0.053	−0.601	0.236
13	−0.107	−0.543	0.264
14	−0.053	−0.695	0.516
15	−0.052	−0.615	0.194
16	−0.121	−0.794	0.584
17	−0.137	−0.985	0.654
18	−0.378	−1.040	0.693
19	−0.503	−1.118	0.775
20	−0.435	−1.075	0.686
21	−0.440	−1.212	0.846
22	−0.590	−1.744	0.702
23	−0.694	−1.691	0.974
24	−0.764	−1.369	1.035
25	−0.733	−1.458	0.969
26	−0.702	−1.792	0.973
27	−0.864	−1.515	0.890
28	−1.077	−1.750	0.794
29	−1.125	−1.789	0.605
30	−1.185	−1.700	0.638
31	−1.135	−1.739	1.037
32	−1.186	−1.671	0.853
33	−1.198	−1.618	1.028
34	−1.053	−1.696	0.762
35	−1.120	−1.719	0.610
36	−1.213	−1.717	0.544
37	−1.057	−1.734	0.647
38	−1.088	−1.621	0.650
39	−1.131	−1.631	0.356
40	−1.176	−1.561	0.322
41	−0.992	−1.602	0.546
42	−1.132	−1.555	0.597
43	−1.101	−1.553	0.915
44	−0.994	−1.558	0.749
45	−0.990	−1.545	0.679
46	−0.857	−1.614	0.988
47	−0.770	−1.392	1.092
48	−0.699	−1.346	1.452

NOTE: The table displays the median and 25th-75th percentiles of the distribution of sectoral price coefficients estimated in equation 2, with weights equal to the average expenditure shares over the sample period. These results are plotted in figure 4a.

Table A2: Proportion of sectors with statistically significant responses

Horizon	HICP	Weighted by expenditure
0	16.22	19.50
1	10.81	11.45
2	12.16	17.90
3	12.16	13.83
4	8.11	10.67
5	8.11	11.61
6	9.46	8.36
7	8.11	6.76
8	8.11	6.74
9	13.51	9.53
10	9.46	7.67
11	10.81	7.94
12	8.11	6.60
13	9.46	11.77
14	13.51	14.74
15	13.51	13.69
16	16.22	15.86
17	18.92	15.29
18	18.92	16.24
19	13.51	14.81
20	16.22	13.67
21	22.97	17.74
22	28.38	29.58
23	29.73	30.99
24	29.73	26.39
25	27.03	29.69
26	31.08	34.88
27	27.03	27.30
28	32.43	38.79
29	36.49	42.54
30	35.14	42.06
31	36.49	42.81
32	31.08	34.23
33	29.73	31.21
34	36.49	34.90
35	31.08	24.58
36	29.73	24.32
37	27.03	21.93
38	25.68	21.72
39	22.97	21.23
40	25.68	20.67
41	24.32	20.66
42	25.68	22.48
43	25.68	24.94
44	18.92	20.34
45	24.32	24.09
46	24.32	25.27
47	18.92	21.20
48	14.86	16.76

NOTE: The table displays the proportion of sectors (in percent) with statistically significant responses following a monetary policy shocks at the 10% significance level. These results are plotted in figure 4b for horizons $6, 12, 24, 36, 48$.

Table A3: Local projections of sectoral prices weighted percentiles following a monetary contraction

Horizon	Median	25th percentile	75th percentile
0	−0.064	−0.224	0.147
1	−0.126	−0.402	0.071
2	−0.102	−0.268	0.139
3	0.047	−0.228	0.316
4	0.105	−0.264	0.386
5	0.254	−0.518	0.676
6	0.208	−0.301	0.553
7	0.135	−0.267	0.532
8	0.208	−0.341	0.716
9	0.177	−0.316	0.640
10	0.207	−0.468	0.806
11	0.125	−0.539	0.898
12	−0.029	−0.646	0.806
13	0.104	−0.911	0.717
14	−0.103	−0.965	0.720
15	0.032	−1.213	0.609
16	−0.359	−1.461	0.535
17	−0.410	−1.538	0.192
18	−0.330	−1.928	0.304
19	−0.651	−1.981	0.412
20	−0.863	−2.228	0.380
21	−0.862	−2.251	0.518
22	−0.921	−2.529	0.365
23	−1.052	−2.533	0.088
24	−1.263	−2.426	0.081
25	−1.251	−2.805	−0.068
26	−1.376	−3.591	−0.054
27	−1.475	−3.310	0.322
28	−1.816	−3.409	−0.111
29	−1.725	−3.553	−0.016
30	−1.870	−3.419	−0.006
31	−1.688	−4.074	0.296
32	−1.885	−3.307	0.468
33	−1.615	−3.371	1.496
34	−1.577	−3.049	1.584
35	−1.501	−2.943	1.422
36	−1.662	−3.341	1.274
37	−1.486	−3.537	0.091
38	−1.389	−3.125	0.792
39	−1.318	−3.389	0.925
40	−1.553	−3.474	0.985
41	−1.768	−3.451	0.919
42	−1.967	−3.703	1.052
43	−1.870	−3.873	1.098
44	−2.034	−3.365	1.319
45	−1.924	−3.536	1.198
46	−1.830	−3.740	1.223
47	−1.674	−3.372	1.049
48	−1.356	−3.634	1.460

NOTE: The table displays the median and 25th-75th percentiles of the distribution of sectoral price $MP^{+}_{m,t}$ coefficients estimated in equation 3, with weights equal to the average expenditure shares over the sample period. These results are plotted in figure 5a.

Table A4: Local projections of sectoral prices weighted percentiles following a monetary expansion

Horizon	Median	25th percentile	75th percentile
0	−0.062	−0.317	0.129
1	0.074	−0.202	0.480
2	0.054	−0.312	0.523
3	−0.088	−0.418	0.649
4	0.237	−0.273	0.852
5	0.191	−0.361	0.877
6	0.004	−0.366	1.165
7	−0.008	−0.723	1.023
8	−0.114	−0.964	0.692
9	−0.320	−0.981	0.586
10	−0.332	−1.108	0.489
11	−0.442	−1.111	0.493
12	−0.629	−1.241	0.335
13	−0.499	−1.369	0.561
14	−0.556	−1.224	0.472
15	−0.356	−0.892	0.570
16	−0.101	−1.131	0.870
17	−0.332	−1.517	0.774
18	−0.486	−1.303	0.842
19	−0.476	−1.203	0.784
20	−0.418	−1.268	0.953
21	−0.705	−1.383	0.943
22	−0.721	−1.612	0.854
23	−0.698	−1.535	0.874
24	−0.589	−1.705	0.949
25	−0.624	−1.415	0.789
26	−0.481	−1.338	0.771
27	−0.194	−1.262	1.444
28	0.095	−1.431	0.977
29	−0.083	−1.230	1.518
30	0.110	−1.312	1.443
31	0.124	−1.062	1.944
32	−0.201	−1.109	1.594
33	0.035	−1.217	2.112
34	0.320	−1.240	1.958
35	0.324	−0.958	2.189
36	0.012	−1.100	2.446
37	0.647	−1.172	2.362
38	0.612	−0.939	2.265
39	0.643	−0.906	2.739
40	0.606	−1.025	2.767
41	0.794	−0.807	3.668
42	0.814	−0.890	3.872
43	0.570	−0.891	3.300
44	0.597	−0.816	3.979
45	0.759	−0.834	4.545
46	0.762	−1.013	4.580
47	0.581	−0.939	4.373
48	0.870	−1.174	4.746

NOTE: The table displays the median and 25th-75th percentiles of the distribution of sectoral price $MP^{-}_{m,t}$ coefficients estimated in equation 3, with weights equal to the average expenditure shares over the sample period. These results are plotted in figure 5b.

Table A5: Proportion of sectors with statistically significant responses to monetary contraction

Horizon	HICP	Weighted by expenditure
0	10.81	18.83
1	10.81	18.09
2	13.51	15.26
3	10.81	13.85
4	9.46	13.19
5	8.11	12.01
6	12.16	16.70
7	9.46	14.35
8	12.16	16.75
9	13.51	16.84
10	12.16	16.13
11	14.86	18.00
12	14.86	17.58
13	18.92	27.81
14	14.86	16.93
15	20.27	26.93
16	25.68	35.90
17	22.97	27.97
18	22.97	22.84
19	24.32	28.88
20	24.32	24.09
21	28.38	31.11
22	24.32	28.02
23	25.68	28.65
24	29.73	32.78
25	32.43	37.93
26	37.84	40.42
27	39.19	41.70
28	44.59	51.72
29	47.30	52.75
30	50.00	53.53
31	48.65	52.88
32	47.30	51.11
33	45.95	45.75
34	45.95	45.95
35	47.30	49.48
36	48.65	49.43
37	48.65	49.43
38	45.95	45.84
39	45.95	46.00
40	47.30	46.25
41	48.65	46.80
42	47.30	46.25
43	47.30	46.25
44	45.95	45.74
45	45.95	42.87
46	44.59	42.78
47	40.54	37.47
48	40.54	37.47

NOTE: The table displays the proportion of sectors (in percent) with statistically significant negative responses following a contractionary monetary policy shock at the 5% significance level. These results are plotted in figure 6a for horizons $6, 12, 24, 36, 48$.

Table A6: Proportion of sectors with statistically significant responses to monetary expansion

Horizon	HICP	Weighted by expenditure
0	8.11	9.88
1	10.81	17.41
2	10.81	14.26
3	6.76	14.88
4	6.76	15.06
5	9.46	12.69
6	6.76	13.38
7	12.16	18.32
8	13.51	18.08
9	9.46	13.44
10	9.46	13.44
11	9.46	8.42
12	8.11	10.37
13	8.11	12.06
14	8.11	12.06
15	9.46	12.13
16	10.81	13.59
17	10.81	13.79
18	12.16	15.00
19	9.46	12.88
20	10.81	13.54
21	9.46	8.79
22	10.81	14.34
23	12.16	15.28
24	9.46	12.88
25	9.46	12.88
26	8.11	12.03
27	8.11	12.07
28	8.11	12.07
29	13.51	15.51
30	9.46	7.64
31	6.76	6.20
32	6.76	6.20
33	6.76	6.20
34	6.76	5.94
35	4.05	3.66
36	4.05	2.34
37	5.41	9.22
38	4.05	2.25
39	8.11	10.05
40	8.11	10.54
41	6.76	3.66
42	9.46	5.46
43	12.16	6.88
44	12.16	6.74
45	16.22	12.31
46	16.22	16.02
47	18.92	16.95
48	17.57	16.49

NOTE: The table displays the proportion of sectors (in percent) with statistically significant positive responses following an expansionary monetary policy shocks at the 5% significance level. These results are plotted in figure 6b for horizons $6, 12, 24, 36, 48$.