Estimating the rise in expected inflation from higher energy prices*

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Abstract

When the price of electricity increases by 1%, households' expected inflation increases by 1.2 to 1.5 basis points. If those expectations have become unanchored, then the effect is higher by 0.2 to 1.5 bps. Further, the causal impact of a supply shock to electricity prices is gradual, peaking only 8 to 12 months after impact. This paper arrives at these estimates by exploiting cross-sectional variation from newly-available panel data on expected inflation by Euro area households across region, gender, education, and income together with time-series variation in the cost of energy across region and source, and by proposing new measures of supply shocks. The estimates imply that households under-react to electricity price changes, that the rise in electricity prices in 2021-23 accounted for a small share of the rise in expected inflation, and that anchoring expectations is important in the face of supply shocks.

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1 Introduction

The time-series correlation between average expected inflation in household surveys and real oil prices is 0.54.[1] At the same time, when people are asked about their sources of information about inflation, they invariably mention energy bills near the very top (D'Acunto and Weber, 2024). One naive conclusion from these two facts is that energy prices are a major driver of average inflation expectations. Another conclusion is that individual expectations are overly-sensitive to energy prices. And a third conclusion is that monetary policy should not keep policy rates steady after energy prices spike ("see through supply shocks") because inflation expectations are not anchored.

This paper provides novel estimates of the relation between energy prices and inflation that exploit better data, convincing sources of variation to deal with confounders, and plausibly exogenous supply shocks to electricity prices to assess causality. Namely, on the data, we use the Consumer Expectations Survey (CES) for the EA, which has between 9,000 and 22,000 monthly respondents across 11 countries between 2020:4 and 2023:12. We focus on electricity prices, which were salient in news coverage during this time, and complement them with diesel, gasoline, and overall prices for energy.

On the variation, we exploit both the sharp changes in energy prices during this time, as well as (and especially) their large variation across countries, while using the many respondents per country to control for the large fixed national differences in expected inflation. Variation across regions within a monetary union differences out the potential monetary policy response to energy shocks, as well as other aggregate demand factors that affect both inflation expectations and the demand for energy. Moreover, the cross-sectional size and richness of the CES data provide measures of unanchoring based on disagreement about the long-run that are systematically different both across countries, as well as across demographic and socio-economic groups, so that we can provide sharp estimates of the role of the anchoring of expectations on their response to energy prices.

By focusing on the special features of the EA electricity market, we propose three new plausibly exogenous measures of electricity supply shocks. These address the reverse causality from expected inflation potentially driving demand for all goods including electricity, and thus affecting electricity prices. The first measure relies on a shift-share strategy that exploits cross-region differences in the weight of electricity in consumers' bas-

[1] This is the correlation between the mean expected inflation in the household survey by the Michigan survey research centre, and the ratio of West Texas Intermediate spot crude oil prices and the consumer price index, for a sample between January of 2020 and August of 2024.

kets. The second uses differential regional exposure to conventional time-series shocks to oil supply. The third exploits variation in the use of wind to generate electricity across time and region. We use these shocks to assess the dynamic causal impact of supply shocks on expected inflation from month to month.

The short but large panel with plenty of cross-sectional variation delivers precise estimates. Our baseline results are that a 1% increase in electricity prices raises EA expected inflation by 1.17–1.53 basis points (bps). When measures of the expectations anchor drift between their average level during 2021 and the one during 2023, expected inflation rises by an additional 0.20–1.50bps. Estimates for the price of gasoline and diesel and for US expected inflation are somewhat larger in magnitude, but are less precisely estimated.

A related question is by how much do higher electricity prices in one country relative to another explain the cross-region heterogeneity in expected inflation that we observe. Our estimate is that 1% higher electricity prices in one country relative to others explains 0.19–0.40 bp higher expected inflation, with the effect increasing by up to 0.76 bp if expectations are unanchored. The ratio of the estimates in this cross-section comparison as opposed to the panel one in the previous paragraph is in line with the predictions of a theory where some inattentive agents only observe their own-country electricity prices.

A third related question is by how much expected inflation rises over time in response to an exogenous shock to electricity prices. We find that, following a one-standard deviation shock, expected inflation is sluggish in its response, peaking only after 8–12 months at 2–46bps. The peak of the impulse response can be twice as high when anchoring is below versus above average.

These estimates over-turn the conventional naive conclusions in the first paragraph. First, we zoom in on the period between May of 2021 and 2022, when annual inflation in the euro area (EA) went from 2% to 8.1%, energy prices rose by 33%, and expected inflation increased by 2.3 percentage points.[2] We calculate the predicted increase in expected EA inflation in 2021-22 solely from the rise in energy prices. It is very small.

Second, we estimate the impact on expected inflation of a rise in electricity prices at each date in the sample. When expectations were most unanchored, in the first half of 2022, a doubling of electricity prices over six months would raise expected inflation by 90–120bps. By the end of our sample, a doubling of electricity prices in the second half of 2023 would raise expected inflation by only 55–75bps. That significant boost empirically

[2] Inflation measured using the 12-month change in the log HICP, energy prices using the energy component of the HICP, and expected inflation is the median answer to the Consumer Expectations Survey.

confirms the importance of keeping inflation expectations anchored, as is often argued by central bankers.

Third, we compare our estimates of the impact of electricity prices on expected inflation with the impact that would be expected given their weight in the consumption basket, or given the empirical connection between electricity prices and actual inflation. Our estimates are lower than either of these benchmarks. This leads us to conclude that people are inattentive in absolute terms to energy prices, even if in relative terms they may be more attentive to energy than to other pieces of information. Households under-react to electricity prices, as opposed to being excessively sensitive.

Contribution to the literature: An old literature emphasized the correlation between households' average inflation expectations and oil prices, or the food and energy components of inflation (Trehan, 2011, Arora, Gomis-Porqueras and Shi, 2013). As with most time-series correlations between two aggregate variables, this one is not reliable: it is unstable across samples and countries, and the two variables are mutually correlated with so many other aggregate time series that controlling for any number of them easily flips the sign of the partial correlation.

Coibion and Gorodnichenko (2015) followed by Binder (2018) used individual data on household expectations of inflation over the year ahead and regressed them on the rate of change of wholesale oil prices over the past 6 months and gasoline prices at the pump. Their estimates were 1.6bp and 1.0bp per 1% increase in oil prices, respectively.[3] Because the oil price is the same for all, and the micro data from the Michigan survey is mostly a repeated cross-section with households interviewed only twice, these estimates come almost entirely from time-series variation.[4] Our estimates instead use the country-group variation within a currency union where common monetary policy and aggregate demand factors are controlled for.[5] We are introducing to the literature on expectations an

[3]Unfortunately, this literature is frequently incorrectly cited as evidence that there is a strong link between gas prices and expected inflation, even though the statistically significant coefficients are numerically very small: a rare doubling of oil prices would raise expected inflation by a mere $1.6 \times \ln(2) = 1.11$ percentage points.

[4]With time fixed effects, there is little variation left, and the estimates become quantitatively and statistically indistinguishable from zero (Armantier et al., 2016).

[5]A complementary literature looked at the impact of changes in oil prices on the expected inflation over the next 5 years in the Michigan survey (Celasun, Mihet and Ratnovski, 2012, Binder, 2018), which arguably may respond less to other short-term shocks. These measures of long-term expectations move much less than the one-year-ahead ones. With this limited time-series variation, it is harder to estimate the effect precisely, and results are varied. The few estimates that are statistically significant and different from zero point to a negligible impact of oil prices on expected inflation.

empirical strategy that has been useful to answer other classic macroeconomic questions, like fiscal multipliers and business cycles (Nakamura and Steinsson, 2014, Beraja, Hurst and Ospina, 2019).

Two recent papers have also exploited cross-sectional variation. Binder and Makridis (2022) used state-level variation in real gasoline prices, but measured their impact on indices of consumer sentiment, as opposed to inflation expectations. Wehrhofer (2023) used cross-household variation on when electricity contracts are renewed to find that, in a context of rising energy prices, a renewal raises expected inflation by 1.8bp. However, lacking information on how much the electricity price rose with the new contract, it cannot estimate the size of the coefficient linking a percentage increase in the price of energy to the percentage increase in expected inflation.[6]

Our paper focuses on EA electricity prices, although we also validate our results with gasoline prices, diesel prices, and US data. Closer to us in identification strategy (and written contemporaneously), two studies also use cross-sectional strategies but focus only on gasoline prices. Hajdini et al. (2024) regress weekly expected inflation on gasoline prices times the share of households in a US county that use their own car for commuting. They explain levels of expectations within one week alone, whereas we focus on their changes over six months or more, so we can answer macro questions. Our impact results are consistent with theirs. Jo and Klopack (2025) measured the impact of temporary changes in gasoline taxes on inflation expectations in five US states in 2022. Their estimates are one order of magnitude larger (13bp) than ours or any other in the literature. Perhaps the difference is explained by the fiscal implications of the tax changes, or perhaps by how households perceived pre-tax energy prices to be persistent but knew that these tax changes were temporary, in which case intertemporal substitution may explain the difference.

To our knowledge, this is the first paper to use household micro data to empirically investigate whether the impact of energy prices on expected inflation is different when expectations are unanchored. Theories of inattention naturally link unanchoring to responsiveness to shocks (Angeletos and Lian, 2016, Mankiw and Reis, 2010), and we theoretically justify our regression building on models by Angeletos, Huo and Sastry (2020),

[6]Earlier studies used the very limited US cross-sectional variation to show that estimates could vary across states and groups. Coibion and Gorodnichenko (2015) had a version of their baseline estimate broken by states and groups. More explicitly, Binder (2018) used the 4 regions in MSC to separately estimate the impact of oil prices on inflation expectations, and found that these line up with expenditure shares, and also correlated expected gas prices and expected headline inflation across the regions.

Flynn and Sastry (2024), and Reis (2020). There are only two (distant) related papers. Bonomo et al. (2024) finds unanchoring linked to a change in monetary policy in Brazil, while we find a smaller but still significant amount of unanchoring during 2021-22 in the EA linked to energy prices. Pfäuti (2023) proposes a model in which after an energy shock, inflation surges, the public's attention to inflation rises, and negative supply shocks become more inflationary. It estimates that between a low- and high-attention regime the impact of a negative supply shock on inflation expectations doubles. This is consistent with our estimates.

Using the focus on electricity prices, as opposed to oil, we put forward three new instruments for supply shocks in an energy market. Kilian and Zhou (2022) used a combination of sign and zero restrictions in a vector autoregression to identify the effects of gasoline price supply shocks. Känzig (2021) constructed high-frequency changes in the oil price expectations reflected in oil price futures around OPEC production announcements in a local projection. Closer to this paper, Miyamoto, Nguyen and Sergeyev (2024) followed Känzig (2021) but separated periods where nominal interest rates were at the zero lower bound in Japan to control for the confounding effect of monetary policy and aggregate demand. Together, these studies found that a 1% increase in gasoline prices raises expected inflation by 1.8–3bp within the first three months, but zero within 6 months.[7] Our instruments are different and, hopefully, can be applied to learn more about the impact of electricity, an increasingly relevant source of energy, on other macroeconomic outcomes. Our estimates are also different, since we find a larger and more persistent effect, perhaps because we focus on a sample where there were large shocks and much variation in expected and actual inflation.

Turning to the applications of our results, Dietrich (2024) finds that households' aggregate inflation expectations put relatively more weight on their expectations of food and energy components than on other components in their basket. Burgi, Srivastava and Whelan (2025) finds that the correlation between household expectations of inflation with the same household's expectation of gasoline prices is lower than the weight of gasoline in the consumption basket. Both are consistent with our conclusion: household expectations under-react to energy prices, even if in relative terms they react more to these than to other prices.

Finally, a recent literature has tried to provide an account the 2021-23 inflation disaster (Dao et al., 2024, Bernanke and Blanchard, 2025). The role of measures of inflation expec-

[7] Wong (2015) and Aastveit, Bjørnland and Cross (2023) found even weaker responses.

tations (Reis, 2023) and measures of energy prices (Gagliardone and Gertler, 2023) have been discussed separately, as well as jointly (Acharya et al., 2023), but quantifying how much energy shocks contributed to the rise in expected inflation has not been answered.

Outline: The paper is structured as follows. The next section discusses the data and the variation we will exploit, while section 3 writes down a theory of expectations that justifies an empirical strategy. Section 4 presents our empirical estimates of the link between energy prices and inflation expectations. Section 5 presents our measures of supply shocks to electricity prices, and our estimates of their dynamic impact on inflation expectations, together with how they are affected by the anchoring of expectations. Section 6 discusses the implications of our estimates for the contribution of electricity shocks to the 2021-22 drift in expected inflation, to the importance of policy keeping inflation expectations anchored, and to the debate on under- or over-reaction of expectations to energy prices. Section 7 concludes.

2 The setting and variation in the data

The period between 2020 and 2023 had a great deal of variation in EA inflation over time and across regions. It turns out that the same is true for expected inflation and for electricity prices—across time, regions, as well as population groups—making this a suitable time to study the link between these two variables.

2.1 Expected inflation

Let $\pi^e_{i,c,g,t}$ be the answer by household i, who is a resident of region/country c, and is part of a demographic or socio-economic group g, in month t, to the question: "How much higher (lower) do you think prices in general will be 12 months from now in the country you currently live in?" The data come from the ECB's CES, where i goes from 9,000 to 22,000 respondents, depending on the month, c are eleven countries in the euro area, there are eight demographic groups g from crossing gender (male/female), income bracket (above/below 60th percentile), and education (college/below), and the months t go from April of 2020 to December of 2023 for six countries, and from April 2022 for the remaining five (first available in February of 2024).[8]

[8] Appendix A has more information on the data.

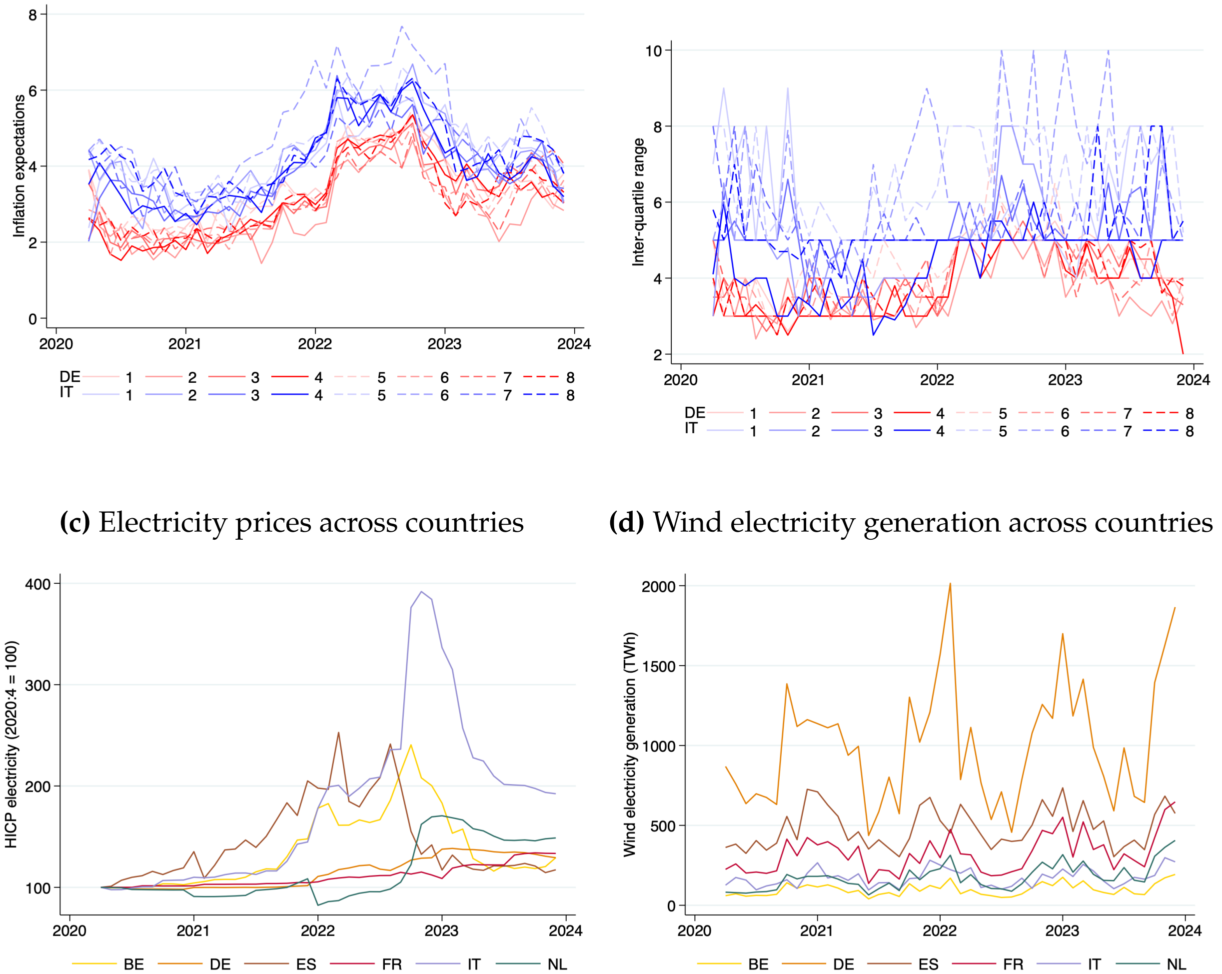
Figure 1: Time-series and cross-sectional variation in the data

(a) Expected inflation: Germans and Italians

(b) Anchored expectations: Germans and Italians

(c) Electricity prices across countries

(d) Wind electricity generation across countries



Note: Panel (a) plots the average expected inflation 12-months ahead by country (for Germany and Italy) and by demographic group. Panel (b) plots the average inter-quartile range of expected inflation three years ahead within country (for Germany and Italy) and demographic group. Groups are defined as follows: male (1,2,3,4) or female (5,6,7,8); college education (3,4,7,8) or below (1,2,5,6); and income bracket above 60th percentile (2,4,6,8) or below (1,3,5,7). Panel (c) plots HICP electricity rescaled with base period 2020:4 for the 6 largest countries in the survey. Panel (d) plots wind electricity generation for the 6 largest countries.

Panel (a) in figure 1 shows the variation in the data, by plotting average expected inflation for the eight groups in two of the countries, following Fofana, Patzelt and Reis (2024). Households in different countries belonging to different groups systematically disagree on what inflation will be. At an extreme, a woman resident of Italy without college that is poorer usually expects much higher inflation than a richer German man with a college degree. At the same time, and important for our goal, beyond these country-group fixed effects, there is significant variation during the sample, with households switching roles between optimists and pessimists.

We measure actual inflation as the log change between the harmonised index of consumer prices from Eurostat in date t and 12 months earlier, per country: $\pi_{c,t}$.[9] The average year-on-year inflation in the last year is $\bar{\pi}_{c,t} = \sum_{j=1}^{12} \pi_{c,t-j}/12$.

2.2 Inflation expectations anchor

The degree of anchoring of inflation expectations within a country-group is $a_{c,g,t}$, where a higher $a_{c,g,t}$ stands for more unanchored.

The literature has used data on longer-term inflation expectations to measure unanchoring in two ways.[10] One uses higher-order moments of the distribution of inflation expectations, arguing that disagreement among households reflects an unanchoring of expectations. This would be the case in models with incomplete information and dispersed expectations. The other uses the difference between expected inflation and the inflation target, arguing that unanchoring reveals itself as a loss of credibility of the target. Models of learning and reputation support these measures.[11]

We use one measure from each of these two classes: the 6-month change in the interquartile range of expected inflation 3-years ahead within country-group, and the 6-month change in the absolute difference between expected inflation 3-years ahead and the ECB's inflation target averaged by country-group.

Panel (b) in figure 1 shows the first of these measures for the same two countries and eight groups. Again, there is a clear country fixed effect: Italians have less anchored expectations than Germans. Again as well, there is significant variation across group-time, as the expectations of different groups un-anchor and then re-anchor during this sample.

2.3 Energy prices

Electricity markets in the EA are segmented across regions (that can include more than one country) connected by distribution networks that use different sources of energy (like renewables, nuclear, or natural gas). The rumours of an imminent Russian invasion of

[9] Figure A8 shows that inflation varied greatly across countries and over time in this short period.

[10] See, for instance, Bonomo et al. (2024).

[11] A third useful measure of unanchoring is to estimate the responsiveness of individual expectations to shocks (Carvalho et al., 2023, Gáti, 2023, Reis, 2026).

Ukraine raised prices everywhere at the end of 2021, but both the size of this increase and its reversal varied widely across regions. Moreover, some countries used electricity subsidies while others did not, some countries have retail markets with long-lived contracts that fix electricity prices while others have variable prices, and some have more pass-through from wholesale to retail prices than others. All together, there is significant regional variability of prices during this time: panel (c) of figure 1 shows the log of the Eurostat index for harmonised electricity prices per country paid by households inclusive of taxes and subsidies ($e_{c,t}$).[12]

This joint time and cross-section variability is higher than the one for the price of oil or gasoline, which helps to identify the impact of energy prices on expectations. Moreover, electricity is, arguably, just as salient as gasoline for households, and it has a larger share of energy spending.[13] We will also study the impact of gasoline and diesel prices in the regions of the EA as well as the HICP for the overall energy sector, which includes all sources. The appendix plots these over time.[14]

2.4 United States data

The FRB New York Survey of Consumer Expectations provides US household inflation expectations $\pi^e_{i,c,g,t}$ from June of 2013 onwards. It only covers approximately 1,300 respondents, across the 50 US states, so that each group-state (c, g) cell often only has a few respondents. The measures of anchoring are therefore imprecise, and often impossible to calculate. Boldly, we measure $a_{c,g,t}$ anyway, as long as there are 5 or more respondents.

An alternative is the Michigan survey of consumer expectations. Its main virtue is that it covers a much longer sample, starting in 1978. However, it has many limitations. First, it splits the respondents into only four large US regions. Even though we can use the variation over socio-economic groups g as before, there is much less variability over regions c, constraining our empirical strategy to answer the first question. Second, the sample of individuals i is even smaller, covering 500 to 700 households per wave. Even over only 4 regions, disagreement is calculated over groups that half of the times have fewer than 50 respondents, and sometimes as few as 4. It is impossible to ascertain the impact of anchoring. Third, the longer time-series span also means that any estimates

[12]The counterpart for the whole EA is e_t. This is a nominal variable, but since we will include inflation as a control variable in all regressions, using instead its real equivalent makes little difference.

[13]In the European HICP energy consumption basket, electricity has a weight of 25% versus 10% for oil and petroleum products.

[14]See figure A5 for diesel and gasoline price changes across countries.

rely more on time-series variation as opposed to cross-section.

To measure US state-level electricity prices, we use residential retail electricity prices from the US Energy Information Administration. The cross-region variability is significantly smaller than in the EA, reflecting the more integrated market. This is even more so for retail gasoline prices, which come from the same source, and which co-move very closely with the national oil prices for West Texas Intermediate (WTI).

3 A model of expectations

This section puts forward a model of expectations linking energy prices to expected inflation so that we can interpret the variation in the data. The micro-foundations are relegated to appendix B; they build on the theoretical literature on inattention.

3.1 Components of expectations

Actual inflation in a country depends mechanically on energy prices $e_{c,t}$ because it has a weight of ω on the consumption basket.[15]

Beyond this direct effect, energy prices provide a signal on how other prices will change, partly because they change costs of production, partly because of shifts in demand across sectors, and partly because of strategic interactions between firms. Let that information component be denoted by $x_{i,c,g,t}$, which may be different for each household in a country and a group depending on their attention to news.

Each group in a country has characteristics that persistently affect both their expectations, as well as how sensitive they are to individual signals. The former is already captured in $x_{i,c,g,t}$. The latter is captured by a term $\lambda^{\varepsilon}_{c,g}\varepsilon_{i,c,g,t}$, which can be correlated with the price of energy.

Finally, all other individual-group-country-time determinants of expectations that are orthogonal to energy prices are captured in the variable $u_{i,c,g,t}$.

All combined, expected inflation $\pi^e_{i,c,g,t}$ depends on energy prices directly through the consumption basket, indirectly through both information and through sensitivity to information, and depends on other independent factors as well:

$$\pi^e_{i,c,g,t} = \omega e_{c,t} + x_{i,c,g,t} + \lambda^{\varepsilon}_{c,g}\varepsilon_{i,c,g,t} + u_{i,c,g,t}\,. \tag{1}$$

[15] It is straightforward to allow this weight to be country specific, so that the regression described below will measure the average of these weights.

3.2 From information to expectations

The information in energy prices can be decomposed into a union-wide component e_t and what is specific to the region, $e_{c,t} - e_t$. If the household pays attention, it will put some weights on these two pieces of information that reflect their forecasting value (optimally or not), call them ϕ and ϕ^c, respectively. With rational expectations and imperfect information, we would have:

$$x_{i,c,g,t} = \phi e_t + \phi^c (e_{c,t} - e_t) + u^x_{i,c,g,t} \,. \tag{2}$$

The term $u^x_{i,c,g,t}$ absorbs all other information beyond energy prices that is useful to forecast, including constants.[16]

However, we allow for the possibility that expectations are not rational. Following the literature on inattention, only a share λ of respondents at a date are aware of the signals. The remainder, $1 - \lambda$ are either completely inattentive (so their individual x is zero) or partially so, only paying attention to their local conditions as a signal.[17] The weight they put on the one pice of information they have—local energy prices—is ϕ^a, which need not be the optimal weight from the Kalman filter. For these inattentive agents:[18]

$$x_{i,c,g,t} = \phi^a e_{c,t} + u^x_{i,c,g,t} \,. \tag{3}$$

Inattention also affects the sensitivity of expectations to news, since they are filtered through a noisy channel. Expectations deviate from the average of $x_{i,c,g,t}$ by an individual random error that reflects an individual-specific idiosyncratic noise $u^\varepsilon_{i,c,g,t}$.

It is a general result in rational inattention that how much noise is in these signals depends on the costs of attention as well as on the marginal benefit of information. Under a linear-quadratic approximation to a rational inattention model, $\varepsilon_{i,c,g,t}$ is a standard normal variable and so $\lambda^\varepsilon_{c,g}$ is the cross-sectional standard deviation of these signals. This depends on group and country, because these have different marginal costs of attention. It also depends on energy prices because of diminishing returns to the value of knowing their precise value. The appendix further shows that the interquartile range of forecasts

[16] Muth (1961) is an early version of this model of rational expectations.

[17] As with the consumption baskets, it is also the case that we could allow this weight to be country-specific, and the regression estimate would be of the average attention parameter.

[18] This formulation nests the combined approaches of Lucas (1972) and Mankiw and Reis (2002), or more recently Angeletos and Lian (2016).

$a_{c,g,t}$ is a statistic for this intensity of attention. Therefore, we can approximate:[19]

$$\lambda^{\varepsilon}_{c,g}\varepsilon_{i,c,g,t} \approx \lambda^{\varepsilon} e_{c,t} a_{c,g,t} + u^{\varepsilon}_{i,c,g,t} \tag{4}$$

3.3 The link between energy prices and inflation expectations

Combining all of the ingredients, summing over agents within a country-group, and grouping terms, gives the following model for observed expectations:

$$\begin{aligned}\sum_i \pi^e_{i,c,g,t} = {} & (\omega + \lambda\phi + (1-\lambda)\phi^a)e_t + (\omega + \lambda\phi^c + (1-\lambda)\phi^a)(e_{c,t} - e_t) \\ & + (1-\lambda)\lambda^{\varepsilon} e_{c,t} a_{c,g,t} + \sum_i (u^x_{i,c,g,t} + u^{\varepsilon}_{i,c,g,t} + u_{i,c,g,t})\,.\end{aligned} \tag{5}$$

The top line shows the combined effect of energy prices on inflation expectations through: their direct impact on inflation (ω), the rational expectations information effect on making forecasts (ϕ^c, ϕ), and the limited information effect of local variables (ϕ^a). More inattention, captured by a smaller λ, mitigates the value of information. This line separates into two terms the impact of country-specific changes in the price of energy ($e_{c,t} - e_t$) relative to aggregate ones e_t. We would expect the latter to be larger since EA energy prices are more relevant to forecast inflation than region-specific ones.

The first term in the second line shows the interaction between energy prices and a measure of the anchoring of expectations via dispersion. A higher cost of attention produces more noise in individual signals, which leads to higher dispersion. The parameter λ^{ε} captures how sensitive the relative value of that attention is.

Finally, the last term in the second line including the u's is not zero when averaged over time, and it may be correlated with energy prices. Starting with the rational expectations residual $u^x_{i,c,g,t}$, it includes both a constant, associated say with the inflation target, as well as other time-varying variables that may be useful to forecast inflation, like past inflation or the state of monetary policy. Next, the group- and country-specific features of inattention in $u^{\varepsilon}_{i,c,g,t}$ appear as country-group fixed effects. Finally, there are persistent differences in actual inflation across countries (e.g., due to Balassa-Samuelson effects) that make the $u_{i,c,g,t}$ not zero.

[19] This follows the formulation in Flynn and Sastry (2024) of the classic approach of Sims (2003).

3.4 An empirical specification

All combined, the model suggests regressing expected inflation on energy prices and a measure of anchoring, while including fixed effects and/or aggregate variables to control for confounders. Having cross-country and cross-group variation is important to sharply estimate the information impact of energy prices on expectations. Having country-group variation is essential to pin down the effect of anchoring. Country and group fixed effects are important because of the large systematic differences in expected inflation in the data.

Whether to include time fixed effects is debatable because they change the question being asked. On the one hand, these fixed effects are the most effective way to deal with aggregate confounders in the u terms. On the other hand, those fixed effects would absorb the first term on the top line, so the estimate would be: $\omega + \lambda\phi^c + (1-\lambda)\phi^a$, which theory predicts is significantly smaller than $\omega + \lambda\phi + (1-\lambda)\phi^a$. We will discuss both and compare them in light of the theory.

We take equation (5) to the data by estimating the following unbalanced-panel regression:

$$\Delta^6 \pi^e_{i,c,g,t} = \beta \Delta^6 e_{c,t} + \gamma \Delta^6 e_{c,t} \times \Delta^6 a_{c,g,t} + \alpha_{c,g,t} + \boldsymbol{\theta} y_{c,t} + \varepsilon_{i,c,g,t} \,. \tag{6}$$

The operator Δ^h refers to the change in a variable relative to its value h months ago. Therefore $\Delta^6 \pi^e_{i,c,g,t} = \pi^e_{i,c,g,t} - \pi^e_{i,c,g,t-6}$, as long as a household answered the survey both in month $t-6$ and again in month t. We multiply expected inflation by 100, so it is measured in basis points. Then, $\alpha_{c,g,t}$ are combinations of country, group, and/or time fixed effects, and $y_{c,t}$ are controls for aggregate country-specific variables.

The two coefficients of interest are β and γ. The first answers the question: by how many basis points does expected inflation over the next year increase on average when electricity prices rise by 1%? We take the theory to the data in 6-month first differences because there was a marked difference in the updating of average expected inflation across countries during the sample period of rising inflation. This may be due to different levels of trust in monetary policy across countries, or to country-specific characteristics affecting prices. First differences over time partly eliminate some of these differences across group-countries, with the remainder absorbed by the country and group fixed effects.[20]

The second coefficient γ measures, from a steady state where the anchor remains sta-

[20] Choosing $h = 12$ ensures that there is no overlap between the observation frequency and the forecast horizons, while choosing $h = 1$ maximizes the number of observations but introduces noise both in expectations and in energy prices, which are volatile and transient. We choose $h = 6$ as a compromise, and discuss robustness in section 4.3.

ble, by how many basis points more will 1-year ahead expected inflation rise with a 1% increase in electricity prices if un-anchoring is higher, as measured by a 1-percentage point higher interquartile range of 3-year ahead inflation expectations. Coincidentally, the average disagreement across all households in 2023 was 1.05 percentage points higher than on average in 2021, so γ measures the approximate extra impact of an energy shock between these two years. The theory pointed to the role of unanchoring this period, as opposed to lagged, and the correlation of disagreement over 6 months is not lagged. The theory is also helpful in stating that it is the change, as opposed to the level, of unanchoring that should be in the regression.

Finally, note that there is no variation in i in any of the right-hand side variables. These are seemingly unrelated regressions, which use the individual variation within country-group to sharpen the estimates of the common coefficients of interest. It is the cross-sectional c, g variation, the novelty in this paper, that sharpens the estimates of β and is crucial to identify γ on the effects of anchoring.

4 Empirical estimates of the impact of energy prices on expected inflation

This section presents the estimates of equation (6).

4.1 Baseline estimates

In the baseline specification, we include country and group fixed effects, and we control for aggregate demand using past inflation $\bar{\pi}_{c,t-6}$ and changes in ECB monetary policy $\Delta^6 r_t$. These two variables capture the main concerns suggested by the theory. First, that the ECB closely watches both expected inflation and energy prices, policy responds to them, this affects inflation and aggregate demand, and through them expectations and energy prices. Second, that a shock to aggregate demand will both raise inflation and expectations of it directly, as well as increase the demand for all goods including energy, and so raise energy prices.

The first column of Table 1 shows that a 1% increase in electricity prices is estimated to raise expected inflation by 1.40bp if there is no change in anchoring. If disagreement increases by as much as the difference between 2021 and 2023, then the higher electricity prices add an extra 0.60bp effect, for a total effect of 2bp. Both effects are statistically significant.

The fit of the regression is low, as expected given that no explanatory variable captures the household variation in expected inflation. The second column instead pools observations within country-group, by replacing the left-hand side variable with $\Delta^6 \pi^e_{c,g,t} = \Delta^6 \sum_i \pi^e_{i,c,g,t} / I_{c,g,t}$, the change in the average expected inflation within a country-group. The R^2 dramatically rises, as expected. The effect without unanchoring stays roughly the same, at 1.17bp, while the impact of unanchoring falls to 0.20bp. Both remain significant.

The third column uses as the measure of unanchoring the distance of 3-year expected inflation from target. The effect of higher electricity prices with no change in anchoring is similar, at 1.22bp. Since this measure of unanchoring increased by 76bp between 2021 and 2023, its coefficient now implies that unanchoring contributed to an extra 1.98bp increase in expected inflation following a 1% rise in electricity prices, a larger effect than in the baseline.

The next three columns explore the role of the cross-country-group variation in driving the results. Column four shows the results using only country, but no group, variation by aggregating across the groups, thus replacing $a_{c,g,t}$ by $a_{c,t}$. The impact without unanchoring is slightly larger, while the extra boost from unanchoring is much larger with a point estimate of 1.50bp. With less identifying variation, the confidence bands are wider.

In the other direction, column (5) includes country-group fixed effects to ascertain whether there is a bias from systematic differences in the way groups within countries changed their expectations during this time. It seems not to be the case, as the estimates are very close to the baseline.

The sixth and final column clusters the standard errors by country rather than month to understand the variation in the cross-section as opposed to the time-series. The precision of the estimates deteriorates, but the coefficients are still significant at the 5% level.

4.2 Cross-country comparisons

The baseline estimates of β and γ reveal the differential impact of energy prices on the expected inflation of two people both at the same time and across time. A different question is what is the impact of the regional component of energy prices on expected inflation for the whole EA. That is: by how much does the resident of a country expect higher inflation on account of electricity prices being higher in their country?

Using time fixed effects delivers the estimates that answer this question. As dis-

Table 1: The impact of electricity prices on expected inflation

Revision of expectation	(1)	(2)	(3)	(4)	(5)	(6)
Change in electricity prices	1.404***	1.167***	1.222***	1.531***	1.397***	1.404**
	(0.296)	(0.103)	(0.229)	(0.329)	(0.294)	(0.470)
Change in electricity prices × Unanchoring	0.596***	0.199***	2.609***	1.499***	0.617***	0.596**
	(0.171)	(0.061)	(0.466)	(0.374)	(0.173)	(0.250)
Average past inflation	0.004	-0.025***	-0.001	0.009	0.005	0.004
	(0.028)	(0.009)	(0.025)	(0.027)	(0.028)	(0.075)
ECB deposit rate change	-0.436***	-0.449***	-0.442***	-0.438***	-0.437***	-0.436
	(0.119)	(0.031)	(0.113)	(0.118)	(0.119)	(0.266)
Observations	362756	2472	362756	362756	362756	362756
R^2	0.016	0.343	0.018	0.016	0.016	0.016
Country & group fixed effects	Yes	Yes	Yes	Yes	No	Yes
Country-group fixed effects	No	No	No	No	Yes	No

Note: This table presents estimates of the regression in equation (6): $\Delta^6 \pi^e_{i,c,g,t} = \beta \Delta^6 e_{c,t} + \gamma \Delta^6 e_{c,t} \times \Delta^6 a_{c,g,t} + \alpha_c + \eta_g + \theta \bar{\pi}_{c,t-6} + \rho \Delta^6 r_t + \varepsilon_{i,c,g,t}$. Column (1) has the baseline estimates, (2) uses the average $\pi^e_{c,g,t}$ as the dependent variable, (3) uses as measure of unanchoring the deviation of long-run expected inflation from target, (4) uses anchoring at the country level only $a_{c,t}$, and (5) includes country-group fixed effects. In parentheses are standard errors clustered by month for the regressions using individual expectations. Column (6) instead clusters by country.

cussed in section 3.3, the estimated coefficient β shifts from capturing ϕ in the theory—the informativeness of EA electricity prices for the rational-expectations forecast of future inflation—to capturing ϕ^c—the informativeness of an individual country's electricity price relative to the union to that same forecast. Since a regression of actual inflation on e_t and $e_{c,t} - e_t$ in our sample period delivers an estimate of the first coefficient that is between 4.6 and 5.7 times larger than the second one (depending on the specification) and ϕ and ϕ^c are rational-expectations parameters, this suggests that ϕ is about five times larger than ϕ^c. Therefore, the estimates of β should be significantly lower with time fixed effects. Similarly, since γ is identified from the change in expected inflation in one country relative to another where electricity prices rose by less and expectations were more anchored relative to the other country-groups, then, with time fixed effects, we expect the estimates to be smaller and less precise.

Table 2 instead shows estimates that deal with the time-series variation in different ways. The first four columns mimic the first four columns of table 1. Matching the theory's predictions, the estimates of β are about four times smaller. They are still statisti-

Table 2: The impact of electricity prices on expected inflation with time fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)
Change in electricity prices	0.372**	0.193**	0.327*	0.395**	1.047***	1.374***
	(0.181)	(0.094)	(0.173)	(0.185)	(0.308)	(0.312)
Change in electricity prices × Unanchoring	0.146	-0.013	0.758***	-0.056	0.432***	0.521***
	(0.089)	(0.050)	(0.260)	(0.191)	(0.113)	(0.156)
Average past inflation	0.004	-0.049**	-0.007	0.007	-0.091*	-0.025
	(0.079)	(0.023)	(0.080)	(0.079)	(0.045)	(0.030)
ECB deposit rate change					0.015	-0.391***
					(0.190)	(0.123)
Observations	362756	2472	362756	362756	235203	362756
R^2	0.032	0.573	0.032	0.032	0.024	0.017
Country & group fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	No	No
Energy & pandemic controls	No	No	No	No	Yes	No
Fiscal policy controls	No	No	No	No	No	Yes

Note: This table estimates the regression in equation (6) focussing on cross-country variation only. Column (1) has the baseline estimates, (2) uses the average $\pi^e_{c,g,t}$ as the dependent variable, (3) uses as measure of unanchoring the deviation of long-run expected inflation from target, (4) uses anchoring at the country level only $a_{c,t}$. Dropping the time fixed effects, column (5) instead adds controls for other energy price changes using the HICP for common transport fuels and natural gas, and changes in the Oxford COVID stringency index. Column (6) instead adds fiscal policy controls, using changes in the quarterly primary surplus, and an indicator for a new or any active policy measure labelled "support for energy bills" as collected by Eurofound EU PolicyWatch. The coefficients on these additional control variables are reported in appendix table A11. In parentheses are standard errors clustered by month for the regressions using individual expectations.

cally significant. The estimates of γ are also uniformly smaller, highlighting that it was the unanchoring and re-anchoring during this period that drives the estimates in table 2, as opposed to the regional differences in the extend of anchoring.[21]

While time fixed effects change the question, one virtue of including them is that they deal with potential omitted-variable bias from any aggregate confounding factor.[22] The fifth and sixth columns in the table investigate the potential role of omitted variables in explaining what drives the estimates with time fixed effects. Column (5) includes time-

[21]Going in the opposite direction, table A6 in the appendix estimates equation (6) separately for each country, giving a set of $\{\beta_c, \gamma_c\}$ estimates that only use the variation in anchoring across groups, and so is close to a time-series regression. Confirming the importance of the country-group variation, this results in very imprecise estimates that are widely different across countries.

[22]Even more radically, if one includes country-time fixed effects, then almost any conceivable confounders would be dealt with, but the interpretation of the estimates becomes peculiar and, for macro purposes, uninteresting. In any case, this is infeasible with our data, since electricity prices do not vary across people within the same time-country.

varying confounders at the country level coming from the supply side of the economy with measures of supply chain disruptions and other drivers of energy prices. Column (6) instead includes controls for national fiscal policy. The results are very close to those in table 1. This supports our interpretation of the role of the time fixed effects in answering a different question and not solely controlling for omitted variables.

4.3 Robustness

Appendix C shows estimates for several alternative specifications to explore the robustness of the results.

First, we consider alternative compositions of the panel. Table A2 considers a balanced panel of only six countries, weights observations by the number of respondents in the country-group, or uses median as opposed to mean expected inflation. These make little difference. Table A3 winsorizes respondents per wave at the 5th and 95th percentile, as opposed to censor them by 20%, since in this time of high and volatile inflation some seeming outliers can perhaps be informative. The estimates are twice as large when we do so. Table A4 further includes only first responders to the survey, since households can change their responses across waves. The point estimates change little but, as expected since so many observations get dropped, the confidence bands are wider.

Second, to understand the role of the cross-sectional variation in the data we consider different interactions of fixed effects in table A5, both a full set of time-country-group joint fixed effects, which even more aggressively isolates the role of the cross-group-regional variation, and well as country and group fixed effects introduced without the other. The estimates confirm the role played by the cross-sectional variation, both across countries and groups, in pinning down our estimates.

Table A7 varies horizon h, by using 1-month, 4-month, and 12-month changes in expected inflation and electricity prices. This makes little difference.

Table A8 uses instead the change in electricity price inflation as opposed to its level, in case of concerns for stationarity of electricity price inflation. The estimates are harder to interpret and disconnected to the theory but remain significant.

Turning to anchoring, in table A9 we also include the measure of anchoring by itself together with its interaction with electricity prices, in order to deal with some possible bias from omitted variables. The estimate of β barely changes, while the estimate of ω is half as large. Another concern is that it might be that anchoring is proxying for lagged high inflation that induces households to update expectations with more information.

To investigate this state dependence, we include both anchoring and lagged inflation as interaction terms with the change in electricity prices in the regression. The coefficient on anchoring remains unchanged and statistically significant.

Finally, in table A10, we instead calculate Huber-White standard errors, Driscoll-Kraay standard errors, as well as clustered standard errors per demographic group, two-way clustered standard errors, and clustering at the country level. They confirm the baseline results.

4.4 Other measures of energy prices

In our baseline specification, we measured $e_{c,t}$ using the HICP electricity price index, which includes many goods. The first column of table 3 uses instead a survey measure of the prices paid by households for electricity in their homes, collected by a regulatory-funded public project for the major capital cities in the different countries. The estimate of the impact of a 1% increase in electricity prices is 52% higher, while the effect of anchoring is half as large.

The second column includes the squared price of electricity. It could be that sharp changes in energy prices have a large impact on expected inflation even for unchanged disagreement in expectations, and our anchoring measure was proxying for this. This turns out not to be the case: the coefficient on squared electricity prices is statistically insignificant. More important, the coefficient on anchoring barely changes.

The third and fourth columns use a different measure of energy prices: the cost of filling one's car at the pump. This is the conventional measure that the literature has used. As we discussed in section 2, it varies less across regions, so our empirical strategy will be less successful in pinning down the relation between energy prices and inflation. The third column uses diesel prices, while the fourth column uses gasoline prices. The estimates with the former are much larger, while those with the latter are much smaller. Both are less precisely estimated.

The fifth column uses instead the HICP for energy, which includes electricity, diesel, gasoline, and all other types of energy bought by households. The impact of a 1% increase in energy prices on expected inflation is 4.2 basis points, with an additional 1.3 basis points if expectations are unanchored. These are three times higher than our estimates with electricity alone.

Finally, the sixth column compares the effect in countries according to the structure of their retail market for electricity. We calculate the correlation of HICP electricity prices

Table 3: Different measures of energy prices

	(1)	(2)	(3)	(4)	(5)	(6)
Change in energy prices	2.130***	1.344***	4.323***	0.297	4.243***	
	(0.264)	(0.260)	(0.630)	(0.983)	(0.500)	
Change in energy prices × Unanchoring	0.305**	0.540***	0.862***	2.335***	1.252***	
	(0.150)	(0.154)	(0.293)	(0.445)	(0.221)	
Change in electricity prices, squared		1.156				
		(0.801)				
Average past inflation	0.019	0.006	-0.063**	-0.054**	0.016	0.008
	(0.030)	(0.028)	(0.023)	(0.026)	(0.023)	(0.028)
ECB deposit rate change	-0.356***	-0.481***	0.176	-0.280**	-0.206**	-0.462***
	(0.104)	(0.137)	(0.127)	(0.138)	(0.081)	(0.124)
Change in elec. prices × Flexible						1.852***
						(0.437)
Change in elec. prices × Rigid						0.599**
						(0.279)
Change in elec. prices × Unanchoring × Flexible						0.715***
						(0.210)
Change in elec. prices × Unanchoring × Rigid						0.279
						(0.218)
Observations	344597	362756	362756	362756	362756	362756
R^2	0.021	0.016	0.021	0.016	0.024	0.017

Note: This table presents estimates of the regression in equation (6): $\Delta^6 \pi^e_{i,c,g,t} = \beta \Delta^6 e_{c,t} + \gamma \Delta^6 e_{c,t} \times \Delta^6 a_{c,g,t} + \alpha_c + \eta_g + \theta \bar{\pi}_{c,t-6} + \rho \Delta^6 r_t + \varepsilon_{i,c,g,t}$. Column (1) uses the household energy price index to measure $e_{c,t}$, (2) includes as a regressor $e^2_{c,t}$, (3) uses diesel prices to measure $e_{c,t}$, (4) uses gasoline prices to measure $e_{c,t}$,(5) uses HICP energy, and (6) includes an interaction dummy on whether the retail electricity market is more flexible or not. Countries are categorised as more flexible if the semi-annual correlation of HICP electricity with household medium band (DC) retail electricity prices from 2010–2024 is above 0.9 (BE, DE, FI, FR, IT), otherwise as more rigid (AT, ES, GR, IE, NL, PT). In parentheses are standard errors clustered by month.

with household medium-band retail electricity prices between 2010 and 2024, and group countries on whether that correlation is above 0.9 (5 countries) or below it (6 countries). As expected, the effect on household expectations is higher when the passthrough is higher for retail electricity prices.

4.5 United States estimates

Table 4 presents a version of table 1 but using the US data from the SCE.

As we discussed in section 2, we expect the coefficient on anchoring to be imprecisely

Table 4: The impact of energy prices on expected inflation in the US Fed SCE

	(1)	(2)	(3)	(4)	(5)	(6)
Change in energy prices	1.804**	1.942***	1.939**	0.300	1.690***	0.864***
	(0.740)	(0.721)	(0.743)	(1.049)	(0.301)	(0.220)
Change in energy prices × Unanchoring	-0.024	0.058	0.766	0.002	0.062	0.043
	(0.132)	(0.100)	(0.478)	(0.137)	(0.086)	(0.049)
Average past inflation	0.002	-0.094	0.005	-0.003	-0.064	-0.067
	(0.085)	(0.061)	(0.085)	(0.097)	(0.077)	(0.081)
Change in FFR	0.047	-0.058	0.033		-0.169	-0.160
	(0.397)	(0.408)	(0.401)		(0.343)	(0.421)
Observations	17903	7100	17903	17903	17907	17907
R^2	0.016	0.008	0.017	0.022	0.018	0.017
State & group fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	No	No	No	Yes	No	No

Note: This table presents estimates of the regression in equation (6): $\Delta^6\pi^e_{i,c,g,t} = \beta\Delta^6 e_{c,t} + \gamma\Delta^6 e_{c,t} \times \Delta^6 a_{c,g,t} + \alpha_c + \eta_g + \theta\bar{\pi}_{c,t-6} + \varepsilon_{i,c,g,t}$ for the US SCE. Columns 1–4 show estimates for state-level electricity prices. Column (1) has the baseline estimates, (2) uses the average $\pi^e_{c,g,t}$ as the dependent variable, (3) uses as measure of unanchoring the deviation of long-run expected inflation from target, and (4) includes time fixed effects. Columns (5) and (6) respectively use the national gas and oil price instead of regional electricity prices. Past inflation is computed using the state-level CPI from Hazell et al. (2022). We exclude all individuals part of state-demographic groups with less than 5 members in the month. In parentheses are standard errors clustered by month for the regressions using individual expectations.

estimated, since the small number of observations makes measures of the anchor very noisy. Table 4 confirms this is the case, as the estimates of γ are statistically insignificant and have wide confidence intervals.

Turning to β, the US results are broadly consistent with those for the EU. The baseline estimate in the first column is that a 1% increase in electricity prices raises expected inflation by 1.80bp, compared with 1.40bp for the EU. This is robust to using the average expectation as the dependent variable (second column) or to the alternative measure of unanchoring (column three). The alternative question involving time fixed effects leads to an estimate of 0.3, which is 1/6th of the size of the previous one, quite similar to the ratio between the relative informativeness of aggregate and local prices that is both suggested by theory and found in the EA data.

Columns five and six use as a measure of energy prices the national retail gasoline prices and the national oil price, respectively. The impact of gasoline prices turns out to be similar to that of electricity prices. This suggests that, in comparing our baseline results with those from the literature before us, the different measure of energy prices is not the source of the difference. Using oil prices, which are arguably less visible to the consumer than gas at the pump, leads to a coefficient that is half as large.[23]

5 The causal dynamic impact on expected inflation of supply shocks to electricity prices

A different set of questions on the link between energy prices and expected inflation are what are the causal effects of supply shocks, and what are their dynamics over time. This section investigates these, focusing exclusively on electricity prices.

5.1 Back to the model: shocks and dynamics

In our model of expectations in section 3 the energy prices $e_{c,t}$ and e_t can be decomposed as the sum of lags of orthogonal supply and demand shocks (under stationarity). Supply and demand may contain different information about future inflation, or households may be differentially attentive to them. Through the many channels we discussed in section 3, and back to equation (5), the impact of a supply shock on expected inflation may be different from the estimates in section 4.

Isolating supply shocks also takes us further in dealing with the components of the u terms creating omitted variable bias in the estimates, since most aggregate confounders work through aggregate demand raising the demand for energy goods, not supply. Moreover, a rise in expected inflation may lead households to buy more goods right away, including energy, which would push energy prices up. Isolating supply shocks deals with this reverse causality.

Turning to dynamics, take derivatives of equation (5) $h-$periods ahead with respect to an energy supply shock today. The informativeness coefficients, (ϕ, ϕ^c, ϕ^a) should decline with the horizon. Energy shocks are often transitory, and they quickly lose forecasting power for inflation as the horizon increases. Instead, the inattention coefficient λ will tend to rise with the horizon approaching one. The more time elapses after the shock, the more households have learned about it. Therefore, the impact of energy shocks on expected inflation may rise or fall at first over the horizon, depending on which of the two effects is stronger. Eventually though, if the shock is transitory, this impact should die out. As for the dynamic effect of unanchoring, as the horizon rises, and more households

[23] Table A12 in appendix D replicates the estimates for the Michigan survey.

learn about the shock, the noise around their signals will fall. Therefore, λ^{ε} falls with horizon, as does $1-\lambda$, so the effect of the initial unanchoring dissipates over time.

Finally, and beyond our model, in many models of the macroeconomy with an energy sector, there are shocks to the supply of energy (from changes in endowments or technologies) that have an impact on multiple aggregate variables of interest, including inflation and its expectation. Other shocks, by affecting output and consumption, will change the demand for energy and its prices. Isolating the impact of energy supply shocks is of independent interest and a significant literature has devoted itself to it (e.g., Känzig, 2021).

5.2 Empirical specification

We estimate a local projection in the panel of data for each horizon $h = 1, ..., 24$:

$$\begin{aligned}\pi^e_{c,g,t+h} =& \beta^h z_{c,t} + \gamma^h z_{c,t} A_{c,g,t} + \sum_{p=1}^{P} \left(\tilde{\beta}^h_p z_{c,t-p} + \tilde{\gamma}^h_p z_{c,t-p} A_{c,g,t} + \psi^h_p \pi^e_{c,g,t-p} \right) \\ &+ \alpha^h_c + \eta^h_g + \theta^h \bar{\pi}_{c,t} + \rho^h r_t + \phi^h + \varepsilon_{c,g,t+h}\,, \end{aligned} \tag{7}$$

where $z_{c,t}$ are measures of supply shocks to the price of electricity.

This measures the impact on average expected inflation in h months of an energy shock in the current month. We include the shock and the expectations in the last $P = 2$ months as a control, although the results are insensitive to this choice. The dummy variable $A_{c,g,t}$ captures whether unanchoring was above average for that country-group. Therefore, β^h is the impact when expectations unanchor by less, while $\beta^h + \gamma^h$ is the impact when they unanchor by more. As before, and for the same reasons, we include country fixed effects α^h_c and group fixed effects η^h_g at each horizon, and control for past inflation with coefficient θ^h and the policy rate with coefficient ϕ^h. Since the left-hand side variable is in levels, we include a horizon intercept ϕ^h.

The β^h and γ^h now answer the following two questions: by how much does expected inflation over the next year increase on average after a 1-standard deviation supply shock to energy? And by how much more does it increase inflation expectations when those expectations are less well anchored? Theory predicts that β^h may rise over h temporarily, as inattention beats informativeness, but eventually will fall, while γ^h will decline towards zero as unanchoring becomes less important as time elapses.

5.3 Measuring supply shocks to EA electricity prices

Using the cross-sectional variation in the data, and focusing on the specific features of the EA electricity market, we put forward three new measures of supply shocks. Note that these are shocks, not instruments. Their impact on expected inflation may work through multiple channels that we care about, aside from isolating the channel that goes solely through the price of electricity. The point, as the discussion of the model clarifies, is to estimate the dynamic response to a sock, while dealing with reverse causality.

For the first, note that there are large differences in how much households spend on electricity across regions. This is in part because of country differences in temperature, whether home heating is mostly based on gas, electricity, or solar panels, and the share of electric vehicles, among other factors. The literature has further shown that household characteristics—like income, location, home ownership, housing tenure—and building characteristics—like heating systems, size of the house, and age—drive a great deal of this variation.[24] The shares of electricity in household consumption per region in 2019 (before the rise of inflation) from the Eurostat HICP, s_c, capture this cross-country variability in the impact of higher electricity prices on household budgets. They should proxy for the visibility of electricity prices to households in forming expectations of inflation, and they are likely exogenous with respect to the future expected inflation.

Consider then a shift-share shock series, which multiplies the aggregate time-series variation in electricity prices with the cross-sectional ex-ante variation in electricity spending: $z_{c,t} = e_t s_c$. Insofar as cross-country differences in expected inflation may drive cross-country spending and electricity prices, but they do not affect EA aggregate demand for electricity and prices, then this is a shock series to the price of electricity. It should not be affected by reverse causality from expectations to the demand for electricity and its price.[25]

Second, the EA electricity market has the following feature. The supply curve is at first approximately horizontal, as electricity is produced using renewable and nuclear sources, which have a large fixed cost but a low marginal cost. These sources are hard to expand or contract in the short run, so they are therefore almost always infra-marginal, and are

[24]See, for instance, Krishnamurthy and Kriström (2015) and Longhi (2015).

[25]One concern (implausible to us) is that some households in 2019 foresaw the energy shock that was coming and adjusted their consumption of electricity accordingly affecting the s_c. Appendix C considers two alternatives for the shares. First, the average expenditure shares over a longer period, between 2015 and 2019. Second, to purge from any quantity variation, the network cost of electricity for households in euro per KWh in 2019. This varies considerably across regional markets.

fully used until installed capacity. Afterwards, the supply curve slopes upwards. The marginal production of electricity uses oil, natural gas, and solid fossil fuels (like coal), with a competitive market switching between them. As a result, the price of electricity and of these energy sources usually, but not always, moves closely together.

Following a cut in the supply of natural gas from Russia, the upward-sloping section of the supply curve becomes steeper (or shifts left). Given the environmental and capacity constraints on expanding fossil fuels, oil prices become a proxy for the EA marginal cost of production of electricity. Känzig (2021) built shocks for oil supply expectations by measuring high-frequency changes in oil futures prices following OPEC production announcements, k_t. These shocks are plausibly exogenous in the sense that inflation expectations between 2020 and 2023 did not directly affect them. Using them leads to a second shift-share measure of electricity shocks in Europe: $z_{c,t} = k_t s_c$. Both the shifter and the share are plausibly exogenous.

Third, an increase in the production of electricity using renewables will shift the flat part of the supply curve for electricity to extend to the right, and so lower electricity prices. Using data from Ember, we measure the monthly change in total energy generated through wind in each region, $w_{c,t}$, plotted in panel (d) of figure 1. Since the marginal cost of producing electricity for installed turbines is very low, variations in wind shift the supply curve, and since they are mostly driven by exogenous fluctuations in the weather, they are not driven by changes in expected inflation. Therefore, $z_{c,t} = w_{c,t}$ provides a third alternative series for supply shocks.[26]

Since our approach to build supply shocks relies on the features of the EU electricity market, it cannot be applied to the US.

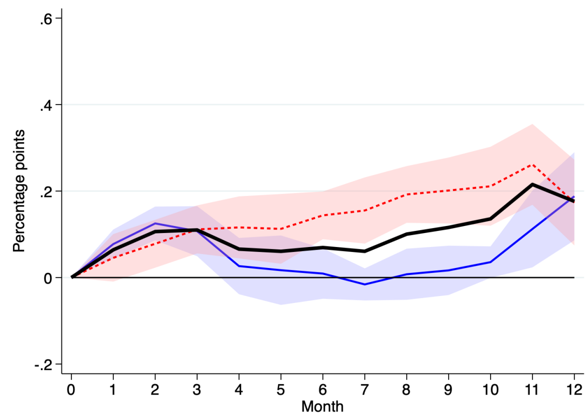
5.4 Local projections

Figure 2 shows the dynamic effects from the local projections following each of the measures of supply shocks in one month. In black-bold are pooled estimates that leave out the anchoring interaction term, with their confidence bands in the appendix E. The other two series and their confidence bands show the estimates with below and above average unanchoring.

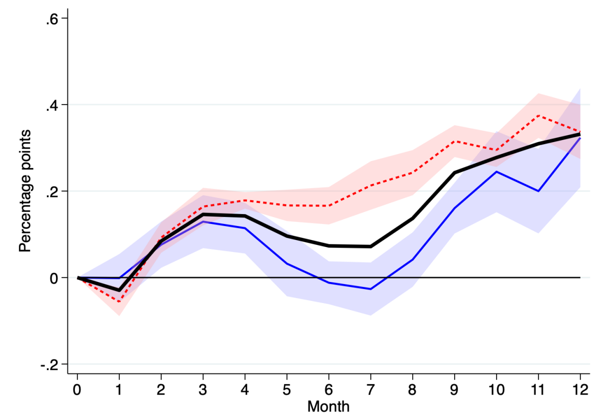
[26]One concern might be that higher expected inflation could lead to building more wind turbines. Yet, installing this capacity takes time. Moreover, the correlation between our $w_{c,t}$ series and a monthly series for mean wind speed by region is high for most countries, especially for those where wind power is a large share of electricity production. This confirms that most of the variation is indeed exogenous.

Figure 2: Impulse response of expected inflation to en electricity supply shock

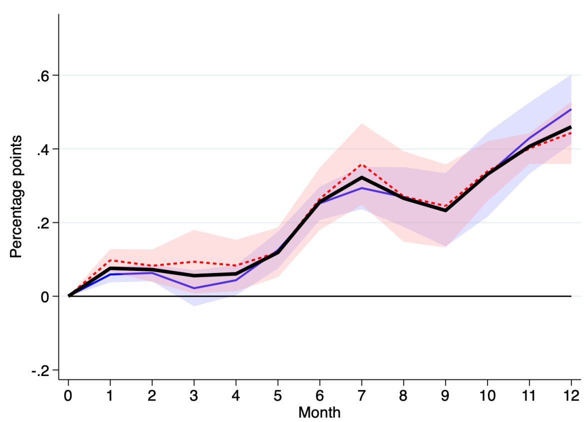
(a) Country electricity prices



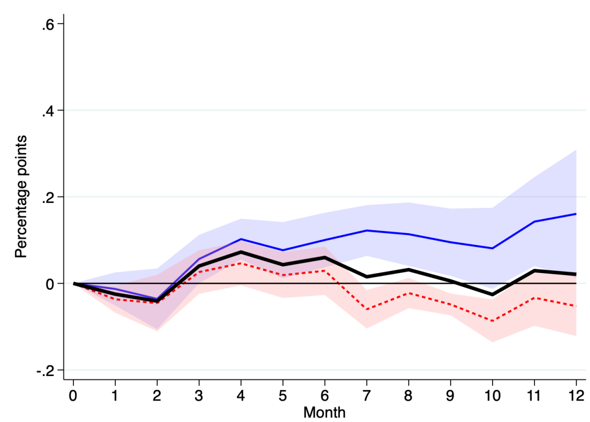
(b) EA electricity prices with country shares



(c) Oil shifts and electricity shares



(d) Wind



Note: Local projection of average expected inflation within a region and group on a 1-month electricity supply shock, controlling for past inflation, the policy rate, country and group fixed effects, pooled across states (thick black line), when unanchoring in the first 6 months is higher (red dashed line) or lower (blue solid line) than average for the country and demographic group. The shocks are scaled by their standard deviation to increase electricity prices. The shock in panel (a) is the change in electricity price by country and time. The shock in panel (b) is the time-varying EA-wide electricity price change times the country-varying expenditure shares. The shock in panel (c) is time-varying oil OPEC supply shocks times the country-varying electricity expenditure shares. The shock in panel (d) is to the country-time contribution of wind to the production of electricity. Standard errors are clustered by country.

Panel a) uses the actual electricity prices as measures of supply shocks. In our sample, it might turn out that these are useful. The increase in electricity prices was driven by the impact on supply from the unexpected invasion of Ukraine, to which each country responded with different measures. While these differential responses may have been correlated with that country's inflation experience (which we control for), they were plausibly not a response to differences in expected inflation. At the same time, these estimates are smaller than those using the two shift-share instruments, consistent with there being some attenuation bias due to the reverse causality from demand shocks.[27]

Panels b) and c) have the estimates using the shift-share shocks. For both, the impact builds up with time, reaching between 5bp and 45bp twelve months later. These results are consistent with theory. They suggest that the impact of slow learning and gradual attention is stronger than that of the depreciation of the informativeness of the shock. After 12 months (not shown), all the estimates quickly approach zero, consistent with the theory.

Also consistent with theory is the impact of anchoring. Depending on the horizon considered, higher than average unanchoring can as much as double the impact of electricity prices on expected inflation. Moreover, the difference between anchored and unanchored becomes negligible once h is high, just as predicted by theory.

Panel d) has the estimates with wind shocks. They are smaller, and peak after 4 months.

6 Applications

Armed with these estimates, we investigate three questions about the connection between expected inflation and energy prices.

6.1 Do inflation expectations under- or over-react to electricity prices?

The weight of electricity in the consumption basket, averaged across the years and countries in our sample, is 3%. In turn, a panel-data regression of the 6-month change in electricity prices 12-months ahead ($\Delta^6 e_{c,t+12}$) on the 6-month change on electricity prices today ($\Delta^6 e_{c,t}$) is 0.09. Therefore, a mechanical rule of thumb is that 1% higher electricity prices should raise expected inflation by $300 \times 0.09 = 27$ bp. Our estimates are instead 1.2–1.5 bp, which are much lower.

As we discussed in section 3, beyond this mechanical effect of electricity prices on inflation, there is also an information effect. The estimate in the previous paragraph cor-

[27]Another way to confirm this is to re-run the regressions in equation (6) but using the supply shocks as opposed to the actual prices replacing electricity prices $_{c,t}$ with supply shock $z_{c,t}$. In standardized units, the estimates of β with the shift-share instruments are larger by factors of 1.8 and 3.3.

Table 5: The impact of electricity prices on actual and expected inflation

	Actual inflation		Expected inflation	
	(1)	(2)	(3)	(4)
Change in electricity prices	10.000***	10.164***	1.523***	1.602***
	(0.641)	(0.639)	(0.228)	(0.226)
Change in electricity prices × Unanchoring		2.046**		0.986***
		(0.835)		(0.295)
Observations	309	309	309	309
R^2	0.514	0.523	0.319	0.344

Note: This table shows estimates of equation (6) with only variation across countries and time and country fixed effects. Columns (3) and (4) have the change in expected inflation, $\Delta^6 \pi^e_{c,t}$ as the dependent variable, while columns (1) and (2) replace it with changes in actual inflation, $\Delta^6 \pi_{c,t}$.

responds to ω in equation (1), but there is also the term $x_{i,c,g,t}$ that depends on energy prices through the coefficients (ϕ, ϕ^c). To estimate its potential size, we replace expected with actual inflation on the left-hand side of our baseline specification in equation (6). Insofar as the panel is sufficiently informative, these econometric estimates would be close to the rational-expectations estimates. Since we do not have individual-specific inflation, these estimates rely only on variation across countries and time.

Table 5 shows the results in the first two columns. Columns (3) and (4) are versions of our baseline estimates but using only country-time variation, with again estimates of the impact on expected inflation around 1.5bp. The impact on actual inflation is between 4 and 8 times larger than the one on expected inflation. Household expected inflation responds significantly less than actual inflation to electricity prices.

The answer to the question is therefore clear: under-react. Going back to the theory, this is consistent with significant inattention. Households choose how much attention to devote to energy to forecast inflation, and this turns out to be little. Therefore, they are less sensitive to energy prices than what rational expectations would predict.

Turning to the dynamic response to identified shocks, section 5 found that the expectations sluggishly and gradually responded. The under-reaction dissipates with time, consistent with our theory. Also consistent with our theory (if $\lambda < 1$ and $\phi^a > \phi^c$) would be the Angeletos, Huo and Sastry (2021) finding that the under-reaction of expectations of inflation becomes an over-reaction after 19 months. Our estimated impulse responses on average roughly double in impact between 6 and 12 months (figure 2). After 18-24 months (not reported) the estimates are unstable and imprecise. A factor of two is not enough to switch from under-reaction to over-reaction, so that even at long horizons, expectations of inflation under-react to energy shocks.

6.2 How much of the sharp rise in expected inflation in 2021-22 was due to higher energy prices?

Between May 2021 (when inflation was on target) and one year later, expected inflation on average across all the households, groups and countries increased by 2.9 percentage points. Aggregating the fitted values from our baseline equation (6), which explains expected inflation using past inflation and electricity prices, predicted expected inflation would have risen by a meagre 0.53 percentage points, as shown in figure 3a.

Moreover, most of this increase is explained by the rise in past inflation. The R^2 of a partial regression isolating the contribution of electricity prices alone to these predicted values is 0.39. It falls to 0.24 if we focus on the six major countries during the whole sample period, and this is already starting from only 0.53/2.9 explained. The predicted increase in expected inflation due to electricity prices is negligible.[28]

The answer to the question is: very little. Energy prices are important for inflation expectations but, by themselves, they fall well short of explaining the movements in expected inflation during the inflation disaster.

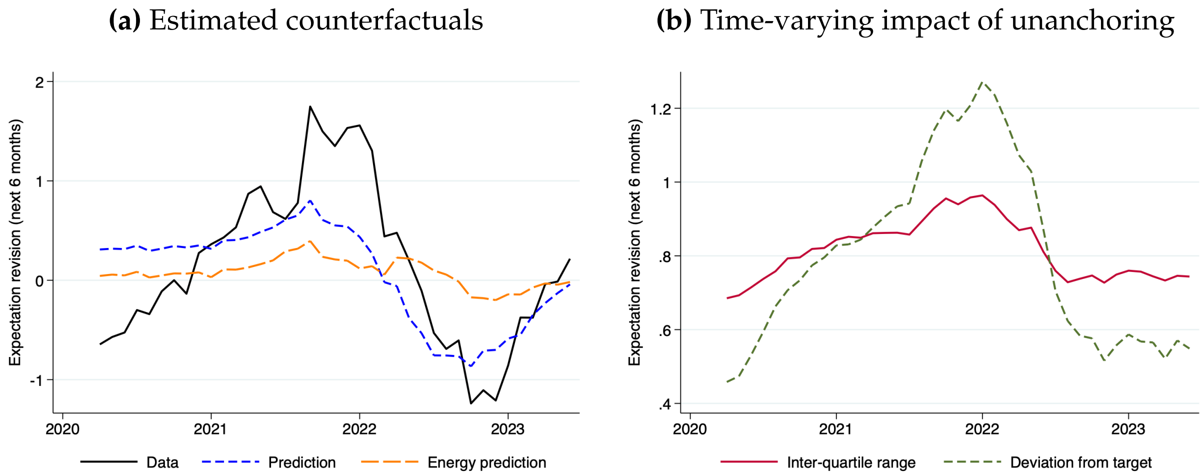
6.3 How important is it to keep inflation expectations anchored in light of supply shocks?

All central banks strive to anchor inflation expectations. Theory suggests that expectations that are sensitive to shocks will amplify these shocks. This is especially relevant with energy supply shocks, since they are often temporary. If expectations are anchored, then the effect of these shocks on inflation will disappear by itself before monetary policy, with its long and variable lags, is able to do much about it. Policy should "see through them" and not respond by changing policy rates. Instead, unanchored expectations call for aggressive and swift monetary tightening to prevent the shock's effects on inflation from persisting.

Figure 3b uses the estimates in table 1 to plot, at each date in time, the impact of a doubling of electricity prices over the following 6 months using each of our two measures

[28]For the US, energy prices also explain little of the variation in overall expected inflation, with our regression predicting less than one quarter of the observed increase between March of 2021 and 2022, and with partial R^2's from energy prices ranging between 0.01 and 0.24.

Figure 3: The contribution of electricity prices to expectation revisions



Note: Panel a) plots the survey-weighted average of actual revisions of expected inflation and the corresponding prediction based on equation (6), over the following six months. The energy prediction series shows the counterfactual expectation revisions due to changes in energy prices and anchoring alone, so including only the β and γ terms. Panel b) plots the predicted effect on average expected inflation from doubling electricity prices over the following 6 months as a function of the extent of unanchoring over the same period, using the coefficients in the first column of table 1 in red and in the third column in green.

of anchoring. That is, it plots a 3rd-order centered moving average of $(\beta + \gamma\Delta^6 a_t)\ln(2)$, where the time variation comes from the smoothed anchoring measure, averaged across countries and groups.

The estimates show that EA expected inflation was significantly more sensitive to energy prices at the start of 2022 than it was at the start of the sample. The scar of the inflation disaster is noticeable. Reassuringly, the re-anchoring of inflation expectations that came with the tightening of monetary policy and the fall in inflation in 2023 have reduced the impact of energy prices today to their pre-disaster level.[29]

[29] As part of the energy cycle, anchoring and the sensitivity of expectations will fluctuate. Flynn and Sastry (2024) incorporate a model of attention similar to ours in a business-cycle framework, and note that this will lead firms to under- and over-produce, depending on whether energy prices are high or low, creating wedges. Energy shocks will then generate endogenous attention wedges that will appear as markup shocks in a Phillips curve.

7 Conclusion

Ever since the 1970s, when large oil price shocks came with a sharp and persistent rise in inflation, economists have been studying the connection between energy prices and inflation. An important, but still poorly understood, channel is through inflation expectations. An often-repeated fact is that household expectations of inflation and energy prices are strongly correlated.[30] Sometimes, this is used to assert that this channel is strong, and other times to dismiss expectations data through the same "see through principle" that justifies dismissing energy shocks. If energy prices matter for expected inflation, how much do they matter?

This paper answered this question following in the footsteps of a wave of research in empirical macroeconomics that uses cross-regional variation within a currency union to make progress. Taking advantage of the recently-released household survey of expectations in the EA that has many more respondents identified by country and group, and of the large variability in electricity prices across the EA in the 2020-23 period, we provided new estimates of the impact of energy prices on inflation expectations. Using the specific features of the electricity market in Europe and the cross-country variation they induce, we built new supply shocks to electricity prices and estimated their dynamic causal impact on inflation expectations.

We found that electricity prices matter more, and in a more sluggish way, for expected inflation than previous estimates. Household expectations under-react to energy prices, consistent with inattention. The shocks of 2021-22 explain a small share of the rise in expected inflation, so something else beyond supply shocks was afoot to explain the inflation disaster of those years. Finally, anchoring expectations significantly reduces the impact of shocks on expected inflation, consistent with a long-held belief of central bankers.

[30] And yet, in the 1970s, US inflation expectations rose well before the oil price shocks (Reis, 2021).

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Appendix

A Data: additional information

A.1 Expected inflation

Our data on inflation expectations comes from the ECB, and was downloaded on 6 February 2024. It ends in December of 2023, and starts in April of 2020 for six countries—Belgium, France, Germany, Italy, the Netherlands, and Spain—and in April of 2022 for another five—Austria, Finland, Greece, Ireland, and Portugal. We censor the individual response if individual point forecasts for inflation exceed 20% in absolute value to ensure robustness to outliers. Table A3 shows the robustness of the baseline results to an alternative censoring procedure of winsorizing within each survey wave.

Table A1 provides additional information per country-group, with the averages over time of: the number of respondents per group, expected inflation, disagreement, and the average 6-month change in expected inflation. This makes clear that there is significant variation in the cross-section, which our estimates rely on.

Figures A1, A2, A3, and A4 complement the table by showing plots of that variation per group for each of the 6 major countries over time for: average expected inflation, dispersion of expectations, anchoring measured by disagreement over time, and anchoring measured as distance from target.

A.2 Energy prices

Turning to energy, our data for electricity prices from HICP suffers from revisions to the methods to calculate them in the Netherlands in June of 2023. We use their research series to have a consistent series throughout our sample. There was also a change in the methods used for the HICP in Spain from January of 2023 onwards, but there is no research series available.

As an alternative series for electricity prices, we use the household energy price index (HEPI) from https://www.energypriceindex.com, commissioned by VaasaETT and funded by Energie-Control Austria and the Hungarian Energy and Public Utility Regulatory Authority MEKH, copyright 2024 VaasaETT Ltd. We have also investigated the robustness of the wholesale electricity prices from the European Network of Transmission System Operators for Electricity (ENTSO-E) collected by Ember.

Turning to gasoline and diesel prices, we use data from the International Energy Agency (IEA). Figure A5 plots these series over time to confirm that while their time-series volatility is similar to that of electricity, their cross-country variation is more limited.

Finally, including all sources of energy, we use the HICP energy price index that includes all energy prices, not just electricity, the HICP indices for petrol, diesel, and natural gas, for direct comparisons.

A.3 Energy shares

The electricity expenditure shares from the HICP s_c are in figure A6, while the exogenous oil price shocks are from Känzig (2021). The data on wind speeds, used to check the correlation with our wind electricity generation series, are sourced from Visual Crossing. We average the daily mean wind speed by EA country and month.

One might be worried that expenditure shares on electricity are correlated with other variables persistently related to inflation expectations. Figure A7 shows that during our sample there is no significant relation between expenditure shares and inflation expectations directly, either across the sample or by country and year. The correlation between average expectations and electricity expenditure shares over the sample is 0.10 and statistically insignificant.

A.4 Macroeconomic controls

The additional country-time varying controls in table 3 come from various sources. We use the stringency index from the Oxford Covid-19 Government Response Tracker (OxCGRT) as a measure of disruptions due to the pandemic (Hale et al., 2021). As a proxy for fiscal policy, we include the government primary surplus as percentage of GDP at quarterly frequency. For energy-related fiscal policy, we rely on the Eurofound's EU PolicyWatch database of national-level policy measures, filtering for those labelled "support for energy bills". The control variables derived are indicators for whether a new policy was introduced in a country in a respective month, and an indicator for months in which any active measure is in place.

A.5 Actual inflation

Finally, figure A8 plots actual inflation during this period. This figure shows the importance of controlling for country fixed effects as well as for the level of inflation in the regressions.

A.6 US data

National gasoline retail prices and state-level electricity prices are provided by the US Energy Information Administration. Regional electricity prices are constructed as within-region unweighted averages of state-level prices. Past inflation by state is computed using the state-level CPI from Hazell et al. (2022). Past inflation by region is computed using the regional CPI from the BLS, which coincides with the MSC regions used except for the inclusion of Guam, Puerto Rico, and the US Virgin Islands.

B A simple micro-founded model of expectations with limited information and inattention

A household chooses expected inflation π^e with an objective function that depends on other relevant state variables including aggregate ($\bar{e}$) and local (e). That objective function is $\mathbb{E}\left[\bar{V}(\pi^e, \bar{e}, e, .)\right]$, where the missing attribute captures the random variables over which the expectation is taken. This objective is concave and differentiable. We omit all known constants and deterministic parts, since they play no useful role.

A fraction λ of agents form rational expectations. They are attentive, so they simply maximize this objective. Their optimal forecast is the solution $x(\bar{e}, e, .)$ to the equation $\mathbb{E}\left(\partial \bar{V}(\pi^e, \bar{e}, e, .)/\partial \pi^e\right)(x(\bar{e}, e, .)) = 0$. A linear approximation of this optimality condition (or quadratic approximation of the objective function) delivers: $x(\bar{e}, e, .) \approx \phi \bar{e} + \phi^c e$. The two weights come from the well-known least-squares regression formulae.

A fraction $1 - \lambda$ are inattentive. They have incomplete information, (potentially) observing only e. Their objective function is then to maximize: $V(\pi^e, e) \equiv \mathbb{E}_{\bar{e}}\left[\mathbb{E}\left[\bar{V}(\pi^e, \bar{e}, e, .)\right]\right]$ where they must take expectations over the unknown aggregate energy prices as well.

Moreover, these agents have limited information, which prevent them from observing e perfectly. Rather, each of them observes energy prices with a noise, which in turn makes her optimal choice noisy as well. As is standard in the literature on inattention, we model this as the agent choosing a stochastic decision rule $p(\pi^e|e)$, taking into account that in the map from energy prices to her expectation, there will be a noise created by her inattention. The agent faces the constraint that the function $p(\pi^e|e)$ is everywhere non-negative and it integrates to one over all the actions.

Her expected payoff is:

$$\mathbb{E}_e \left[\int \left(V(\pi^e, e) - \bar{\lambda} \log \left(p(\pi^e|e) \right) \right) p(\pi^e|e) d\pi^e \right]. \tag{A1}$$

which takes expectations over the unknown e, as well as over the noise induced by the noisy signal (in the integral). The second term inside the integral is the cost of paying attention. It is written here in terms of the entropy of the decision rule, following Flynn and Sastry (2024)'s formulation. They modify the cost function from the classic Sims (2003) formulation to depend on the entropy of the decision function, as opposed to the mutual information between prior and posterior, and so eliminate the influence of the prior on the final solution. A crucial parameter is $\bar{\lambda}$: the marginal cost of an extra bit of attention.

If $\bar{\lambda} = 0$, then the imperfectly informed inattentive agent forms her expectation according to $x(e)$, which is the solution to: $\left(\partial V(\pi^e, e)/\partial \pi^e\right)(x(e), e) = 0$. A linear approximation of this is $x(e) \approx \phi^a e$. It is well-known that, if e is Gaussian, then ϕ^a will just be the optimal gain from the Kalman filter.

Using the implicit function theorem:

$$x'(e) = -\frac{\left(\partial^2 V(\pi^e, e)/\partial \pi^e \partial e\right)(x(e), e)}{\left(\partial^2 V(\pi^e, e)/\partial (\pi^e)^2\right)(x(e), e)}. \tag{A2}$$

It then follows that a quadratic approximation of the objective function around $x(e)$ is:

$$\begin{aligned} V(\pi^e, e) &\approx V(x(e), e) + 0.5 \left[(\partial^2 V(\pi^e, e)/\partial (\pi^e)^2)(x(e), e) \right] (\pi^e - x(e))^2 \\ &\propto \left(\frac{v(e)}{x'(e)} \right) (\pi^e - x(e))^2 , \end{aligned} \tag{A3}$$

where we define $v(e) = -\left(\partial^2 V(\pi^e, e)/\partial \pi^e \partial e\right)(x(e), e)$.

Letting e have a density $f(e)$, the optimization problem has the Lagrangian:

$$\mathcal{L} = \int_e \int_\pi^e \Big(\big(v(e)/x'(e)\big) \left(\pi^e - x(e)\right)^2 - \bar{\lambda} \log\left(p(\pi^e|e)\right) + \kappa(\pi^e, e) \Big) p(\pi^e|e) d\pi^e f(e) de$$
$$+ \int_e \gamma(e) \left(\int_\pi^e p(\pi^e|e) d\pi^e - 1 \right) f(e) de. \tag{A4}$$

The $\kappa(\pi^e, e)$ are the Lagrange multipliers for each choice and state so that their probability is non-negative. The $\gamma(e)$ are the Lagrange multipliers so that, at every state, the choice probabilities integrate to 1.

The first-order condition for optimality is:

$$\big(v(e)/x'(e)\big) \left(\pi^e - x(e)\right)^2 + \kappa(\pi^e, e) + \gamma(e) = \lambda \log\left(p(\pi^e|e)\right) + \bar{\lambda}. \tag{A5}$$

Integrating over π^e and using the constraint that $\int_\pi^e p(\pi^e|e) d\pi^e = 1$, this optimality condition becomes:

$$p(\pi^e|e) = \frac{\exp\left(\frac{(\pi^e - x(e))^2}{\left|\bar{\lambda} x'(e)/v(e)\right|} \right)}{\int_\pi^e \exp\left(\frac{(\pi^e - x(e))^2}{\left|\bar{\lambda} x'(e)/v(e)\right|} \right) d\pi^e}. \tag{A6}$$

From this it follows that π^e follows a normal distribution, with mean $x(e)$ and with variance $\left|\bar{\lambda} x'(e)/v(e)\right|$.

In other words, the expectation of the inattentive agent is:

$$\pi^e = x(e) + \underbrace{\sqrt{\left| \frac{\bar{\lambda} x'(e)}{v(e)} \right|}}_{\equiv \lambda^\varepsilon(e)} \varepsilon, \tag{A7}$$

where ε has a standard normal distribution.

Intuitively, the larger is the cost of attention, $\bar{\lambda}$, the less attention she pays, and so the larger are the errors she makes $\lambda^\varepsilon(e)$. In the other direction, the larger is the impact of errors from inattention on her well-being, captured by a lower $\bar{x}'(e)/v(e)$, the more attention she will pay leading to a lower $\lambda^\varepsilon(e)$.

Now, going back to the linear solution for $x(e)$, this delivers $\pi^e = \phi^a e + \lambda^\varepsilon(e)\varepsilon$ just as in the text. However, $\lambda^\varepsilon(e)$ depends on $\bar{x}'(e)/v(e)$, which depends on e. There is a relevant second-order term there, which leads to an interaction effect of attention with energy prices.

The standard deviation of expectations across agents who each make an idiosyncratic error is $\lambda^{\varepsilon}(e)$. In turn the interquartile range of a standard normal distribution is 1.34898. Therefore the interquartile range of π^e across the agents is:

$$a(e) = 1.34898\sqrt{|\bar{\lambda}x'(e)/v(e)|} \quad \Rightarrow \quad x'(e) = \left(\frac{v(e)}{2\bar{\lambda}}\right) a(e)^2. \tag{A8}$$

More unanchoring is associated with a larger response of inflation expectations to energy prices. The intuition is that when expectations are very sensitive to shocks, then the mistakes in forming those expectations must not be so costly. Therefore, she is less attentive, and so there is more unanchoring.

But then, a linear approximation is $\lambda^{\varepsilon}(e) \approx \lambda^{\varepsilon} e_{c,t} a_{c,g,t}$, just as we wrote in the text.

C Alternative specifications

This appendix shows the alternative specifications discussed in section 4.3. They complement the baseline results, and inform what drives the variation, as explained in the text.

Table A2 restricts the sample to a balanced panel of 6 countries, pools the individual observations via the median as opposed to the average, or weights the country-group averages by their respective number of respondents. The main inferences on β are relatively robust to these different specifications. At the same time, they highlight the importance of taking disagreement into account when investigating micro data on expected inflation.

Table A3 repeats the analysis in table 1 using an alternative censoring procedure for individual survey responses, winsorizing if individual point forecasts for inflation fall within the top or bottom 5% for the survey wave. This approach is more flexible during high inflation periods and less restrictive than our baseline censoring approach at 20% in absolute value. The β coefficients are larger compared to the baseline, but the additional unanchoring effect γ remains similar.

Table A4 includes only first responders to the survey, with little impact on β and γ.

Table A5 adds different interactions of fixed effects to the baseline regression with time fixed effects, using either country-group, country-time, or group-time fixed effects, each for individual and mean expectations. Results are similar to the version in column 6 of table 1 using only country, group and time effects separately, except for electricity prices without unanchoring when adding country-time fixed effects, since electricity prices only vary on this level.

Table A6 shows the regression equation estimated separately for each country. The estimates vary significantly across countries showing the importance of exploiting this cross-country variation.

Table A7 compares the results across choices of the revision horizon h. The data is much more noisy so, as expected, with $h = 1$ the R^2 falls and the standard errors rise. At the same time, in size and sign, the estimates remain similar. With $h = 12$, as opposed to 6 months, on the one hand, some of the effect may reverse with the horizon, as the estimate is a little lower at 1.13bp. On the other hand, because now we consider a 12-month change in anchoring as well, the impact of this prolonged unanchoring is larger at 0.81bp.

Table A8 replaces energy prices with energy inflation.

Table A9 includes anchoring as a separate regressor.

Table A10 repeats table 1 but now lists three alternatives to account for estimation uncertainty: standard errors with Huber-White adjustment for heteroskedasticity, clustering per demographic group, and Driscoll-Kraay standard errors accounting for serial correlation. The errors rise, but the two key estimates of interest remain statistically significant at conventional significance levels.

D US estimates using the Michigan data

Table A12 shows the results of estimating equation (6) on the Michigan data.

In the first three columns, a 1% rise in US electricity prices raises expected inflation by 2.41 to 3.33bp, significantly more than in the Euro area but also with wider confidence bands.

The effects of the (poorly measured) unanchoring series are small and statistically insignificant. This conclusion is not robust, as slight changes in the specification (like the choice of h) lead to large changes on the coefficient on unanchoring. For instance, column two simply lags the unanchoring variable, and its extra boost rises to a large and statistically significant coefficient of 0.49bp. Column three further confirms this by using the alternative measure of anchoring based on the distance from target. The coefficient on anchoring is now quite large, but very imprecise, while the impact of oil prices falls by one third to 2.80bp.

As for a 1% rise in national gasoline or oil prices, it raises expected inflation by 2.80–3.99bp, see the next three columns. Column four replicates the specification of Coibion and Gorodnichenko (2015) with our longer sample and slightly different treatment of outliers in the data. Our estimate is close to theirs. This involves using oil as measure of energy prices. Columns five and six replicate the baseline regression using gas at the pump and oil prices.

E Dynamic causal effects: confidence bands

Figure A10 shows the impact of supply shocks on expected inflation with error bands, omitting the anchoring dummy variable. In the first two rows, the effects are, as expected, in between the ones in figure 2, and statistically significant.

The figure also shows, in the bottom row, the impact of the oil shift-share, but now using the average expenditure shares between 2015-19, or the network cost of electricity paid by households in 2019. The effects are very similar.

Table A1: Descriptive statistics by country and group

Country	Group	Number of respondents	Inflation expectation	Dis-agreement	6-month revision
AT	1	210	5.66	4.90	-1.07
AT	2	143	5.12	4.47	-1.02
AT	3	75	5.48	3.86	-0.93
AT	4	79	5.50	2.95	-0.41
AT	5	268	5.41	5.75	-1.37
AT	6	126	5.16	5.00	-1.62
AT	7	85	5.52	5.69	-1.17
AT	8	78	4.63	5.35	-0.97
BE	1	148	3.59	4.40	-0.03
BE	2	74	3.66	4.13	0.05
BE	3	131	3.69	3.95	0.03
BE	4	157	3.31	2.84	0.06
BE	5	182	4.11	5.24	-0.08
BE	6	59	4.17	3.89	-0.07
BE	7	159	4.00	4.20	0.21
BE	8	125	3.95	4.19	0.04
DE	1	419	3.44	4.10	0.15
DE	2	199	2.81	3.63	0.04
DE	3	348	3.18	4.04	0.31
DE	4	421	3.16	3.72	0.16
DE	5	495	3.46	4.52	0.06
DE	6	201	3.10	4.01	0.22
DE	7	306	3.09	3.97	0.22
DE	8	266	3.18	3.99	0.11
GR	1	137	6.32	10.00	-0.24
GR	2	42	7.03	8.83	0.17
GR	3	163	8.27	11.28	0.07
GR	4	170	6.41	9.72	-0.05
GR	5	148	7.14	10.09	-0.44
GR	6	45	6.53	8.49	0.06
GR	7	204	6.88	9.76	-0.23
GR	8	124	6.89	9.48	-0.14
ES	1	372	3.55	5.23	0.17
ES	2	168	3.07	4.28	0.35
ES	3	340	3.40	4.34	0.09
ES	4	487	3.51	3.40	0.17
ES	5	435	3.71	5.90	0.34
ES	6	115	4.00	5.71	0.12
ES	7	466	3.69	5.52	0.11
ES	8	364	3.69	4.69	0.18
FI	1	189	4.78	4.92	-1.31
FI	2	81	4.08	4.53	-1.19
FI	3	111	4.72	4.80	-1.24
FI	4	133	4.48	3.77	-1.21
FI	5	187	4.79	5.44	-1.39
FI	6	84	5.01	4.76	-1.34
FI	7	177	5.52	4.78	-1.59
FI	8	119	4.56	4.33	-1.33
FR	1	273	2.98	4.45	-0.14
FR	2	154	2.83	3.88	0.08
FR	3	443	3.25	4.09	0.10
FR	4	489	3.30	3.67	0.06
FR	5	377	3.13	4.62	-0.09
FR	6	117	3.14	4.61	0.02
FR	7	540	3.51	4.62	0.07
FR	8	373	3.49	4.11	-0.18
IE	1	94	4.93	6.31	-1.93
IE	2	38	4.02	5.94	-1.88
IE	3	132	5.57	4.54	-1.15
IE	4	120	5.34	4.80	-1.28
IE	5	163	5.36	8.03	-1.45
IE	6	49	4.62	6.30	-1.57
IE	7	219	5.37	6.87	-1.30
IE	8	171	5.51	5.88	-1.25
IT	1	488	4.17	5.72	0.03
IT	2	240	4.23	4.92	0.01
IT	3	308	3.94	5.26	0.19
IT	4	324	4.01	4.35	0.07
IT	5	636	4.57	6.73	-0.04
IT	6	195	4.87	6.50	0.05
IT	7	392	4.16	5.33	-0.03
IT	8	268	4.38	5.26	-0.13
NL	1	161	3.63	3.43	-0.03
NL	2	80	3.84	2.81	0.03
NL	3	88	3.44	2.82	-0.08
NL	4	147	3.58	2.22	0.22
NL	5	230	3.99	3.98	-0.03
NL	6	75	3.84	3.20	0.04
NL	7	113	3.55	3.72	0.01
NL	8	103	3.76	3.30	-0.01
PT	1	188	5.22	7.04	-1.01
PT	2	80	5.45	6.22	-1.26
PT	3	117	5.04	5.50	-0.79
PT	4	159	4.74	4.59	-1.27
PT	5	169	4.92	7.66	-1.36
PT	6	46	6.00	6.06	-1.19
PT	7	205	5.24	6.81	-1.02
PT	8	151	5.49	5.63	-0.88

Note: The table shows average values by country and demographic group across survey waves. Groups are split by: Male (1,2,3,4) or female (5,6,7,8); college education (3,4,7,8) or below (1,2,5,6); and income bracket above 60th percentile (2,4,6,8) or below (1,3,5,7).

Table A2: Alternative panel composition and weighting

	Balanced panel	Weighted mean	Median	
	(1)	(2)	(3)	(4)
Change in electricity prices	1.402***	1.127***	0.733***	0.705***
	(0.305)	(0.097)	(0.118)	(0.118)
Change in electricity prices × Unanchoring (Disagreement)	0.643***	0.409***	0.226***	
	(0.171)	(0.063)	(0.069)	
Change in electricity prices × Unanchoring (Target distance)				0.899***
				(0.175)
Average past inflation	0.009	0.004	-0.106***	-0.108***
	(0.030)	(0.009)	(0.010)	(0.010)
ECB deposit rate change	-0.444***	-0.444***	-0.283***	-0.286***
	(0.126)	(0.030)	(0.035)	(0.035)
Observations	322987	2472	2472	2472
R^2	0.014	0.287	0.288	0.292

Note: This table shows estimates of equation (6) using alternative panel composition or aggregation. In column (1) we estimate the baseline regression but restrict the sample to a balanced panel of 6 countries. Column (2) weights the country-group averages by their respective number of respondents. Columns (3) and (4) show results for median instead of mean expectations for the baseline with each anchoring measure.

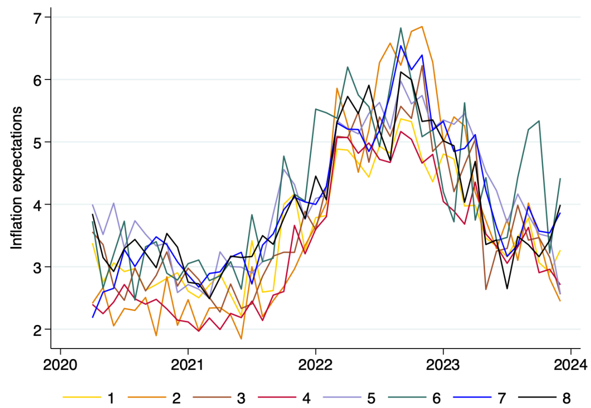
Table A3: Baseline results when winsorizing at 5th and 95th percentiles per wave

	(1)	(2)	(3)	(4)	(5)	(6)
Change in electricity prices	2.705***	2.327***	2.530***	2.756***	2.691***	1.064***
	(0.493)	(0.153)	(0.506)	(0.497)	(0.491)	(0.389)
Change in electricity prices × Unanchoring	0.917***	0.489***	2.591***	1.366***	0.956***	0.454***
	(0.236)	(0.063)	(0.528)	(0.318)	(0.234)	(0.154)
Average past inflation	0.016	0.001	0.006	0.023	0.018	0.011
	(0.049)	(0.013)	(0.048)	(0.047)	(0.048)	(0.101)
ECB deposit rate change	-0.680***	-0.804***	-0.674***	-0.677***	-0.680***	
	(0.214)	(0.045)	(0.218)	(0.220)	(0.215)	
Observations	408163	2472	408163	408163	408163	408163
R^2	0.031	0.396	0.036	0.034	0.032	0.057
Country & group fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	No	No	No	No	No	Yes
Country-group fixed effects	No	No	No	No	Yes	No

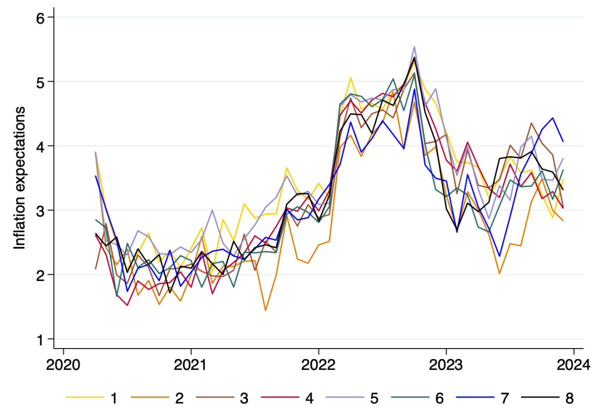
Note: This table re-estimates table 1 using a different censoring procedure for individual survey responses, winsorizing individual responses at the 5th and 95th percentiles within each survey wave.

Figure A1: Variation in expected inflation by major EA country

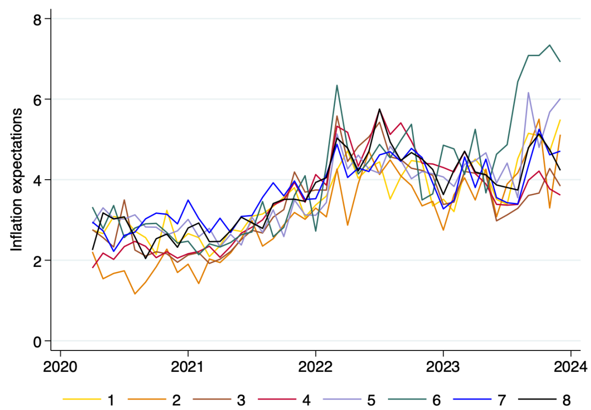
(a) BE



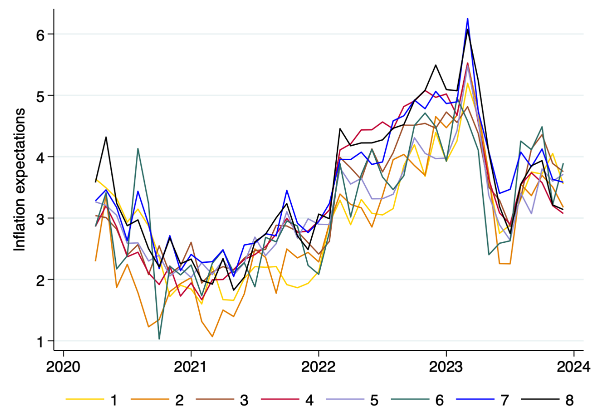
(b) DE



(c) ES

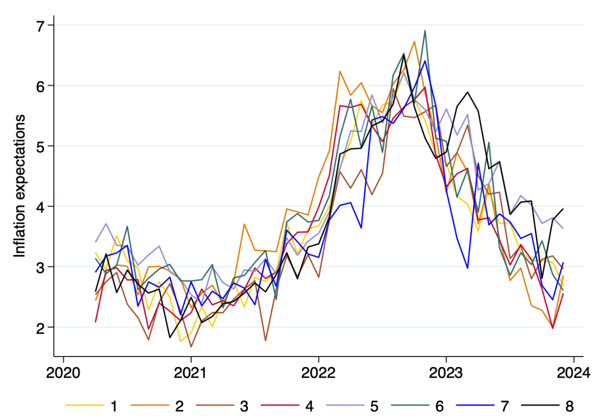


(d) FR



(e) IT

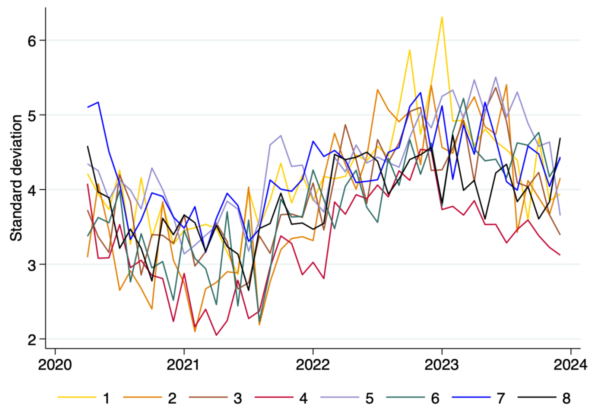
(f) NL



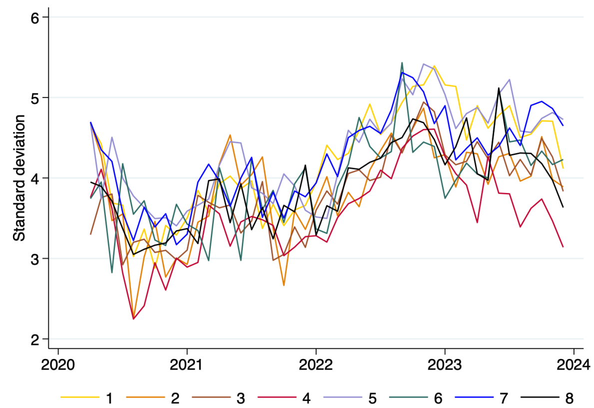
Note: The figure plots the average expected inflation 12-months ahead by country and by demographic group. Groups are defined as follows: male (1,2,3,4) or female (5,6,7,8); college education (3,4,7,8) or below (1,2,5,6); and income bracket above 60th percentile (2,4,6,8) or below (1,3,5,7).

Figure A2: Variation in expectations (1-year SD) by major EA country

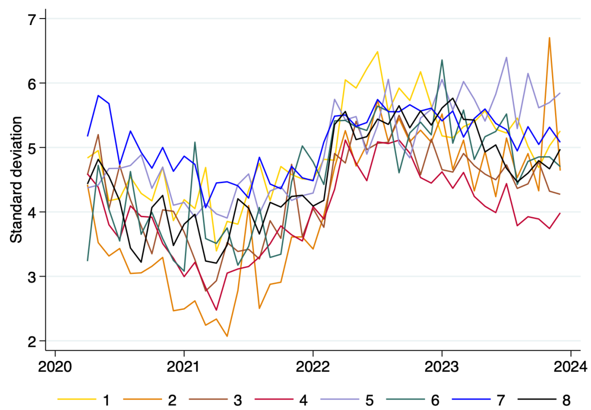
(a) BE



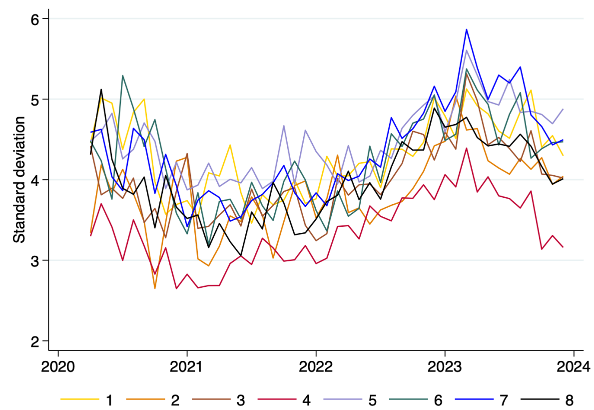
(b) DE



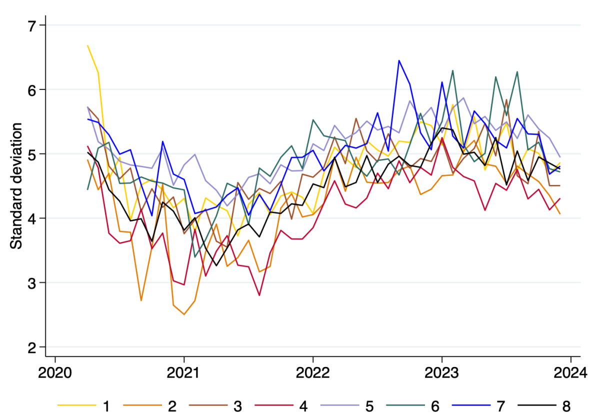
(c) ES



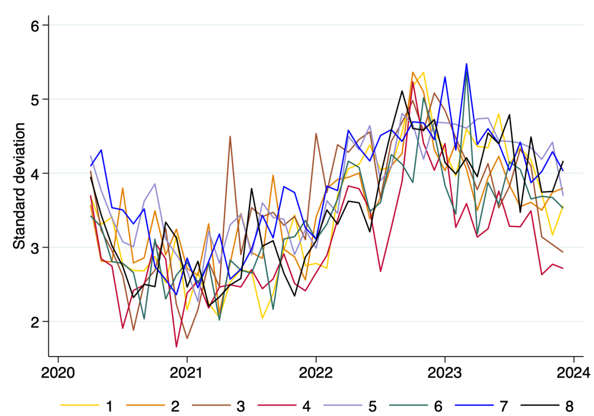
(d) FR



(e) IT

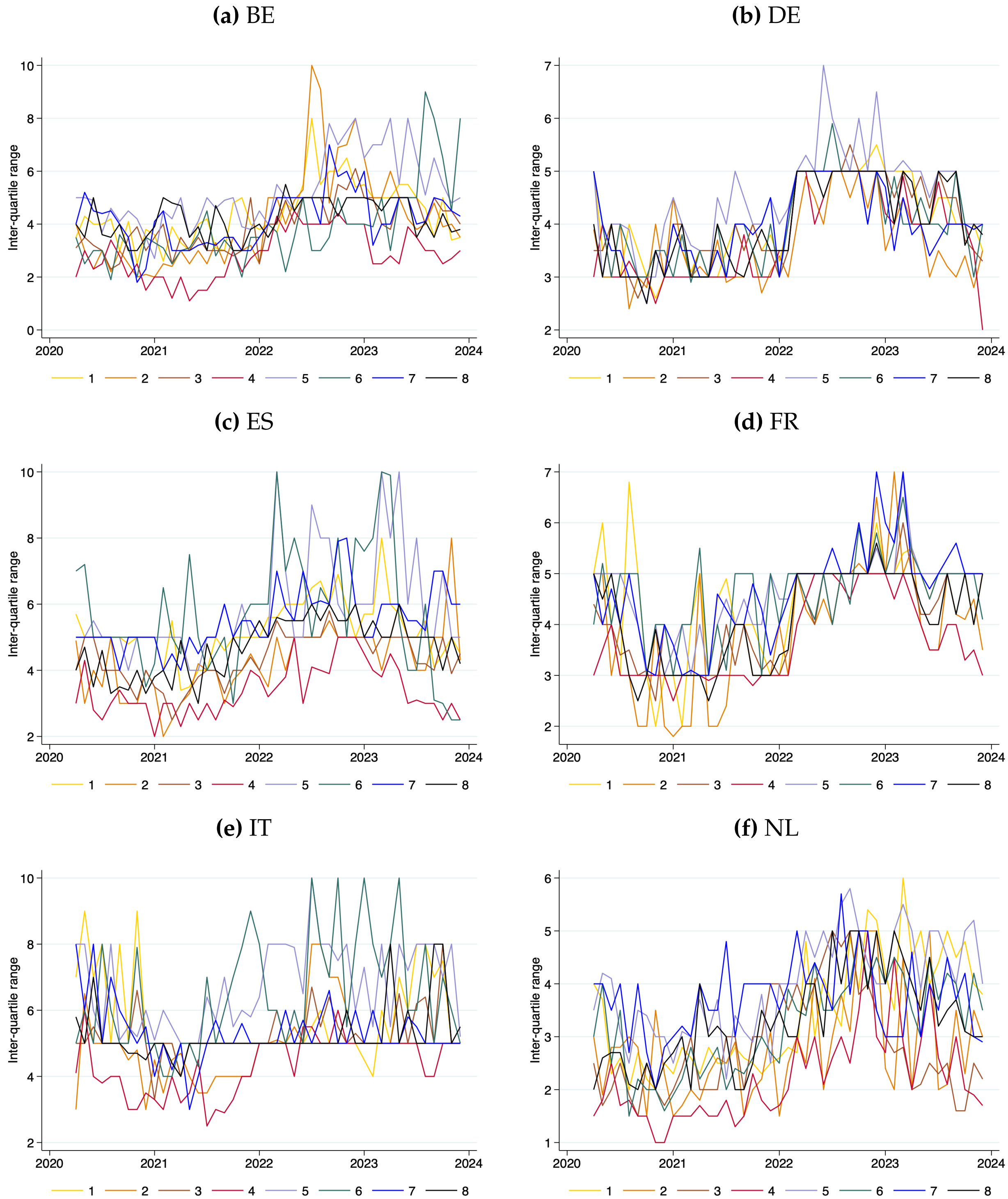


(f) NL



Note: The figure plots the standard deviation of expected inflation one year ahead within country and demographic group. Groups are defined as follows: male (1,2,3,4) or female (5,6,7,8); college education (3,4,7,8) or below (1,2,5,6); and income bracket above 60th percentile (2,4,6,8) or below (1,3,5,7).

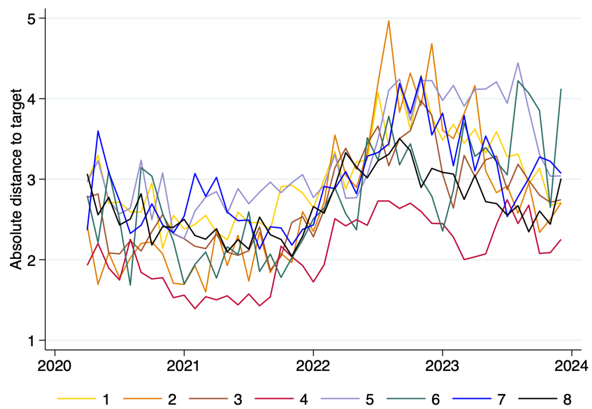
Figure A3: Variation in anchoring (3-year IQR) by major EA country



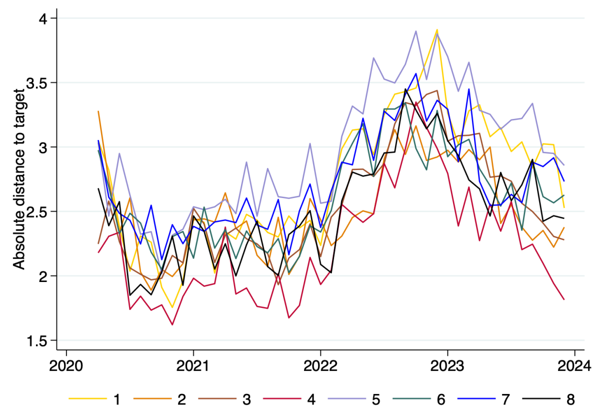
Note: The figure plots the average inter-quartile range of expected inflation three years ahead within country and demographic group. Groups are defined as follows: male (1,2,3,4) or female (5,6,7,8); college education (3,4,7,8) or below (1,2,5,6); and income bracket above 60th percentile (2,4,6,8) or below (1,3,5,7).

Figure A4: Variation in anchoring (distance to target) by major EA country

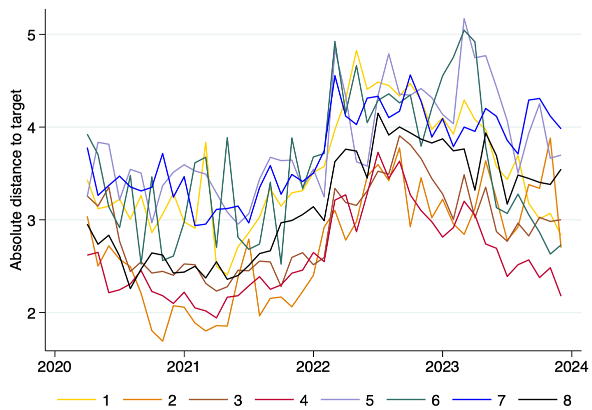
(a) BE



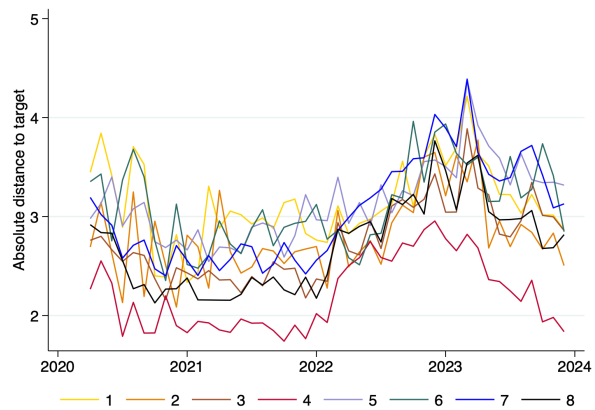
(b) DE



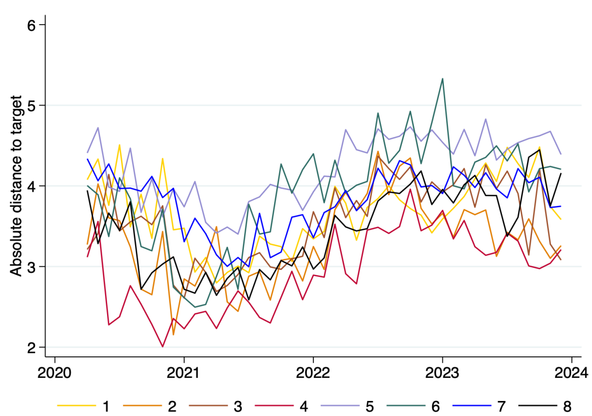
(c) ES



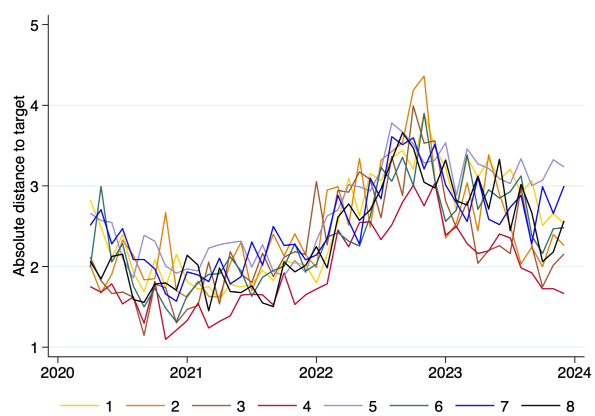
(d) FR



(e) IT



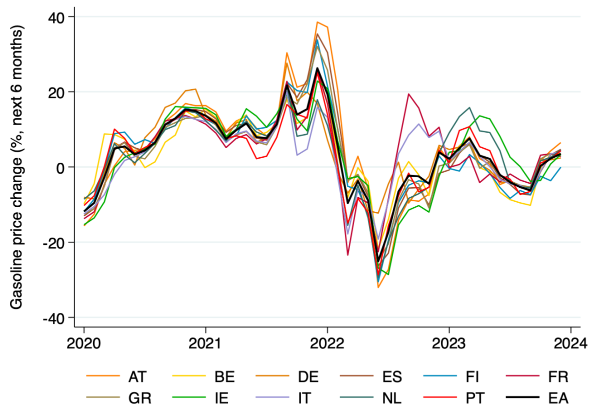
(f) NL



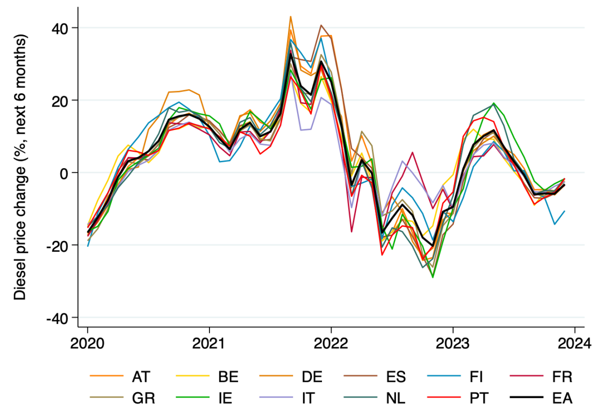
Note: The figure plots the average absolute distance from the inflation target of expected inflation three years ahead within country and demographic group. Groups are defined as follows: male (1,2,3,4) or female (5,6,7,8); college education (3,4,7,8) or below (1,2,5,6); and income bracket above 60th percentile (2,4,6,8) or below (1,3,5,7).

Figure A5: Gasoline and diesel prices in the EA

(a) Gasoline prices

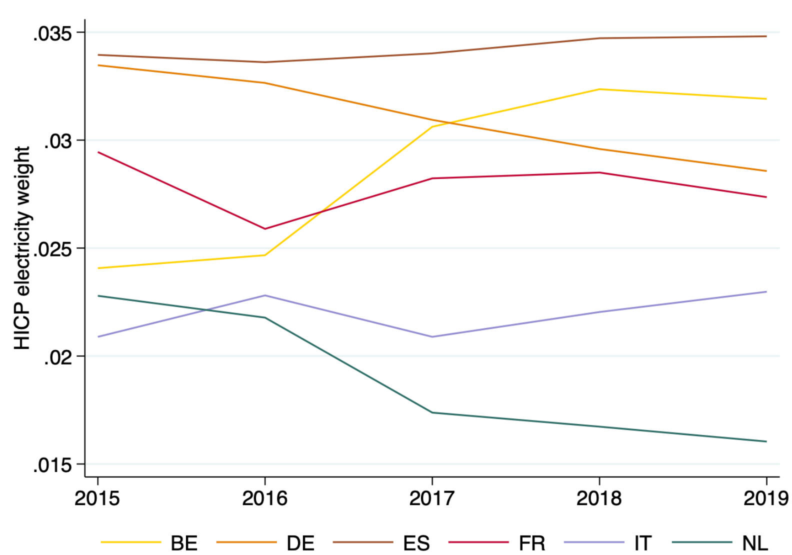


(b) Diesel prices



Note: This figure plots the percentage price changes over the following 6 months, in panel a) for gasoline prices and in panel b) for automotive diesel prices. Price data by country is provided by the International Energy Agency in €/liter. The EA series is calculated as an unweighted average across sample countries.

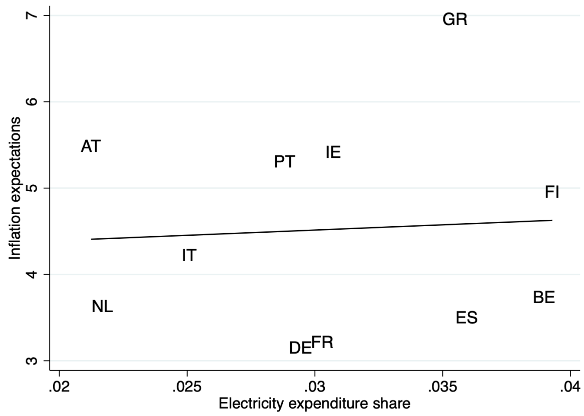
Figure A6: Electricity expenditure shares by country



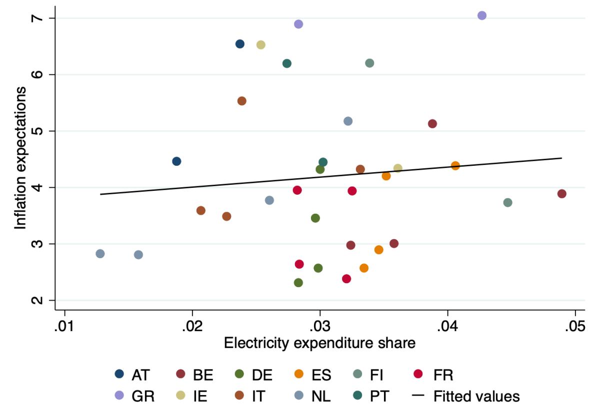
Note: The figure plots the weight of HICP electricity in the HICP by country and year during the pre-sample.

Figure A7: Electricity expenditure shares and average expectations

(a) Country averages

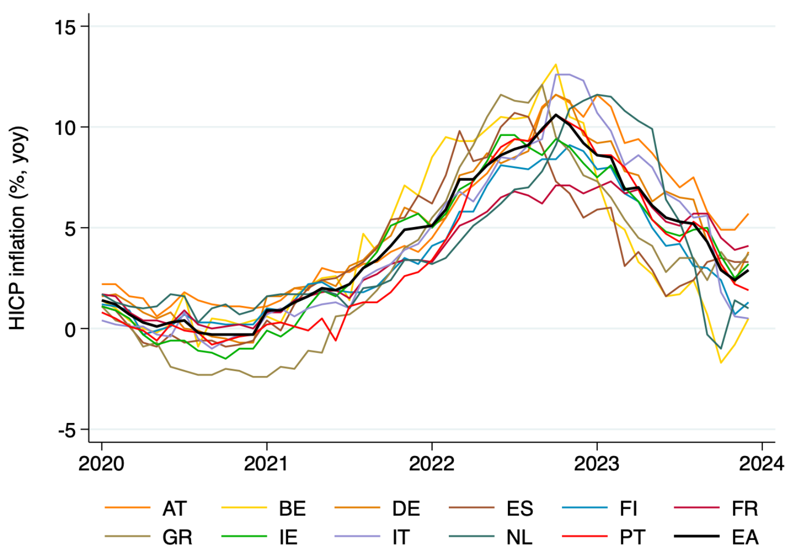


(b) By country and year



Note: The figure plots the weight of HICP electricity in the HICP and average inflation expectations by country over the sample. Panel a) plots sample averages by country, while panel b) plots annual averages by country.

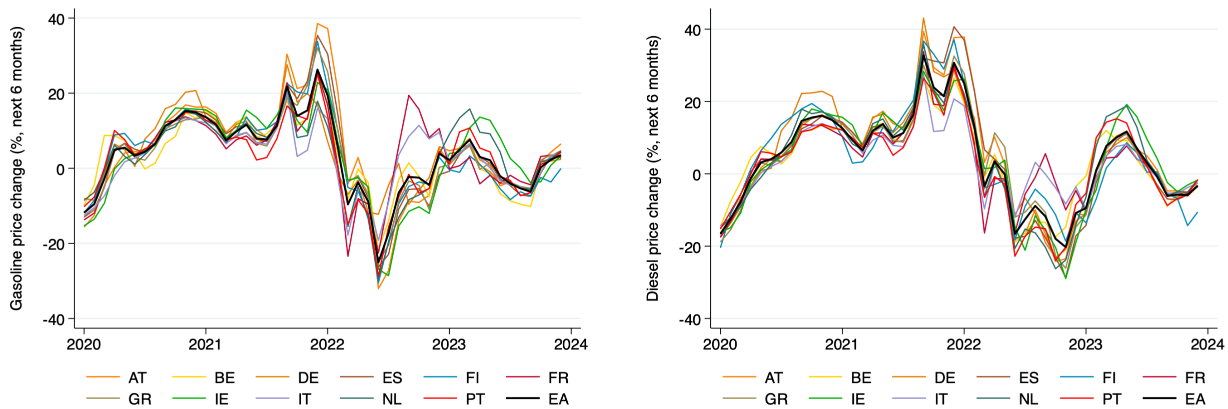
Figure A8: Actual inflation during the sample period by country



Note: The figure plots HICP 12-month inflation for the EA as a whole and for the 11 countries in our sample.

Figure A9: Gasoline and diesel price changes during the sample period by country

(a) Gasoline **(b)** Diesel



Note: The figure plots 6-month changes in euro a) gasoline and b) diesel retail prices for the 11 countries in our sample from the IEA and as simple average over all sample countries for the EA.

Table A4: Baseline results when including only first responders

	(1)	(2)	(3)	(4)	(5)	(6)
Change in electricity prices	2.835**	2.403***	2.702**	2.415**	2.925**	0.411
	(1.354)	(0.225)	(1.167)	(1.145)	(1.349)	(1.059)
Change in electricity prices × Unanchoring	0.249	0.293***	1.506*	2.416***	0.230	-0.143
	(0.226)	(0.051)	(0.808)	(0.640)	(0.230)	(0.189)
Average past inflation	0.123	-0.037*	0.120	0.121	0.126	0.250
	(0.099)	(0.020)	(0.099)	(0.093)	(0.098)	(0.259)
ECB deposit rate change	-1.265**	-1.236***	-1.266**	-1.239***	-1.298***	
	(0.492)	(0.067)	(0.497)	(0.448)	(0.465)	
Observations	8906	2472	8906	8906	8906	8906
R^2	0.018	0.312	0.021	0.026	0.029	0.056
Country & group fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	No	No	No	No	No	Yes
Country-group fixed effects	No	No	No	No	Yes	No

Note: This table re-estimates table 1 including only households who are responding to the survey for the first time and winsorizing individual responses at the 5th and 95th percentiles within each survey wave.

Table A5: Baseline results with different fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Change in electricity prices	1.401***	1.339***	0.372**	0.386**	0.193**	0.327*	0.368**
	(0.295)	(0.298)	(0.181)	(0.182)	(0.094)	(0.173)	(0.182)
Change in electricity prices × Unanchoring	0.598***	0.594***	0.146	0.140	-0.013	0.758***	0.145
	(0.170)	(0.176)	(0.089)	(0.093)	(0.050)	(0.260)	(0.087)
Average past inflation	0.004	-0.001	0.004	0.002	-0.049**	-0.007	0.004
	(0.028)	(0.028)	(0.079)	(0.079)	(0.023)	(0.080)	(0.078)
ECB deposit rate change	-0.435***	-0.454***					
	(0.119)	(0.122)					
Observations	362756	362756	362756	362756	2472	362756	362756
R^2	0.016	0.015	0.032	0.034	0.573	0.032	0.032
Country fixed effects	Yes	No	Yes	Yes	Yes	Yes	Yes
Group fixed effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	No	No	Yes	Yes	Yes	Yes	Yes
Group-month fixed effects	No	No	No	Yes	No	No	No
Country-group fixed effects	No	No	No	No	No	No	Yes

Note: This table shows estimates of equation (6) adding different time fixed effects and further fixed effect combinations. Column (1) and (2) include only country or group fixed effects, respectively. Column (3) includes time fixed effects, column (4) adds group-time fixed effects, and column (5) shows results for average expectations within country-group with time fixed effects. Column (6) repeats column (3) but uses the average absolute distance from target as anchoring measure. Column (7) adds country-group fixed effects to the specification in column (3).

Table A6: Baseline results by country

	AT	BE	DE	ES	FI	FR	GR	IE	IT	NL	PT
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Change in electricity prices	0.204	2.410***	2.596*	0.896	1.391	5.457	-0.951	-0.886	2.570***	0.307	1.133
	(1.111)	(0.452)	(1.415)	(0.709)	(1.199)	(5.389)	(4.271)	(3.172)	(0.372)	(0.787)	(1.582)
Change in electricity prices × Unanchoring	-0.176	0.483**	4.302***	0.511*	-0.385	11.650***	0.113	-0.195	0.238*	-0.292	-0.406
	(0.309)	(0.218)	(1.011)	(0.253)	(0.332)	(1.009)	(0.202)	(0.195)	(0.124)	(0.222)	(0.363)
Average past inflation	-0.340**	-0.036	0.046	0.115**	-0.337**	-0.342***	-0.120	-0.589*	0.214***	-0.253***	-0.207
	(0.124)	(0.055)	(0.042)	(0.048)	(0.127)	(0.106)	(0.291)	(0.326)	(0.060)	(0.059)	(0.127)
ECB deposit rate change	-1.341***	-0.204	-0.546**	-0.685**	-1.420***	0.573***	-1.059*	-1.686***	-1.175***	-0.379*	-1.066
	(0.440)	(0.196)	(0.203)	(0.313)	(0.229)	(0.136)	(0.578)	(0.382)	(0.177)	(0.212)	(0.802)
Observations	9473	25618	68611	66437	10034	71166	4738	6614	66480	24675	8910
R^2	0.016	0.040	0.022	0.011	0.019	0.028	0.010	0.026	0.032	0.052	0.018

Note: This table shows estimates of equation (6) separately by country.

Table A7: Results for h-month changes in all variables

	1-month changes		4-month changes		12-month changes	
	(1)	(2)	(3)	(4)	(5)	(6)
Change in electricity prices	0.963**	0.602***	1.298***	1.100***	1.133***	0.879***
	(0.407)	(0.175)	(0.279)	(0.112)	(0.216)	(0.110)
Change in electricity prices × Unanchoring	0.255	-0.169	0.544***	0.318***	0.810***	0.446***
	(0.454)	(0.126)	(0.148)	(0.069)	(0.137)	(0.051)
Average past inflation	-0.013	-0.018***	-0.005	-0.032***	-0.063	-0.016
	(0.012)	(0.005)	(0.028)	(0.007)	(0.049)	(0.022)
ECB deposit rate change	0.001	0.002	-0.241*	-0.216***	-0.665***	-0.918***
	(0.052)	(0.017)	(0.127)	(0.025)	(0.128)	(0.054)
Observations	518748	2912	414988	2648	237269	1944
R^2	0.001	0.022	0.007	0.197	0.043	0.625

Note: Columns (1), (3) and (5) show results for individual expectations, $\Delta^h \pi^e_{i,c,g,t}$, while columns (2), (4) and (6) show results for average expectations within country and group, $\Delta^h \pi^e_{c,g,t}$.

Table A8: Results for electricity inflation rate change

	(1)	(2)	(3)	(4)	(5)	(6)
Change in electricity inflation	0.200**	0.125***	0.197***	0.209**	0.198**	-0.066
	(0.077)	(0.022)	(0.072)	(0.079)	(0.077)	(0.041)
Change in electricity inflation × Unanchoring	0.048	0.029**	0.226**	0.023	0.051	0.005
	(0.043)	(0.015)	(0.110)	(0.118)	(0.046)	(0.023)
Average past inflation	-0.020	-0.074***	-0.027	-0.017	-0.018	-0.185
	(0.048)	(0.016)	(0.048)	(0.050)	(0.048)	(0.149)
ECB deposit rate change	-0.431**	-0.416***	-0.406**	-0.445***	-0.435***	3.774**
	(0.159)	(0.044)	(0.158)	(0.162)	(0.160)	(1.524)
Observations	241379	1408	241379	241379	241379	241379
R^2	0.020	0.459	0.020	0.020	0.020	0.039
Country & group fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	No	No	No	No	No	Yes
Country-group fixed effects	No	No	No	No	Yes	No

Note: This table shows estimates of equation (6), replacing the change in electricity prices with the change in the year-on-year inflation rate in electricity prices, $\Delta^6 \pi^e_{c,t}$

Table A9: Alternative specification of anchoring

	(1)	(2)	(3)	(4)
Change in electricity prices	1.548***	1.327***	1.002***	2.704***
	(0.358)	(0.242)	(0.185)	(0.684)
Unanchoring (Disagreement)		0.354***		
		(0.035)		
Change in electricity prices × Unanchoring (Disagreement)		0.290**		0.522***
		(0.117)		(0.152)
Unanchoring (Target distance)			1.016***	
			(0.067)	
Change in electricity prices × Unanchoring (Target distance)			0.917***	
			(0.331)	
Change in electricity prices × Previous inflation				-0.178**
				(0.075)
Average past inflation	0.007	0.015	0.040**	0.008
	(0.029)	(0.023)	(0.019)	(0.028)
ECB deposit rate change	-0.458***	-0.406***	-0.502***	-0.431***
	(0.122)	(0.097)	(0.079)	(0.122)
Observations	362756	362756	362756	362756
R^2	0.015	0.023	0.028	0.016

Note: This table shows estimates of equation (6) using alternative specifications of anchoring. Column (1) excludes anchoring, while (2) and (3) include the respective anchoring measures as a separate regressor in addition to the interaction term. Column (4) includes an additional interaction with inflation to account for state dependence.

Table A10: Results with different calculations of standard errors

	Huber-White	Group clustering	Two-way clustering	Driscoll-Kraay
	(1)	(2)	(3)	(4)
Change in electricity prices	1.404***	1.404***	1.404**	1.404***
	(0.064)	(0.124)	(0.488)	(0.453)
Change in electricity prices × Unanchoring	0.596***	0.596***	0.596**	0.596**
	(0.046)	(0.166)	(0.267)	(0.240)
Average past inflation	0.004	0.004	0.004	0.004
	(0.006)	(0.017)	(0.076)	(0.045)
ECB deposit rate change	-0.436***	-0.436***	-0.436	-0.436**
	(0.019)	(0.045)	(0.272)	(0.190)
Observations	362756	362756	362756	362756
R^2	0.016	0.016	0.016	0.016

Note: This table re-estimates the first column of table 1 using different types of approaches to calculate the standard errors. Two-way clustering is applied by month and country.

Table A11: The impact of electricity prices on expected inflation with time fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)
Change in electricity prices	0.372**	0.193**	0.327*	0.395**	1.047***	1.374***
	(0.181)	(0.094)	(0.173)	(0.185)	(0.308)	(0.312)
Change in electricity prices × Unanchoring	0.146	-0.013	0.758***	-0.056	0.432***	0.521***
	(0.089)	(0.050)	(0.260)	(0.191)	(0.113)	(0.156)
Average past inflation	0.004	-0.049**	-0.007	0.007	-0.091*	-0.025
	(0.079)	(0.023)	(0.080)	(0.079)	(0.045)	(0.030)
ECB deposit rate change					0.015	-0.391***
					(0.190)	(0.123)
Change in petrol prices					-3.874***	
					(1.271)	
Change in diesel prices					6.757***	
					(1.044)	
Change in natural gas prices					1.234***	
					(0.205)	
Change in COVID stringency index					-0.604***	
					(0.074)	
Change in primary surplus						0.056***
						(0.015)
New fiscal energy policy=1						-0.310
						(0.207)
Active fiscal energy policy=1						0.111
						(0.189)
Observations	362756	2472	362756	362756	235203	362756
R^2	0.032	0.573	0.032	0.032	0.024	0.017
Country & group fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	No	No
Country-group fixed effects	No	No	No	No	No	No

Note: This table shows all coefficient estimates for the specifications in table 2. Column (1) has the baseline estimates, (2) uses the average $\pi^e_{c,g,t}$ as the dependent variable, (3) uses as measure of unanchoring the deviation of long-run expected inflation from target, (4) uses anchoring at the country level only $a_{c,t}$. Column (5) estimates equation (6) and adds controls for other energy price changes using the HICP for common transport fuels and natural gas, and changes in the Oxford COVID stringency index. Column (6) instead adds fiscal policy controls, using changes in the quarterly primary surplus, and an indicator for a new or any active policy measure labelled "support for energy bills" as collected by Eurofound EU PolicyWatch. In parentheses are standard errors clustered by month for the regressions using individual expectations.

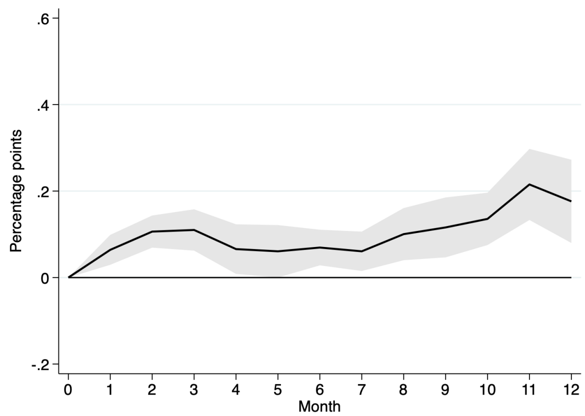
Table A12: The impact of energy prices on expected inflation in the US Michigan survey

	(1)	(2)	(3)	(4)	(5)	(6)
Change in energy prices	3.075***	3.331***	2.409***	1.980***	4.210***	2.297***
	(0.712)	(0.141)	(0.722)	(0.231)	(0.325)	(0.274)
Change in energy prices × Unanchoring	0.209	0.114**	1.589**		0.077	0.078
	(0.210)	(0.044)	(0.754)		(0.092)	(0.065)
Average past inflation	0.036	0.124***	0.109***		-0.067***	-0.060**
	(0.036)	(0.007)	(0.033)		(0.024)	(0.024)
Change in FFR	-0.126	-0.047***	-0.580***		-0.126**	-0.077
	(0.107)	(0.013)	(0.095)		(0.049)	(0.049)
Observations	44650	8380	24597	89144	59205	65129
R^2	0.003	0.116	0.011	0.011	0.024	0.017
Country & group fixed effects	Yes	Yes	Yes	No	Yes	Yes
Month fixed effects	No	No	No	No	No	No

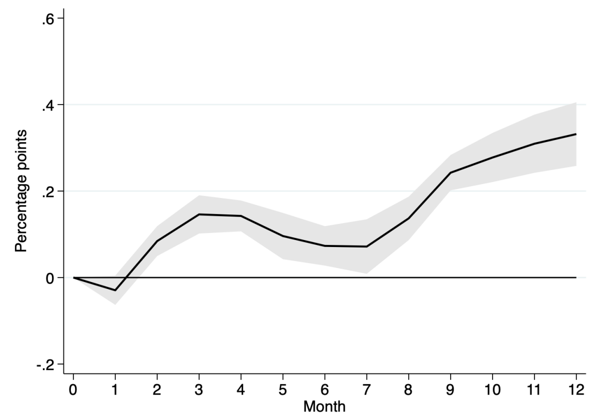
Note: This table presents estimates of the regression in equation (6): $\Delta^6 \pi^e_{i,c,g,t} = \beta \Delta^6 e_{c,t} + \gamma \Delta^6 e_{c,t} \times \Delta^6 a_{c,g,t} + \alpha_c + \eta_g + \theta \bar{\pi}_{c,t-6} + \rho \Delta^6 r_t + \varepsilon_{i,c,g,t}$ for the US. Columns 1–4 show estimates for regional electricity prices. Column (1) has the baseline estimates, (2) uses the average $\pi^e_{c,g,t}$ as the dependent variable, and (3) uses as measure of unanchoring the deviation of long-run expected inflation from target. Column (4) replicates the result of Coibion and Gorodnichenko (2015) with wholesale oil prices for our updated sample and censoring procedure: $\Delta^6 \pi^e_{i,t} = \beta \Delta^6 e_t + \alpha + \varepsilon_{i,t}$. Columns (5) and (6) respectively use the national gas and oil price instead of regional electricity prices in our baseline specification. In parentheses are standard errors clustered by month for the regressions using individual expectations.

Figure A10: Impulse response of expected inflation to a shock to energy prices

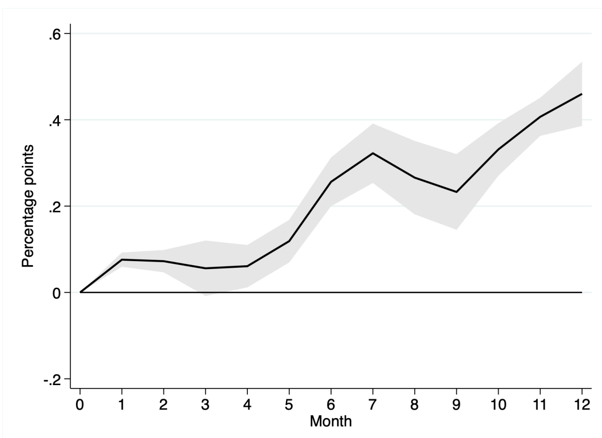
(a) Country electricity prices



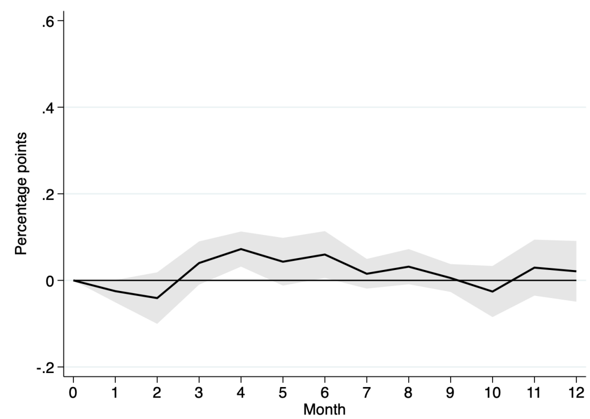
(b) EA electricity prices with country shares



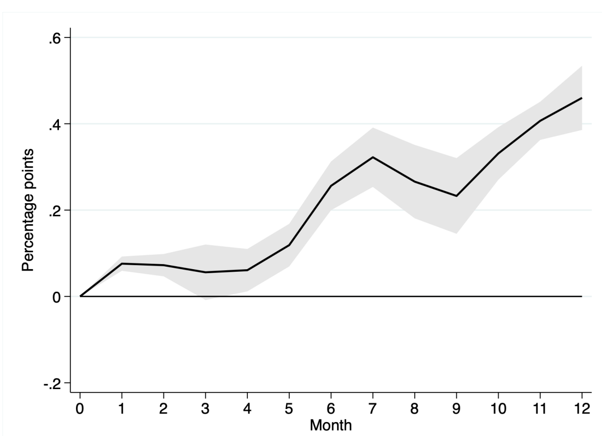
(c) Oil shifts and energy shares



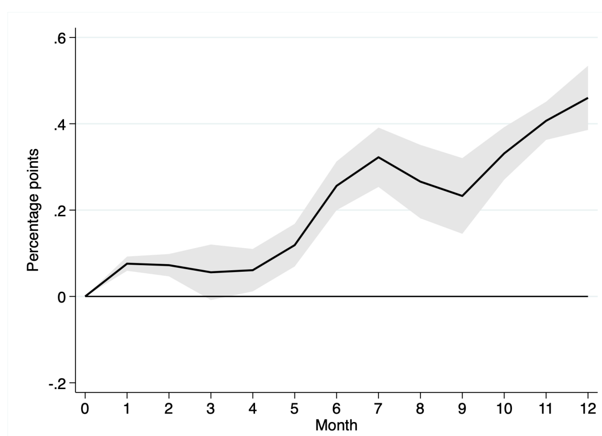
(d) Wind



(e) Oil shocks with 2015-19 expenditure shares



(f) Oil shocks with network-cost weights



Note: Local projection of average expected inflation within a region and group on 3-month cumulated energy price shock, controlling for inflation, country and group fixed effects. The shocks are scaled by their standard deviation and the standard errors are clustered by country. Panels (a) to (d) show the confidence bands corresponding to the pooled estimates in figure 2. Panels (e) and (f) investigate the robustness of the oil series by using alternative variables to measure the shares.