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When Bad News Breeds Bias: Cross-country Evidence on Inflation-as-a-Bad and Overreaction in Inflation Expectations

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When Bad News Breeds Bias: Cross-country Evidence on Inflation-as-a-Bad and Overreaction in Inflation Expectations*

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Abstract

Utilizing a very large household-level dataset of inflation expectations for twelve euro-area economies, we attempt to assess the formation and accuracy of inflation expectations following major disruptions of the macroeconomy which we identify during the period from 2004:1 to 2025:02. We find that these adverse events tend to increase the degree of inaccuracy in inflation expectations. We also find that this happens because inflation expectations tend to go up in response to these shocks relative to the 12-month ahead inflation realizations, which offers direct evidence of overestimation of inflation. This is consistent with overreaction of inflation expectations in response to inflationary news and with inflation-as-a-bad behavioral patterns in response to adverse non-inflationary shocks. We infer that such behavioral biases appear to have played an important role in the formation of inflation expectations in the euro-area following adverse shocks during the past two decades.

Keywords: forecast errors, behavioral bias, macroeconomic shocks.

JEL Classification: D84, E31, E70

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1 Introduction

Utilizing a very large household-level dataset across the euro-area for the period from 2004:1 to 2025:02, we dissect the effects of major macroeconomic disruptions on household expectations in these economies. In particular, we are interested in how these shocks affect the formation and accuracy of households' inflation expectations.

We exploit stock market volatility as a proxy for uncertainty and identify major disruptions during this period using the VSTOXX index which measures the expected volatility of the main European equity index. Although our selection algorithm is conceptually similar to Bloom (2009), unlike the latter paper which treats events as identical uncertainty shocks, we do this on an event-by-event basis. Our selection algorithm captures large events that were plausibly relevant for all countries in the sample. Importantly, this ends up selecting events that make intuitive sense, such as the Global Financial Crisis, the European Sovereign Debt Crisis, the Brexit Referendum, the Covid Pandemic and the Russian Invasion of Ukraine. The main contribution of our paper is to offer a structured approach in measuring the impact of these adverse identified macroeconomic events on the formation and accuracy of inflation expectations.

We find that following adverse events, the overall degree of inaccuracy as captured by the absolute forecast error typically rises. This increased inaccuracy following macroeconomic disruptions is driven by an increase in inflation expectations relative to the 12-month ahead inflation realizations. The latter finding suggests that households associate adverse events with higher expected inflation, so that they tend to overestimate inflation following such events.

Related to this, following certain adverse events, such as the Covid episode, which bring about a fall in inflation in some countries and have no inflationary effects in other countries, inflation expectations tend to go up relative to inflation realizations, providing direct evidence that inflation-as-a-bad (IAAB) is at work. This evidence is consistent with Tsiaplias (2024) who find that IAAB perceptions relate to adverse shocks and influence the response of inflation expectations to them. Our evidence is in line with Bhandari et al. (2025) who develop a theoretical model where subjective beliefs play a role in aggregate fluctuations so that an increase in pessimism generates upward biases in inflation forecasts. In our context, adverse shocks can be thought of as bringing about pessimistic waves that increase inflation expectations even when these shocks do not increase inflation or even tend to bring future inflation down. Our evidence here is also consistent with the empirical findings in Hou and Wang (2024) which point to the relevance of subjective models of expectation formation, and broadly in line with Binetti et al. (2024) which find that "inflation is perceived as an unambiguously negative phenomenon."

A recent literature has documented different forms of overreaction by households, professional forecasters and other agents. Kohlhas and Walther (2021) provide a wide range of survey evidence consistent with overreaction of output and inflation expectations to recent events where individuals extrapolate from recent conditions, coinciding with underreaction to average new information as measured by average forecast revisions (as in Coibion and Gorodnichenko (2015)). Considering professional forecasters' revisions of inflation expectations, Bordalo et al. (2020) present evidence that individual inflation forecasts typically overreact to news while consensus forecasts underreact relative to full information rational expectations.[1] Cornand et al. (2020) provide extensive evidence for overreaction in households' inflation expectations forecast errors to individual forecast revisions. Given that we do not have a panel, we cannot examine overreaction to individual forecast revisions.

However, we provide direct evidence for overreaction to adverse inflationary events, notably the Russian Invasion of Ukraine, in that, in response to this inflationary shock, individual households inflation expectations tend to go up more than the 12-month ahead inflation realizations. This provides empirical evidence for overreaction to recent inflationary news as captured by our shock identification exercise. We also find overreaction of inflation expectations to recent realizations of the forecasted variable, a more standard measure of recent inflationary news, consistent with individuals extrapolating from recent conditions as in Kohlhas and Walther (2021).

[1]Thus, Bordalo et al. (2020) analyzes a different type of overreactions in survey expectations (overreactions to individual forecast revisions) to that documented in Kohlhas and Walther (2021) who emphasize overreactions to recent realizations of the forecasted variable.

We note that, throughout, we control for the households' current perception of inflation over the past 12 months which captures idiosyncratic aspects of each household such as its tendency to overestimate inflation. Thus, our findings regarding pervasive overestimation of inflation, IAAB in the presence of non-inflationary shocks, and overreaction to inflationary shocks, are net of such idiosyncratic influences.

The next section describes our data and the identification of adverse events during the period under study. Following that, we present our household-level regression estimation and results. The final section briefly concludes.

2 Data and Variables Construction

2.1 Macroeconomic Data

The source of macroeconomic data for inflation, unemployment and production which we utilize in our regression analysis is the Eurostat database. We measure realized inflation using the annual rate of change of the harmonized consumer price index (HICP) for all items. For each country, we construct 12-month-ahead realized inflation and combine it with survey data on inflation expectations to calculate forecast errors and absolute forecast errors, where we follow the literature in defining forecast errors as inflation realizations at t+12 minus individual inflation expectations at t regarding t+12. These measures serve as the dependent variables in our regression analysis shown in Figures 3 to 6 and Tables A1 to A4, as well as in Tables 2, A5 and A6. We also utilize the HICP for fuel to measure fuel inflation and the HICP for food to measure food inflation. These serve as independent variables in our regression analysis in Table 2, while fuel inflation is also included as a control in all Tables of results. Finally, we incorporate the seasonally adjusted unemployment rate and the annual growth rate of industrial production, which are likewise used as independent variables across our regression analyses. These variables, together with fuel inflation, are employed to capture broader macroeconomic conditions and energy-related cost pressures that may shape both realized and perceived inflation.

Financial market uncertainty is measured by the implied volatility index for the major stock market index (Euro Stoxx 50 Price Index), VSTOXX. The VSTOXX data are daily and their source is the London Stock Exchange Group Data & Analytics, formerly Refinitiv. The VSTOXX index is based on EURO STOXX 50 options prices and designed to reflect the market expectations of near-term up to long-term volatility by measuring the square root of the implied variance across all options of a given time to expiration.

2.2 Survey Data

We use survey-based measures of consumers' expectations over the next 12 months in twelve euro area economies. The data we use are from the Joint Harmonized EU Programme of Business and Consumer Surveys (BCS) of European households.[2] The sample size of the survey varies across countries and is generally positively related to their respective population size. In our paper we utilize the micro data set on consumers' quantitative inflation perceptions and expectations provided by the European Commission. The data are monthly, start from January 2004 to February 2025.

We use the data from the following two questions in the survey to construct the main variables in our baseline analysis. Questions 5 and 6 are two-part questions where the respondent is asked to provide a quantitative number of consumer price change:
Data for consumers' price perception are obtained from Question 5: "How do you think that consumer prices have developed over the last 12 months?". Possible answers are categorical and include: "risen a lot", "risen moderately", "risen slightly", "stayed about the same", "fallen" and "don't know".

If Question 5 was answered by "risen a lot", "risen moderately", "risen slightly" or "fallen", then the respondent is subsequently asked to provide a quantitative estimate in Question 51. Question 51 asks "By how many per cent do you think that consumer prices have gone up/down over the past 12 months? Consumer prices have increased by _____,_ %

[2]This same dataset is used in Kourtellos et al. (2025) to investigate the relation between the distribution of current expectations of future inflation across households with current inflation realizations. An earlier edition of this dataset for May 2003 to December 2016 was used in Duca-Radu et al. (2021), before publicly released, to study the response of households' consumption intentions to their beliefs about future inflation.

/ decreased by _____,_ %." We rely on the quantitative responses from Question 51 as it contains more information on the magnitude of perceived past inflation, compared to the qualitative responses from Question 5. This variable, which we denote as *"Past Prices Perception"*, serves as a dependent variable in our regression analysis.

Data for consumers' inflation expectations are obtained from Question 6: "By comparison with the past 12 months, how do you expect that consumer prices will develop in the next 12 months?". Possible answers are categorical and include: "increase more rapidly", "increase at the same rate", "increase at a slower rate", "stay about the same", "fall" and "don't know".

If Question 6 was answered by "increase more rapidly", "increase at the same rate", "increase at a slower rate", and "fall", then the respondent is subsequently asked to provide a quantitative estimate in Question 61. Question 61 asks "By how many per cent do you expect consumer prices to go up/down change in the next 12 months? Consumer prices will increase by _____,_ % / decreased by _____,_ %." We rely on the quantitative responses from Question 61 as it contains more information on the magnitude of inflation expectations, as compared to the qualitative responses from Question 6. This variable, which we denote as *"Inflation Expectations"*, is used to construct forecast errors and absolute forecast errors subsequently used as dependent variables in our analysis.

To prepare the data for our analysis, we assign a value of zero to Question 51 when the respondent's answer to Question 5 is "stay about the same" and analogously assign value of zero to Question 61 to zero when the respondent's answer to Question 6 is "stay about the same". Furthermore, we impose sign consistency by recoding responses such that the numerical entry in Question 51 is negative if the corresponding categorical response in Question 5 is "fallen" and similarly, the entry in Question 61 is negative if the categorical response in Question 6 is "fall". Finally, to mitigate the influence of outliers and prevent extreme responses from disproportionately affecting the results, we follow Curtin (1996) and truncate the data at -10 and +50 percent.

We further draw on survey information on household income, respondent occupation, education, gender, and age. These characteristics are included as controls for individual fixed effects in our regression specifications, thereby accounting for systematic differences in inflation perceptions across demographic groups.

2.3 Constructing a financial shock measure

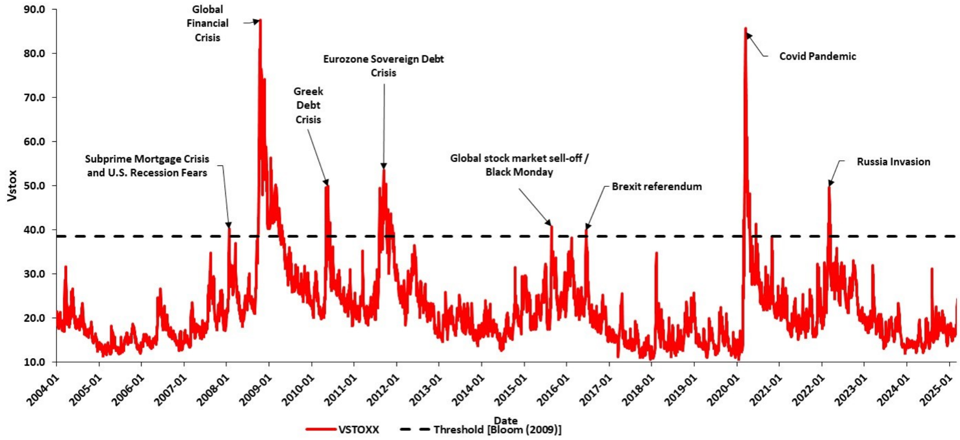
We begin by identifying market disruptions using the VSTOXX index and the Bloom (2009) methodology. We also consider identification of adverse events based on the Markov Regime Switching approach from Hamilton (1989), which we present in Table 1 on page 9 alongside the adverse events identified based on the Bloom (2009) approach.

The VSTOXX index is a market instrument representing the markets's expectation of the 30-day forward volatility of EURO STOXX 50, the main European equity index. It is based on EURO STOXX 50 options prices and is designed to reflect the market expectations of near-term up to long-term volatility by measuring the square root of the implied variance across all options of a given time to expiration. Bloom (2009) uses stock market volatility as a proxy for uncertainty, where spikes in volatility are correlated with other measures of uncertainty. A spike of the VSTOXX index could indicate a possible market disruption in the European markets. We define substantial VSTOXX movement any VSTOXX level that is higher than the VSTOXX mean by at least 1.65 of standard deviation. As we can see in Figure 1, uncertainty jumps at the onset and during major events like the 2008 Financial Crisis, the European Sovereign Debt Crisis, the Covid-19 Pandemic and the Russian invasion of Ukraine.

We identify market disruptions using daily VSTOXX index data, following a similar methodology to Bloom (2009). In our study, we have chosen 23 "VSTOXX Events" where the VSTOXX index was significantly above the mean, taking the value 1 when the market volatility index is above the threshold and 0 otherwise. The threshold we use is 1.65 standard deviations above the mean, selected as the 5% one-tailed significance level treating each month as an independent observation.

These "VSTOXX Events" include the 2008 Financial Crisis (January 2008 and from Septem-

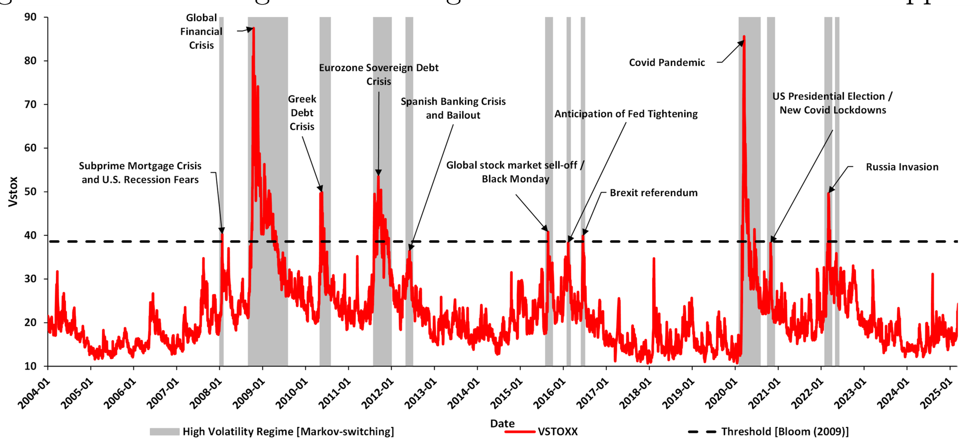
Figure 1: Bloom (2009) VSTOXX-based identification approach



Notes: Daily Eurostoxx market volatility (VSTOXX) measures the implied volatility of European STOXX 50 index. Implied volatility is derived from option values, which represents the estimates and assumptions of market participants. The threshold (mean + 1.65 standard deviation) is shown by the dotted line, with value 39.3. The events identified are above the dotted line.

ber 2008 to April 2009), the European Sovereign Debt Crisis (May 2010, June 2010, and from August 2011 to December 2011), the global stock market sell-off (August 2015), the Covid-19 Pandemic (from February 2020 to April 2020, and June 2020) and the Russian invasion of Ukraine (March 2022).

Figure 2: Markov Regime Switching VSTOXX-based identification approach



Notes: VSTOXX measures the implied volatility of European STOXX 50 index. Implied volatility is derived from option values, which represents the estimates and assumptions of market participants. The events identified when VSTOXX is in high volatility regime, as estimated using the Markov Regime Switching approach, are shown by the grey shaded area. The events identified using the Bloom (2009) approach are above the dotted line.

As an alternative to the Bloom (2009) identification approach, we also employ a Markov Regime Switching approach to detect episodes of elevated uncertainty. Before estimation, we first assess the time series properties of the VSTOXX by conducting an Augmented Dickey-Fuller (ADF) test. The results of the ADF test do not support the null of a unit root, indicating that the VSTOXX series is stationary.

Consistent with the interpretation in Bloom (2009), we assume that regimes characterized by high volatility in the stock market serve as a proxy for periods of elevated uncertainty. To capture such dynamics, we estimate a two-state Markov Regime Switching model, specified with regime-specific constant but common rather than regime-specific variance, as defined below:

$$\begin{gathered} Vstoxx_t = \mu_{s_t} + \epsilon_t, \\ \epsilon_t \sim \mathcal{N}(0, \sigma^2) \end{gathered} \tag{1}$$

where $Vstoxx_t$ is the Vstoxx market index, s_t is the latent regime at time t (1 or 2), following a Markov chain, μ_{s_t} is the regime-specific constant, and σ^2 is the common (not regime-specific) variance.

Using the Markov Regime Switching model, we identify 37 "VSTOXX Events", defined as periods in which the estimated probability of being in the high-volatility regime at time t, conditional on the information set available up to t, exceeds 0.5. As we can see in Figure 2, the set of events identified based on the Bloom (2009) approach is a subset of the adverse events identified based on the Markov Regime Switching approach. The latter approach identifies additional events such as the Spanish Banking Crisis and Bailout from May 2012 to June 2012, the Anticipation of the Fed Tightening (February 2016), and the US Presidential Election / New Covid Lockdowns from October 2020 to November 2020.

The interviews for the Business and Consumer Surveys (BCS) are typically conducted during the first week of each month. Consequently, when estimating the effects of adverse events on inflation expectations for a given month, it is essential to account for events identified in the preceding month. For instance, an event occurring in January 2008 would likely not influence the interviews recorded in the same month, as it would most likely have occurred after the interviews were conducted. Therefore, its impact on inflation expectations is captured more accurately by considering survey responses in February 2008. In our regression analysis, this type of event is labeled as "Event_200801", and is assigned a value one exclusively in

January 2008, while in all other periods its value remains zero, with its lag included in the regressions to align the timing of the event with the survey responses.

Table 1: Macroeconomic Events Identified

Dates	Episode/Event	Markov-switching regression model	Bloom (2009)
2008-01	Subprime Mortgage Crisis and U.S. Recession Fears	Event_200801	Event_200801
2008-09	Global Financial Crisis	GFC_Episode	GFC_Episode
2008-10	Global Financial Crisis	GFC_Episode	GFC_Episode
2008-11	Global Financial Crisis	GFC_Episode	GFC_Episode
2008-12	Global Financial Crisis	GFC_Episode	GFC_Episode
2009-01	Global Financial Crisis	GFC_Episode	GFC_Episode
2009-02	Global Financial Crisis	GFC_Episode	GFC_Episode
2009-03	Global Financial Crisis	GFC_Episode	GFC_Episode
2009-04	Global Financial Crisis	GFC_Episode	GFC_Episode
2009-05	Global Financial Crisis	GFC_Episode	
2009-06	Global Financial Crisis	GFC_Episode	
2009-07	Global Financial Crisis	GFC_Episode	
2010-05	Greek Debt Crisis	GDC_Episode	GDC_Episode
2010-06	Greek Debt Crisis	GDC_Episode	GDC_Episode
2010-07	Greek Debt Crisis	GDC_Episode	
2011-08	European Sovereign Debt Crisis	SDC_Episode	SDC_Episode
2011-09	European Sovereign Debt Crisis	SDC_Episode	SDC_Episode
2011-10	European Sovereign Debt Crisis	SDC_Episode	SDC_Episode
2011-11	European Sovereign Debt Crisis	SDC_Episode	SDC_Episode
2011-12	European Sovereign Debt Crisis	SDC_Episode	SDC_Episode
2012-05	Spanish Banking Crisis and Bailout	SBC_Episode	
2012-06	Spanish Banking Crisis and Bailout	SBC_Episode	
2015-08	Global stock market sell-off / Black Monday	BM_Episode	Event_201508
2015-09	Global stock market sell-off / Black Monday	BM_Episode	
2016-02	Anticipation of Fed Tightening	Event_201602	
2016-06	Brexit referendum	Event_201606	Event_201606
2020-02	Covid Pandemic	Covid_Episode	Covid_Episode
2020-03	Covid Pandemic	Covid_Episode	Covid_Episode
2020-04	Covid Pandemic	Covid_Episode	Covid_Episode
2020-05	Covid Pandemic	Covid_Episode	
2020-06	Covid Pandemic	Covid_Episode	Covid_Episode
2020-07	Covid Pandemic	Covid_Episode	
2020-10	US Presidential Election / New Covid Lockdowns	USelect_Episode	
2020-11	US Presidential Election / New Covid Lockdowns	USelect_Episode	
2022-02	Russian Invasion	War_Episode	
2022-03	Russian Invasion	War_Episode	Event_202203
2022-05	Russian Invasion	War_Episode	

At the bottom of tables A1 to A6, we report the estimated 12-month cumulative impact of adverse events on realized inflation, obtained using the local projection method of Jorda (2005) as detailed in Appendix A.2. Presenting these results alongside the baseline regressions provides a concise summary of the effects of these adverse events on inflation across countries, facilitating direct comparison with the respective responses of households' inflation forecast errors. Appendix A.2 presents visual evidence of the impact of the events over a 12-month horizon across countries. As we can see there and in tables A1 to A6, the impact of the events on realized inflation, when statistically significant, is in the same direction across all countries, with rare exceptions.[3]

3 Estimation and results

3.1 The Impact on Inflation Expectations Accuracy

We begin by trying to understand how the events we have identified affect the accuracy of inflation forecasts. More specifically, we explain the absolute forecast error of inflation expectations[4] with the events we have identified previously, as follows:

$$AFE_{i,c,t} = \alpha_0 + \sum_{j=1}^{4} \beta_j Event_{j,t} + \sum_{j=1}^{11} \gamma_j Month_{j,t} + \lambda X_{i,c,t} + \psi W_{c,t} + \alpha_1 z_{i,c,t} + u_{i,c,t} \tag{2}$$

$$AFE_{i,c,t} = |\pi_{c,t+12} - \pi^e_{i,c,t}| \tag{3}$$

$\pi^e_{i,c,t}$: Inflation expectations over the next 12 months for individual i at time t for country c

$\pi_{c,t+12}$: 12-month ahead inflation for country c at time t

$AFE_{i,c,t}$: Inflation expectations absolute forecast error over the next 12 months for individual i, at time t, for country c

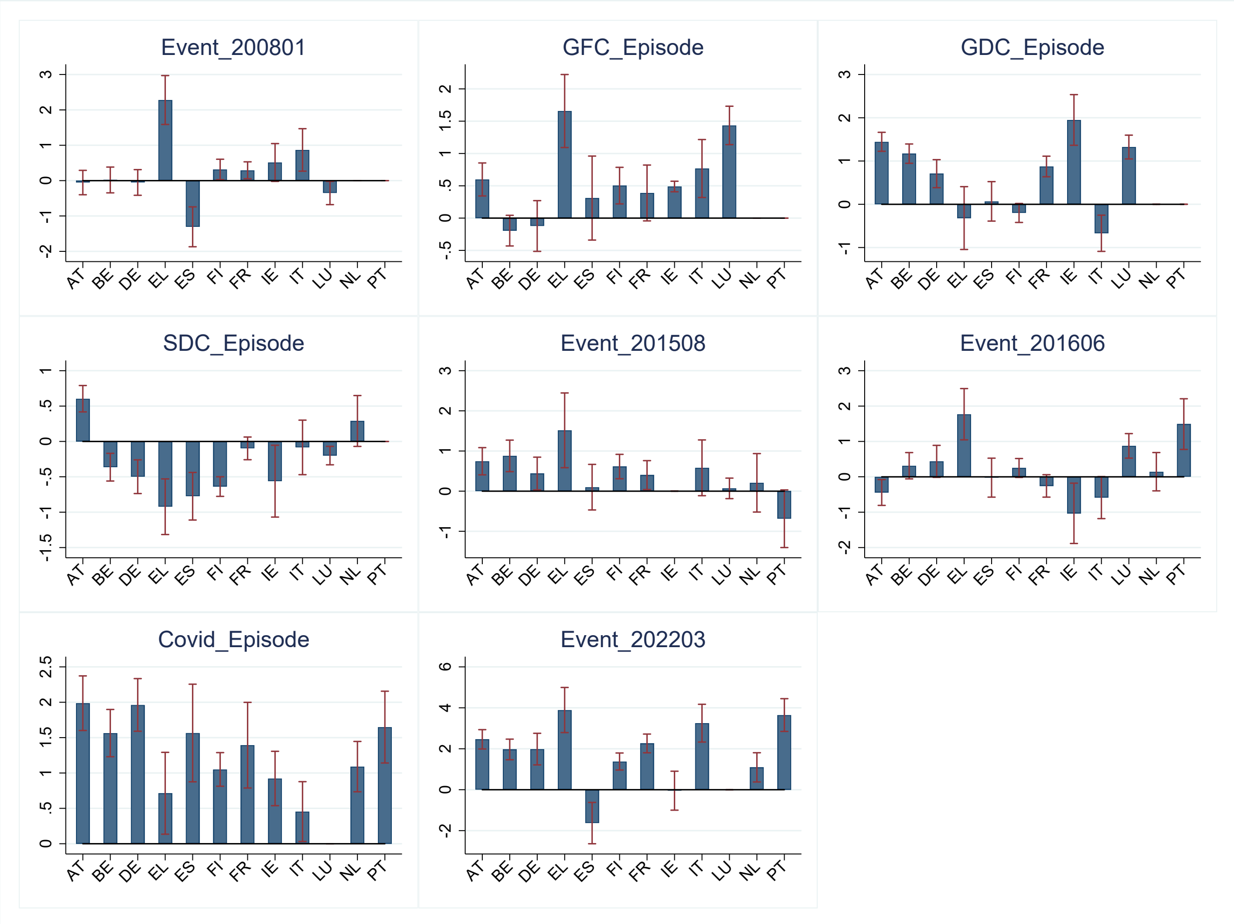
$X_{i,c,t}$: Vector of individual i characteristics (age, gender, occupation, income and education)

$W_{c,t}$: Vector of country c characteristics (unemployment annual rate, fuel inflation and industrial production annual rate)

[3]The exceptions are Austria and Luxembourg during Covid (where we observe an increase in inflation only in these two countries), for Austria and Ireland in response to the February 2016 event, and for Belgium during the Spanish Banking Crisis event.

[4]We measure the degree of inaccuracy using absolute forecast errors since raw forecast errors would not accurately capture the accuracy of forecasts. To see this, consider households which systematically tend to make large upward and large downward forecast errors that cancel each other out for this type of households, and compare with a second type of households which always make small negative forecast errors. In this case, while the latter households are in fact more accurate, their raw forecast errors will be greater than those of the former more inaccurate type of households.

Figure 3: Effects of Events on Absolute Forecast Errors



Notes: Forecast errors are in percentage points. For consecutive events, i.e. episodes, we show the average effect over the respective period.

$z_{i,c,t}$: Inflation perception over the past 12 months for individual i, at time t, for country c

We note that controlling for current perceptions regarding inflation over the past 12 months captures idiosyncratic aspects of each household, e.g. differences in their tendency to exaggerate when answering survey questions or differences in the basket of items consumed by the household, that would be impossible to capture using any of the other available variables here.[5]

Higher absolute forecast errors in response to these shocks would imply that the degree of inaccuracy goes up. Indeed, as we can see in Figure 3 and Table A1, absolute forecast

[5]Interestingly, we find that individuals that believe inflation to have been higher over the past 12 months tend to make more inaccurate forecasts, and that this is the case in every single country.

errors typically rise following the arrival of these events, except in the case of the European Sovereign Debt Crisis that led to higher inflation forecast accuracy in many of these euro-area economies.[6] We note that the adverse events we identify typically have the same qualitative impact on infation expectation forecast errors and the degree of inaccuracy of these forecast errors across countries.[7] However, they often have quantitatively different impact across countries consistent with some degree of heteregeneity in how big the effect of these events is on inflation expectations formation across the euro area.

Overall, our estimates suggest that macroeconomic uncertainty tends to increase the inaccuracy of inflation forecasts in the euro area. This appears inconsistent with rational inattention models which link higher uncertainty with higher marginal returns from forming accurate forecasts so that capacity is reallocated to allow increased accuracy when variability is higher. Alternatively, this increase in inaccuracy could indicate that the cost of paying attention (which relates to the noise to signal ratio) increases more than the benefits from paying attention following these adverse events.

3.2 The Impact on Inflation Expectations Forecasting Errors

Next, we proceed to examine inflation expectations forecast errors which can help us understand our previous finding regarding heightened inaccuracy in response to macroeconomic disruptions related to high uncertainty. We explain inflation expectations forecast errors with the events and other controls as follows:

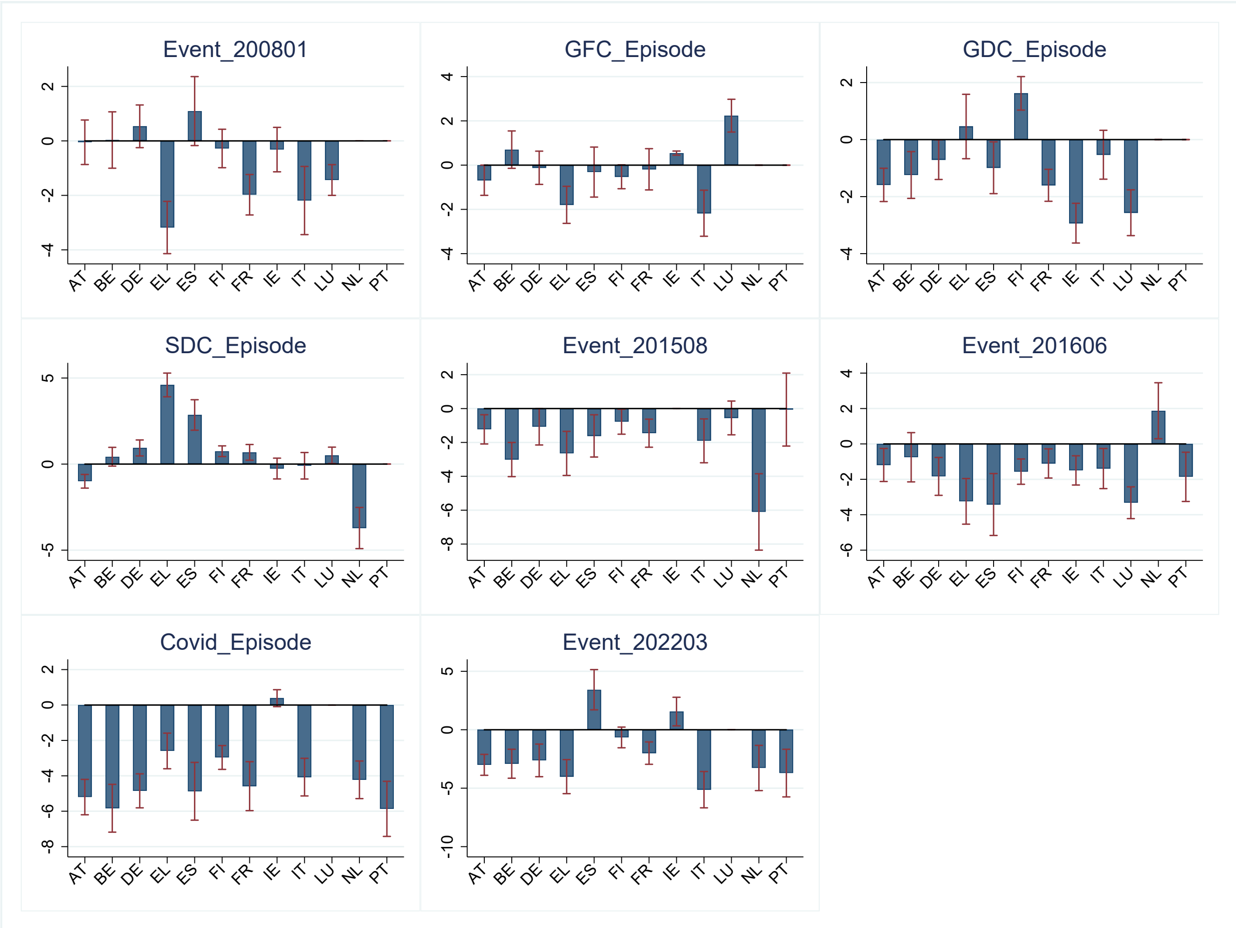
$$FE_{i,c,t} = \alpha_0 + \sum_{j=1}^{4} \beta_j Event_{j,t} + \sum_{j=1}^{11} \gamma_j Month_{j,t} + \lambda X_{i,c,t} + \psi W_{c,t} + \alpha_1 z_{i,c,t} + u_{i,c,t} \tag{4}$$

$$FE_{i,c,t} = \pi_{c,t+12} - \pi^e_{i,c,t} \tag{5}$$

[6]This includes Greece, Ireland and Spain in addition to Belgium, Finland, Germany and Luxembourg.

[7]The impact is qualitatively different for less than ten percent of the possible cases across events and countries with available data: 7 of the possible 88 cases in Figure 3 and Table A1, 8 of the 88 possible cases in Figure 4 and Table A2, and 8 of 108 cases in Figures 5 and 6 and Tables A3 and A4, ranging from 7.4 percent to 9.1 percent of the possible cases.

Figure 4: Effects of Events on Forecast Errors



Notes: Forecast errors are in percentage points. For consecutive events, i.e. episodes, we show the average effect over the respective period.

$FE_{i,c,t}$: inflation expectations forecast error over the next 12 months for individual i, at time t, for country c.

We define forecast errors as above following the previous literature going back to Coibion and Gorodnichenko (2015).[8] Defining forecast errors as inflation realizations 12 months ahead minus current inflation expectations, negative errors would, e.g., suggest overreaction to inflationary news in that current expectations about future inflation increase more than 12-months ahead inflation. In this case, negative estimates in a regression of the forecast error on current realizations of the forecasted variable or other inflationary news (like our

[8] This literature considers forecast revisions and defines forecast errors as inflation realizations 12 months ahead minus current inflation expectations, so that negative estimates in a regression of the forecast error on forecast revisions suggests overreaction.

identified inflationary event of the Russian invasion of Ukraine) would suggest overreaction.[9]

As we can see in Figure 4 and Table A2, with the exception of the European sovereign debt crisis episode, forecast errors typically go down in response to the shocks we consider here, providing evidence for overestimation of inflation in these euro-area economies.[10] Furthermore, this response of the forecast error implies that the heightened inaccuracy observed in the previous sub-section is due to individuals overestimating future inflation after the arrival of macroeconomic disruptions such as the ones we consider here.

Notably, several adverse events are being perceived as inflationary even when they tend to bring inflation down as is more prominently evident for many countries (Austria, Germany, Italy, the Netherlands and Spain) for the event that occurred on August 2015 related to the Black Monday Global stock market sell-off, providing striking evidence for IAAB. More generally, IAAB is a phenomenon where inflation expectations go up following adverse events that bring about a fall in inflation or have no inflationary effects in an economy. This occurs for most countries in the case of the August 2015 event (in Austria, Belgium, France, Germany, Greece, Italy, the Netherlands and Spain). It also occurs during the Covid episode in most of the countries (for France, Greece, Italy, the Netherlands and Portugal where inflation falls in response to this adverse shock but also for Austria, Belgium, Finland, Germany and Spain where inflation does not rise), and again in the Brexit referendum event of June 2016 for ten of the twelve countries (in France, Finland and Ireland where inflation falls in response to this adverse shock, but also for Austria, Germany, Greece, Italy, Luxembourg, Portugal and Spain, where inflation does not go up in response to this shock). Finally, we also observe IAAB in some countries in response to the US-economy-related shock of January 2008 (for France, Greece, Italy and Luxembourg, where inflation

[9]We opt to go with the above definition so as to be consistent with the previous literature. However, we note that, as we do not consider forecast revisions, it would perhaps be more natural here to consider forecast errors as the difference between inflation expectations and inflation realizations so that positive errors suggest overreaction to news in that inflation expectations react more than 12-months ahead inflation.

[10]We note again that we control for the households' current perception of inflation over the past 12 months, which can capture the tendency of a specific household to overestimate inflation. As we can see in Table A2, indeed households which perceived higher inflation over the past 12 months tend to overestimate inflation over the next 12 months and this is the case in every one of these countries. Thus, our findings reported in this sub-section regarding pervasive overestimation of inflation, IAAB in the presence of non-inflationary shocks, and overreaction to inflationary shocks, are net of such idiosyncratic influences.

actually falls in response to this adverse shock) and for the Global Financial Crisis episode (for Greece and Italy).

Importantly, we also observe direct evidence for overreaction to adverse inflationary events, notably the Russian Invasion, in that, in response to this inflationary shock, inflation expectations go up by more than 12-month ahead inflation realizations in several euro-area countries. As we can see in the last row of Table A2, this shock that occurred on March 2022 raised inflation significantly in eight of the twelve euro-area economies we consider here, and in six of these eight euro area countries (Austria, France, Germany, Greece, Italy and Portugal), inflation expectations increased by more than inflation realizations. This provides empirical evidence for overreaction to recent inflationary news, as captured by our identification exercise.

Moreover, we find overreaction of inflation expectations to recent realizations of the forecasted variable, consistent with individuals extrapolating from recent conditions. This is evident by looking at the tenth row of Table A2, where the response of the forecast error to the recent realization of fuel inflation is shown to be significantly negative in all twelve euro-area economies considered here. We revisit this relation later in Table 2, section 3.4, where we consider HICP inflation and Food inflation in addition to Fuel inflation in a specification that more closely resembles Kohlhas and Walther (2021).

3.3 Utilizing macroeconomic disruptions identified by the Markov Regime Switching approach

In this section, we consider the same specifications as in regression equations 2 and 4 for absolute forecast errors and forecast errors respectively, but utilizing macroeconomic disruptions based on a Markov Regime Switching identification instead of the methodology from Bloom (2009) utilized in the last two subsections. As shown in the third column of Table 1, this identification approach provides a larger set of episodes and events that encompasses the subset of events and episodes identified based on the Bloom (2009) methodology. As such, this provides a check for the sensitivity of our main inferences to the specific identification of macroeconomic disruptions related to uncertainty. As can be seen in Figures 5 and 6 and Tables A3 and A4, our main results remain intact. However, we note that to the extent that the Markov Regime Switching methodology enables somewhat more objective identification as compared to the Bloom (2009) methodology, this should be seen as more than a robustness exercise.

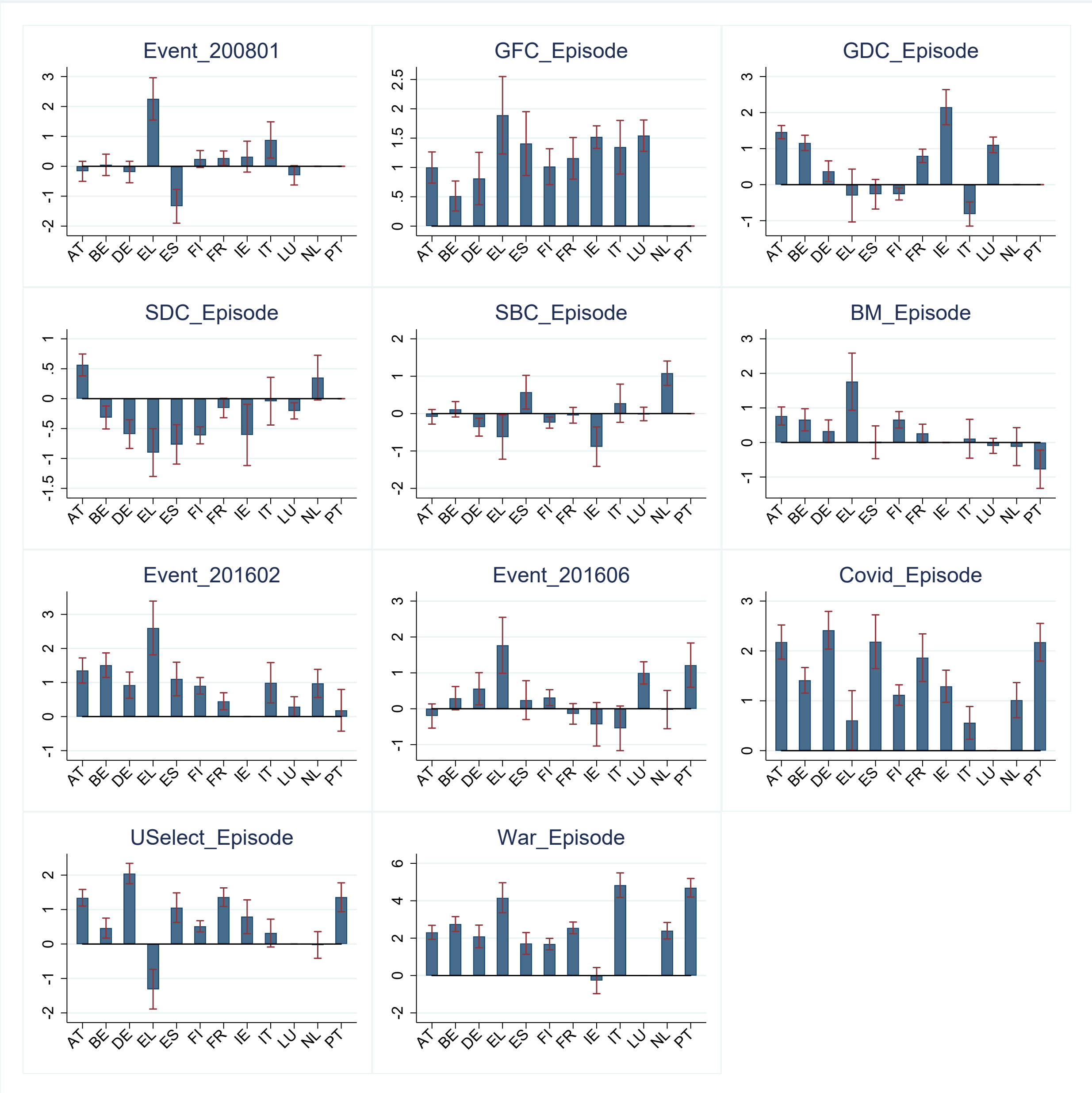
More specifically, as we can see in Figure 5 and Table A3, similarly to the earlier results in Figure 3 and Table A1, absolute forecast errors typically rise following these macroeconomic disruptions, with the exception of the European Sovereign Debt Crisis (SDC) and the newly identified Spanish Banking Crisis (SBC). This implies again an increase in the degree of forecast inaccuracy following macroeconomic disruptions related to high uncertainty.

Moreover, in Figure 6 and Table A4, similarly to the results in Figure 4 and Table A2, we can see that this heightened forecast inaccuracy can be attributed to inflation expectations typically going up relative to 12-month ahead inflation as individuals overestimate future inflation after the arrival of macroeconomic disruptions such as the ones we identify here. As we can see there, with the exception of the European sovereign debt crisis (SDC) and the newly identified Spanish Banking Crisis (SBC), forecast errors become more negative. This, again, provides evidence of overestimation of inflation in these euro-area economies.

Once again, we observe striking evidence of IAAB. More specifically, in Figure 6 and Table A4 we see that forecast errors typically go down in response to non-inflationary shocks such as the Black Monday Global stock market sell-off that occurred in 2015, the February 2016 US-economy-related event, the Brexit referendum event of June 2016 and the Covid pandemic episode identified between February and July of 2020.

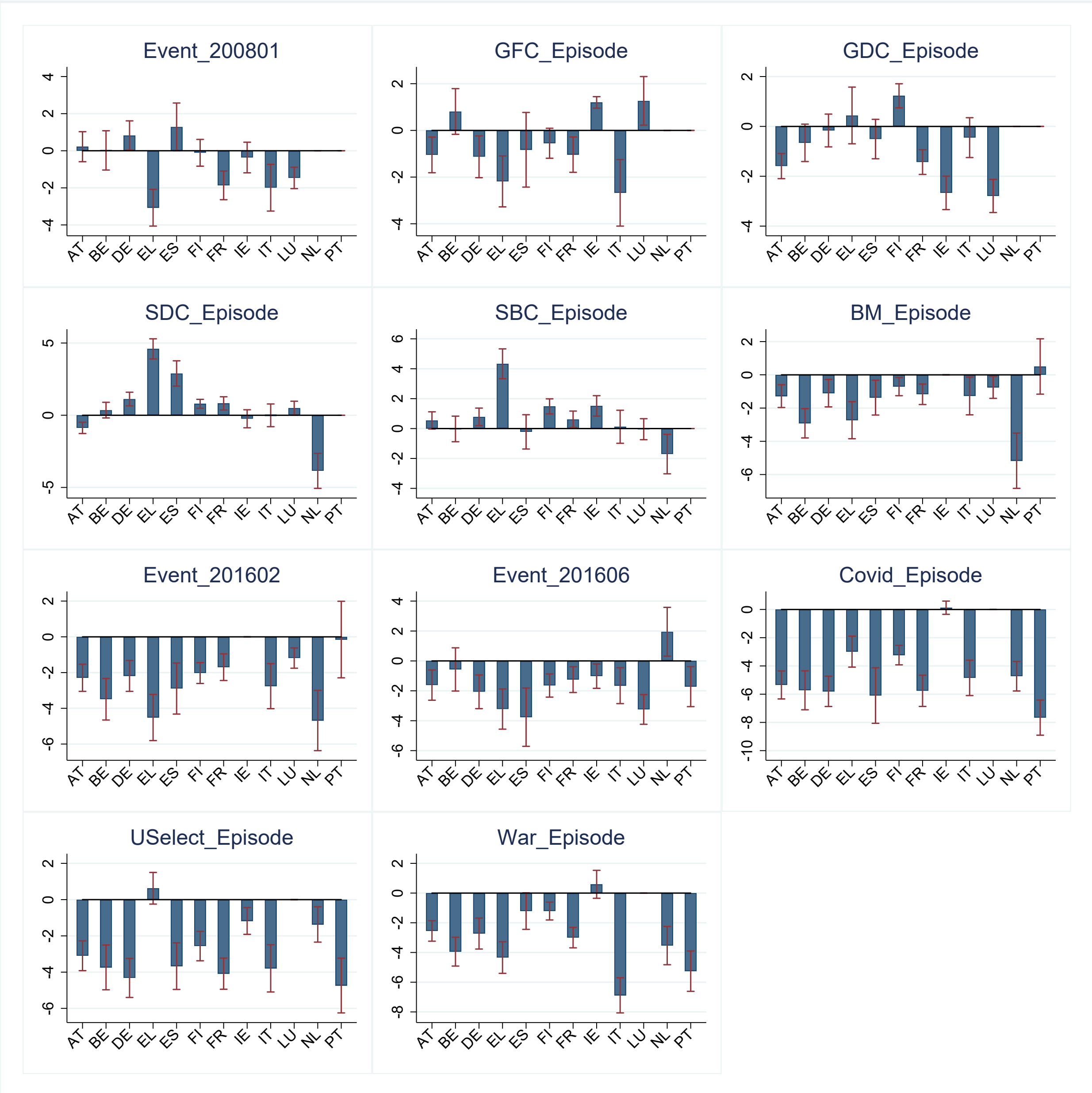
In the case of the 2015 Black Monday Global stock market sell-off, IAAB is observed for Austria, Germany, Italy, Luxembourg, the Netherlands and Spain where inflation actually falls in response to this shock, but also for Belgium, Finland, France and Greece where inflation does not go up in response to this shock. For the newly identified February 2016 shock, IAAB is observed in most of these economies: Austria, Belgium, Finland, Germany, Italy, Luxembourg, the Netherlands and Spain, where inflation does not go up. For the

Figure 5: Effects of Events on Absolute Forecast Errors (selected based on the Markov Regime Switching approach)



Notes: Forecast errors are in percentage points. For consecutive events, i.e. episodes, we show the average effect over the respective period.

Figure 6: Effects of Events on Forecast Errors (selected based on the Markov Regime Switching approach)



Notes: Forecast errors are in percentage points. For consecutive events, i.e. episodes, we show the average effect over the respective period.

Brexit referendum event of June 2016, IAAB is observed for ten of the twelve euro-area economies in our sample (Austria, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Portugal and Spain where inflation does not go up). For the Covid episode, we observe IAAB for nine of these euro-area economies (Belgium, Finland, France, Germany, Greece, Italy, the Netherlands, Portugal and Spain, where inflation actually goes down in response to this shock in the latter four countries).

Finally, we also observe IAAB in some countries in response to the US-economy-related shock of January 2008 (for France, Greece, Italy and Luxembourg, where inflation actually falls in response to this shock) and for the Global Financial Crisis episode (for Austria, France, Germany, Greece and Italy).

We conclude that, if anything, the evidence for IAAB is even stronger when considering the Markov Regime Switching identification methodology in this sub-section as compared to the Bloom (2009) methodology considered in the previous sub-section.

We also observe again evidence for overreaction of inflation expectations to inflationary shocks. More specifically, in response to the Russian Invasion episode, inflation expectations go up by more than 12-month ahead inflation realizations in several euro-area economies. As we can see in the last row of Table A4, this shock that occurred on March 2022 raised inflation significantly in eight of the twelve euro-area economies we consider here, and in seven of these eight countries (Austria, Finland, France, Germany, Greece, Italy and Portugal), inflation expectations increased by more than inflation realizations, providing evidence for overreaction to recent inflationary news as captured by the identification exercise of this sub-section.

Again, we also find overreaction of inflation expectations to recent realizations of the forecasted variable, consistent with individuals extrapolating from recent conditions. This is shown in the tenth row of Table A2, where the response of the forecast error to the recent realization of fuel inflation is significantly negative in all twelve euro-area economies considered here. We revisit this relation below in the next section.

3.4 Overreaction to recent outcomes

Next, we proceed to examine inflation expectations forecast errors' reaction to recent inflation realizations which can help us understand whether respondents extrapolate from and overreact to recent events. Here, we consider a regression of forecast errors on current realizations of the forecasted variable that resembles Kohlhas and Walther (2021), with the addition of some control variables that capture individual characteristics:

$$FE_{i,c,t} = \alpha_0 + \lambda X_{i,c,t} + \gamma_c Inflation_{c,t} + u_{i,c,t} \tag{6}$$

$FE_{i,c,t}$: Inflation Expectations Forecast Error over the next 12 months for individual i, at time t, for country c.

$X_{i,c,t}$: Vector of individual i characteristics (age, gender, occupation, income and education)

$Inflation_{c,t}$: $\pi_{c,t}$ or $\pi e_{c,t}$ or $\pi f_{c,t}$

$\pi_{c,t}$: Inflation realization over the past 12 months at time t for country c

$\pi e_{c,t}$: Fuel Inflation realization over the past 12 months at time t for country c

$\pi f_{c,t}$: Food Inflation realization over the past 12 months at time t for country c

As compared to the Kohlhas and Walther (2021) specification, we do not incorporate individual fixed effects since we have repeated cross-sections where we do not observe the same individual at each point in time, rather than panel data as in the latter paper. Again, we define forecast errors similarly to the literature considering forecast revisions that goes back to Coibion and Gorodnichenko (2015), defining forecast errors as inflation realizations 12 months ahead minus current expectations of future inflation so that negative estimates in a regression of the forecast error on realized inflation indicate overreaction.

Indeed, in Table 2, we find that the forecast errors of the respondents react negatively to recent inflation realizations which suggests overreaction in that current expectations regarding inflation 12 months from now go up by more than 12-month ahead inflation realizations, after individuals observe that recent inflation has gone up. This result is

Table 2: Inflation Expectation Forecast Error reactions across the Eurozone

Variable	AT	BE	DE	EL	ES	FI	FR	IT	LU	NL	IE	PT
Regression model 1: $FE_{i,c,t} = \alpha_0 + \lambda X_{i,c,t} + \gamma_c \pi_{c,t} + u_{i,c,t}$												
LagInflation	-0.429***	-0.428***	-0.682***	-1.271***	-0.964***	-0.469***	-0.596***	-0.39***	-0.228**	-0.308***	-0.312***	-0.867***
	(0.095)	(0.093)	(0.095)	(0.069)	(0.084)	(0.072)	(0.101)	(0.134)	(0.115)	(0.087)	(0.081)	(0.123)
Regression model 2: $FE_{i,c,t} = \alpha_0 + \lambda X_{i,c,t} + \gamma_c \pi e_{c,t} + u_{i,c,t}$												
LagFuelInflation	-0.087***	-0.064***	-0.113***	-0.125***	-0.164***	-0.094***	-0.094***	-0.142***	-0.061***	-0.148***	-0.068***	-0.188***
	(0.007)	(0.011)	(0.01)	(0.017)	(0.014)	(0.007)	(0.009)	(0.02)	(0.013)	(0.02)	(0.011)	(0.028)
Regression model 3: $FE_{i,c,t} = \alpha_0 + \lambda X_{i,c,t} + \gamma_c \pi f_{c,t} + u_{i,c,t}$												
LagFoodInflation	-0.225***	0.224***	-0.278***	-0.738***	-0.231**	-0.092**	-0.136*	-0.065	0.465***	0.268***	-0.063	-0.447***
	(0.072)	(0.07)	(0.072)	(0.102)	(0.094)	(0.04)	(0.071)	(0.109)	(0.134)	(0.097)	(0.056)	(0.09)
Observations	287883	297229	322769	240245	266897	269702	261443	261714	60349	115332	144825	82545

Note: Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$
All regression models include household-specific charactiristics (age, gender, occupation, income and education).

strongest in magnitude using CPI inflation but is also present for fuel inflation (which was used in our baseline in the previous sub-section) that is found to be highly significant in all twelve euro-area countries we consider here,[11] and for food inflation except in Italy and Ireland.

3.5 Income-related heterogeneity

In this subsection, we consider the potentially heterogeneous responses of individuals with high income by adding interactions of the latter with our previously identified shocks. The specifications in Tables A5 and A6 are otherwise identical to the baseline regressions in Tables A1 and A2 for absolute forecast errors and forecast errors respectively.

The estimates in Table A5 where we explain absolute errors of individual inflation forecasts, provide a somewhat mixed picture. For the Black Monday Global stock market sell-off (BM) that occurred in August of 2008, the Brexit referendum event of June 2016, the Covid Pandemic episode, and the Russian invasion of Ukraine, while we find a pervasive increase in the inaccuracy of inflation forecasts in most euro-area countries, we estimate the response of high-income individuals to be relatively more accurate in most cases. By contrast, for the Global Financial Crisis (GFC), while we also find a pervasive increase in the inaccuracy of inflation forecasts in most euro-area countries, we often estimate the response of high-income

[11] As compared to Table A2, where we control in additon for the identified events, country characteristics, and country fixed effects, the estimates in Table 2 are generally larger in size, except for Portugal.

individuals to be even less accurate as compared to other individuals, possibly because the financial shock created relatively more uncertainty for high income individuals that are, e.g., more likely to own stock.

In Table A6, we turn to explaining inflation forecast errors and find that while, with the exception of the European sovereign debt crisis episode (SDC), individuals overestimate future inflation so that forecast errors typically become more negative in response to the shocks we consider here, high-income individuals tend to overestimate inflation less in response to some of these events. In particular, the latter occurs in several of these economies following the Black Monday Global stock market sell-off (BM) that occurred in August of 2008, the Brexit referendum event of June 2016, the Covid Pandemic episode, and the Russian invasion of Ukraine. Thus, high-income individuals are not as prone to the IAAB malady (in the case of the first three non-inflationary events), nor as prone to overreaction in the case of the last inflationary event.

4 Conclusion

We have utilized a very large household-level dataset of inflation expectations across the euro-area during the period from 2004:1 to 2025:02, in order to assess the formation and accuracy of inflation expectations following major disruptions of the macroeconomy. Our main contribution has been to identify these macroeconomic disruptions in the euro-area and measuring their impact on the formation and accuracy of inflation expectations.

We found that following the adverse events we identified, the overall degree of inaccuracy of inflation expectations increases, driven by an increase in inflation expectations relative to the 12-month ahead inflation realizations. The latter finding suggests that households associate adverse events with higher expected inflation, so that they tend to overestimate inflation following such events. In the case of the inflationary event related to the Russian invasion of Ukraine, this suggests overreaction of inflation expectations to recent inflationary news. We also find evidence of pervasive overreaction of inflation expectations to recent realizations of the forecasted variable, consistent with individuals extrapolating from recent conditions, in line with Kohlhas and Walther (2021).

Moreover, following certain adverse events, such as the Covid episode, which bring about a fall in inflation in some countries and have no inflationary effects in other countries, inflation expectations tend to go up, providing direct evidence that IAAB is at work. Thus, adverse shocks can be thought of as bringing about pessimistic waves that increase inflation expectations even when these shocks do not increase inflation or even tend to bring future inflation down.

Overall, our results suggest that macroeconomic disruptions can bring about an increase in the inaccuracy of households' inflation forecasts and that this increased inaccuracy can be associated with biases related to overreaction and IAAB phenomena among the population. Such behavioral forces appear to have played an important role in the formation of economic expectations in the euro area during the past two decades. This suggests that going beyond standard imperfect information macroeconomic models to models that incorporate such biases along the lines of Bordalo et al. (2020), Kohlhas and Walther (2021), Broer and Kohlhas (2024), Kohlhas and Robertson (2025) and Bhandari et al. (2025) among others, is needed in order to reconcile the empirical evidence with macroeconomic theory and to understand how expectations respond to macroeconomic shocks.

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Appendix

A.1 Detailed Tables of Results

Table A1: Inflation Expectation Absolute Forecast Error Formation across the Eurozone

Variable	AT	BE	DE	EL	ES	FI	FR	IT	LU	NL	IE	PT
Event_200801	-0.0546	0.0194	-0.0521	2.279***	-1.306***	0.316*	0.292**	0.868**	-0.350*		0.513	
	(0.209)	(0.221)	(0.220)	(0.419)	(0.342)	(0.175)	(0.145)	(0.364)	(0.199)		(0.324)	
GFC_Episode	4.783***	-1.554	-0.978	13.260***	2.478	4.022***	3.110	6.140***	11.478***		3.913***	
	(1.238)	(1.150)	(1.904)	(2.739)	(3.152)	(1.371)	(2.096)	(2.175)	(1.440)		(0.395)	
GDC_Episode	2.889***	2.341***	1.416***	-0.637	0.136	-0.401	1.748***	-1.340***	2.647***		3.899***	
	(0.266)	(0.271)	(0.392)	(0.880)	(0.553)	(0.266)	(0.289)	(0.507)	(0.333)		(0.710)	
SDC_Episode	3.020***	-1.819***	-2.493***	-4.613***	-3.874***	-3.190***	-0.491	-0.423	-1.000**	1.447	-2.807*	
	(0.565)	(0.593)	(0.722)	(1.192)	(1.018)	(0.420)	(0.486)	(1.168)	(0.395)	(1.089)	(1.539)	
Event_201508	0.745***	0.878***	0.439*	1.515***	0.0989	0.613***	0.400*	0.581	0.0689	0.207		-0.687
	(0.205)	(0.238)	(0.247)	(0.564)	(0.344)	(0.184)	(0.218)	(0.421)	(0.155)	(0.441)		(0.435)
Event_201606	-0.443**	0.313	0.437	1.770***	-0.0236	0.250	-0.258	-0.588	0.874***	0.144	-1.032**	1.490***
	(0.221)	(0.225)	(0.274)	(0.439)	(0.334)	(0.162)	(0.192)	(0.360)	(0.210)	(0.328)	(0.517)	(0.434)
Covid_Episode	7.947***	6.256***	7.849***	2.854**	6.261***	4.202***	5.572***	1.818*		4.361***	3.689***	6.595***
	(0.936)	(0.810)	(0.902)	(1.402)	(1.673)	(0.576)	(1.468)	(1.025)		(0.862)	(0.932)	(1.230)
Event_202203	2.462***	1.968***	1.984***	3.892***	-1.631***	1.377***	2.261***	3.251***		1.092**	-0.0481	3.647***
	(0.286)	(0.305)	(0.468)	(0.668)	(0.611)	(0.252)	(0.277)	(0.559)		(0.433)	(0.577)	(0.485)
Past Prices Perception	0.495***	0.462***	0.569***	0.508***	0.457***	0.489***	0.517***	0.331***	0.433***	0.488***	0.481***	0.523***
	(0.00847)	(0.00784)	(0.0114)	(0.0123)	(0.00813)	(0.0119)	(0.00980)	(0.00793)	(0.0130)	(0.0175)	(0.0180)	(0.0159)
LagFuelInflation	0.0153***	0.000499	0.0329***	0.0434***	0.0379***	0.0236***	0.0227***	0.0733***	-0.0105**	0.0347***	0.00752	0.0937***
	(0.00536)	(0.00501)	(0.00725)	(0.00940)	(0.00886)	(0.00472)	(0.00548)	(0.0140)	(0.00461)	(0.0115)	(0.00795)	(0.0125)
LagUnemployment	0.362***	0.0934	-0.0569**	-0.0337*	-0.0132	0.235***	0.305***	0.107***	0.0237	0.207**	0.141***	-0.0687
	(0.0965)	(0.0663)	(0.0247)	(0.0179)	(0.0198)	(0.0477)	(0.0459)	(0.0349)	(0.0793)	(0.101)	(0.0280)	(0.0680)
LagIndustrialProduction	0.0133	0.0213**	-0.0371**	0.0716**	-0.00144	-0.0205**	-0.0130	-0.0291***	-0.0111	-0.0322	-0.00779	-0.0321*
	(0.0150)	(0.0106)	(0.0153)	(0.0308)	(0.0193)	(0.0102)	(0.0207)	(0.0111)	(0.00868)	(0.0315)	(0.00609)	(0.0179)
Constant	-0.451	0.921*	1.503***	4.821***	3.274***	-0.537	-2.099***	1.095**	1.776***	-0.110	1.778***	2.865***
	(0.563)	(0.558)	(0.300)	(0.664)	(0.582)	(0.418)	(0.472)	(0.502)	(0.481)	(0.772)	(0.460)	(0.956)
Observations	282,987	265,292	315,857	223,785	247,305	261,339	224,216	239,081	58,595	107,972	139,348	72,651
R-squared	0.446	0.405	0.555	0.380	0.402	0.477	0.516	0.279	0.399	0.472	0.389	0.553
Impact of Each Event on 12 months ahead inflation												
Event_200801	-2.189**	-1.008	-1.727***	-3.059***	-2.761***	-0.098	-3.159***	-1.958***	-2.722***	-1.823**	-1.481**	-2.292***
GFC_Episode	1.154	-11.413***	-7.862***	-9.137***	-4.135	-5.415	-10.052***	-10.052***	-0.484	-22.441***	-18.854**	-15.174***
GDC_Episode	2.364***	1.590	0.674	-1.255	3.007**	3.312***	0.957**	0.644	0.275	-0.466	2.445**	3.634***
SDC_Episode	2.783	0.324	-1.943	0.015	11.319***	6.843***	1.374	2.946*	1.049	8.393***	7.752***	5.340**
Event_201508	-2.206***	-0.620	-1.652***	0.192	-2.083**	-0.422	-0.266	-1.893**	-2.214***	-1.211***	-1.805***	-0.319
Event_201606	0.009	-0.826**	0.182	0.130	0.077	-0.924*	-0.364*	-0.145	-0.626	-0.556*	-2.421***	-0.532
Covid_Episode	4.329	-10.213	0.278	-11.300***	-2.622	-1.870	-7.591**	-5.105***	9.969**	-9.145**	-2.420	-10.903**
Event_202203	4.301***	1.311	4.488***	1.802**	-0.155	2.945***	2.951***	3.603**	-1.483	-0.664	3.961***	3.884***

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: In the above regressions, we control for demographic characteristics (age, gender, income, education, and occupation), month fixed effects (not reported in the tables), past prices perception, lagged fuel inflation, lagged unemployment, and lagged industrial production. Because the survey interviews are typically conducted in the first week of each month, we use the previous month's values of fuel inflation, the unemployment rate, and the annual change in industrial production to capture their influence on expectations reported in the subsequent month. To account for potential within-month correlation across multiple observations, standard errors are clustered at the monthly level. The variable Event_200801 is a dummy equal to 1 in February 2008 and zero otherwise, reflecting the January 2008 VSTOXX event that is observed in the February survey (see Section 2.3). Similarly for Event_201508, Event_201606 and Event_202203. The variables GFC_Episode, GDC_Episode, SDC_Episode and Covid_Episode correspond to the cumulative impact of events during the Global Financial Crisis, the Greek Debt Crisis, the European Sovereign Debt Crisis, and the COVID-19 pandemic, respectively. For each of these episodes and events, the effect on 12-month-ahead realized inflation is estimated using the local projection method of Jorda (2005), as detailed in Appendix A.2. Missing data for Luxembourg, the Netherlands, Ireland and Portugal for specific sub-periods, preclude estimating the impact of some of these events.

Table A2: Inflation Expectation Forecast Error Formation across the Eurozone

Variable	AT	BE	DE	EL	ES	FI	FR	IT	LU	NL	IE	PT
Event_200801	-0.0506	0.0322	0.535	-3.180***	1.094	-0.278	-1.977***	-2.190***	-1.436***		-0.320	
	(0.495)	(0.627)	(0.475)	(0.581)	(0.767)	(0.428)	(0.450)	(0.758)	(0.342)		(0.494)	
GFC_Episode	-5.457	5.599	-0.960	-14.356***	-2.514	-4.215	-1.505	-17.392***	17.882***		4.343***	
	(3.310)	(4.092)	(3.640)	(4.058)	(5.478)	(2.617)	(4.516)	(5.046)	(3.586)		(0.456)	
GDC_Episode	-3.178***	-2.484**	-1.410*	0.917	-1.975*	3.243***	-3.205***	-1.062	-5.129***		-5.862***	
	(0.708)	(0.995)	(0.842)	(1.369)	(1.101)	(0.712)	(0.680)	(1.039)	(0.974)		(0.844)	
SDC_Episode	-4.994***	2.137	4.683***	22.985***	14.265***	3.733***	3.401**	-0.495	2.536*	-18.582***	-1.298	
	(1.204)	(1.652)	(1.408)	(2.084)	(2.684)	(0.941)	(1.384)	(2.330)	(1.444)	(3.624)	(1.828)	
Event_201508	-1.228**	-3.011***	-1.076*	-2.647***	-1.614**	-0.775*	-1.454***	-1.905**	-0.554	-6.103***		-0.0600
	(0.523)	(0.611)	(0.651)	(0.789)	(0.756)	(0.447)	(0.502)	(0.785)	(0.604)	(1.367)		(1.305)
Event_201606	-1.189**	-0.754	-1.836***	-3.245***	-3.423***	-1.565***	-1.103**	-1.392**	-3.322***	1.874*	-1.496***	-1.859**
	(0.565)	(0.843)	(0.648)	(0.781)	(1.059)	(0.434)	(0.500)	(0.687)	(0.544)	(0.958)	(0.501)	(0.843)
Covid_Episode	-20.803***	-23.325***	-19.394***	-10.378***	-19.494***	-11.856***	-18.338***	-16.295***		-16.899***	1.541	-23.466***
	(2.423)	(3.274)	(2.326)	(2.441)	(3.954)	(1.631)	(3.351)	(2.577)		(2.576)	(1.160)	(3.772)
Event_202203	-3.003***	-2.910***	-2.623***	-4.012***	3.423***	-0.658	-2.000***	-5.128***		-3.271***	1.556**	-3.708***
	(0.542)	(0.751)	(0.846)	(0.883)	(1.043)	(0.537)	(0.580)	(0.941)		(1.172)	(0.741)	(1.235)
Past Prices Perception	-0.512***	-0.456***	-0.600***	-0.539***	-0.441***	-0.513***	-0.546***	-0.316***	-0.473***	-0.482***	-0.537***	-0.530***
	(0.00805)	(0.00997)	(0.0113)	(0.0140)	(0.0104)	(0.0132)	(0.00876)	(0.00937)	(0.0117)	(0.0179)	(0.0164)	(0.0139)
LagFuelInflation	-0.0458***	-0.0360**	-0.0611***	-0.0701***	-0.0950***	-0.0670***	-0.0978***	-0.121***	-0.0775***	-0.0981***	-0.0339***	-0.212***
	(0.0115)	(0.0148)	(0.0136)	(0.0148)	(0.0215)	(0.0125)	(0.0122)	(0.0254)	(0.0173)	(0.0335)	(0.0106)	(0.0254)
LagUnemployment	-1.241***	-1.149***	0.141***	-0.0269	-0.0471	-0.531***	-1.446***	-0.638***	-1.975***	-1.887***	-0.212***	-0.564***
	(0.264)	(0.212)	(0.0430)	(0.0268)	(0.0322)	(0.123)	(0.141)	(0.0922)	(0.296)	(0.277)	(0.0377)	(0.140)
LagIndustrialProduction	-0.132***	-0.166***	-0.0498*	-0.169***	-0.102***	-0.117***	0.0118	-0.0653**	-0.103***	-0.415***	-0.00363	0.0176
	(0.0289)	(0.0330)	(0.0279)	(0.0413)	(0.0327)	(0.0179)	(0.0423)	(0.0294)	(0.0182)	(0.104)	(0.00901)	(0.0519)
Constant	7.413***	10.94***	-0.524	-1.605*	0.0706	4.898***	14.49***	6.851***	11.34***	14.67***	1.538**	4.545**
	(1.495)	(1.817)	(0.575)	(0.849)	(0.875)	(1.075)	(1.375)	(1.183)	(1.578)	(2.098)	(0.615)	(1.815)
Observations	282,987	265,292	315,857	223,785	247,305	261,339	224,216	239,081	58,595	107,972	139,348	72,651
R-squared	0.394	0.323	0.520	0.345	0.312	0.433	0.451	0.188	0.379	0.359	0.388	0.468
Impact of Each Event on 12 months ahead inflation												
Event_200801	-2.189**	-1.008	-1.727***	-3.059***	-2.761***	-0.098	-3.159***	-1.958***	-2.722***	-1.823**	-1.481**	-2.292***
GFC_Episode	1.154	-11.413***	-7.862***	-9.137***	-4.135	-5.415	-10.052***	-10.052***	-0.484	-22.441***	-18.854**	-15.174***
GDC_Episode	2.364***	1.590	0.674	-1.255	3.007**	3.312***	0.957**	0.644	0.275	-0.466	2.445**	3.634***
SDC_Episode	2.783	0.324	-1.943	0.015	11.319***	6.843***	1.374	2.946*	1.049	8.393***	7.752***	5.340**
Event_201508	-2.206***	-0.620	-1.652***	0.192	-2.083**	-0.422	-0.266	-1.893**	-2.214***	-1.211***	-1.805***	-0.319
Event_201606	0.009	-0.826**	0.182	0.130	0.077	-0.924*	-0.364*	-0.145	-0.626	-0.556*	-2.421***	-0.532
Covid_Episode	4.329	-10.213	0.278	-11.300***	-2.622	-1.870	-7.591**	-5.105***	9.969**	-9.145**	-2.420	-10.903**
Event_202203	4.301***	1.311	4.488***	1.802**	-0.155	2.945***	2.951***	3.603**	-1.483	-0.664	3.961***	3.884***

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: In the above regressions, we control for demographic characteristics (age, gender, income, education, and occupation), month fixed effects (not reported in the tables), past prices perception, lagged fuel inflation, lagged unemployment, and lagged industrial production. Because the survey interviews are typically conducted in the first week of each month, we use the previous month's values of fuel inflation, the unemployment rate, and the annual change in industrial production to capture their influence on expectations reported in the subsequent month. To account for potential within-month correlation across multiple observations, standard errors are clustered at the monthly level. The variable Event_200801 is a dummy equal to 1 in February 2008 and zero otherwise, reflecting the January 2008 VSTOXX event that is observed in the February survey (see Section 2.3). Similarly for Event_201508, Event_201606 and Event_202203. The variables GFC_Episode, GDC_Episode, SDC_Episode and Covid_Episode correspond to the cumulative impact of events during the Global Financial Crisis, the Greek Debt Crisis, the European Sovereign Debt Crisis, and the COVID-19 pandemic, respectively. For each of these episodes and events, the effect on 12-month-ahead realized inflation is estimated using the local projection method of Jorda (2005), as detailed in Appendix A.2. Missing data for Luxembourg, the Netherlands, Ireland and Portugal for specific sub-periods, preclude estimating the impact of some of these events.

Table A3: Inflation Expectation Absolute Forecast Error Formation across the Eurozone (Markov switching identification)

Variable	AT	BE	DE	EL	ES	FI	FR	IT	LU	NL	IE	PT
Event_200801	-0.168	0.0485	-0.191	2.253***	-1.336***	0.242	0.273*	0.882**	-0.302		0.323	
	(0.203)	(0.217)	(0.218)	(0.429)	(0.343)	(0.172)	(0.146)	(0.367)	(0.196)		(0.313)	
GFC_episode	10.993***	5.645***	8.920***	20.788***	15.478***	11.142***	12.713***	14.800***	16.964***		16.694***	
	(1.772)	(1.705)	(2.979)	(4.401)	(3.630)	(2.043)	(2.364)	(3.043)	(1.780)		(1.284)	
GDC_episode	4.378***	3.476***	1.116**	-0.905	-0.799	-0.775**	2.400***	-2.449***	3.311***		6.451***	
	(0.330)	(0.386)	(0.524)	(1.333)	(0.747)	(0.305)	(0.337)	(0.608)	(0.394)		(0.887)	
SDC_Episode	2.816***	-1.572***	-2.963***	-4.505***	-3.824***	-3.065***	-0.780	-0.211	-1.021**	1.756	-3.033*	
	(0.555)	(0.581)	(0.725)	(1.212)	(0.998)	(0.433)	(0.494)	(1.208)	(0.410)	(1.133)	(1.551)	
SBC_episode	-0.172	0.232	-0.723**	-1.253*	1.146**	-0.482***	-0.088	0.556	-0.021	2.161***	-1.769***	
	(0.237)	(0.250)	(0.291)	(0.719)	(0.546)	(0.181)	(0.256)	(0.619)	(0.220)	(0.395)	(0.640)	
BM_episode	1.534***	1.312***	0.650	3.518***	0.010	1.313***	0.524	0.215	-0.196	-0.240		-1.549**
	(0.316)	(0.388)	(0.397)	(1.003)	(0.576)	(0.288)	(0.323)	(0.681)	(0.264)	(0.666)		(0.672)
Event_201602	1.353***	1.509***	0.922***	2.601***	1.103***	0.905***	0.450***	0.993***	0.293*	0.973***		0.184
	(0.223)	(0.218)	(0.233)	(0.478)	(0.299)	(0.147)	(0.151)	(0.359)	(0.176)	(0.250)		(0.371)
Event_201606	-0.202	0.295	0.557**	1.768***	0.241	0.310**	-0.143	-0.545	0.999***	-0.0230	-0.433	1.216***
	(0.204)	(0.197)	(0.272)	(0.473)	(0.328)	(0.134)	(0.174)	(0.377)	(0.188)	(0.323)	(0.367)	(0.374)
Covid_episode	13.076***	8.463***	14.490***	3.649*	13.109***	6.692***	11.190***	3.339***		6.078***	7.754***	13.050***
	(1.241)	(0.933)	(1.375)	(2.167)	(1.963)	(0.745)	(1.738)	(1.196)		(1.281)	(1.170)	(1.373)
USelect_episode	2.685***	0.923***	4.091***	-2.624***	2.111***	1.027***	2.720***	0.635		-0.055	1.582***	2.713***
	(0.292)	(0.352)	(0.358)	(0.697)	(0.520)	(0.197)	(0.326)	(0.490)		(0.470)	(0.594)	(0.508)
War_Episode	6.939***	8.259***	6.272***	12.479***	5.148***	5.046***	7.654***	14.496***		7.193***	-0.814	14.090***
	(0.678)	(0.724)	(1.101)	(1.462)	(1.059)	(0.558)	(0.565)	(1.195)		(0.802)	(1.270)	(0.901)
Past Prices Perception	0.495***	0.462***	0.570***	0.506***	0.457***	0.491***	0.518***	0.332***	0.434***	0.489***	0.486***	0.524***
	(0.00833)	(0.00767)	(0.0112)	(0.0123)	(0.00791)	(0.0119)	(0.00975)	(0.00783)	(0.0129)	(0.0175)	(0.0174)	(0.0157)
LagFuelInflation	0.0151***	0.000895	0.0340***	0.0439***	0.0404***	0.0236***	0.0248***	0.0687***	-0.00690	0.0287**	0.0195**	0.0827***
	(0.00533)	(0.00515)	(0.00765)	(0.0102)	(0.00815)	(0.00456)	(0.00504)	(0.0141)	(0.00444)	(0.0111)	(0.00824)	(0.00930)
LagUnemployment	0.304***	0.160***	-0.0763***	-0.0251	-0.00964	0.246***	0.350***	0.123***	0.0715	0.256**	0.138***	-0.0249
	(0.0914)	(0.0563)	(0.0242)	(0.0175)	(0.0197)	(0.0473)	(0.0453)	(0.0354)	(0.0785)	(0.101)	(0.0279)	(0.0620)
LagIndustrialProduction	0.0278**	0.0242**	-0.00766	0.0748**	0.0254*	-0.00553	0.0126	-0.0199**	-0.00297	-0.0316	-0.00688	-0.00533
	(0.0134)	(0.0106)	(0.0162)	(0.0332)	(0.0140)	(0.0103)	(0.0146)	(0.00808)	(0.00815)	(0.0321)	(0.00677)	(0.0128)
Constant	-0.135	0.427	1.598***	4.658***	3.261***	-0.647	-2.507***	1.007**	1.449***	-0.439	1.651***	2.368***
	(0.544)	(0.506)	(0.290)	(0.662)	(0.574)	(0.415)	(0.480)	(0.505)	(0.484)	(0.783)	(0.447)	(0.879)
Observations	282,987	265,292	315,857	223,785	247,305	261,339	224,216	239,081	58,595	107,972	139,348	72,651
R-squared	0.448	0.408	0.557	0.383	0.404	0.480	0.518	0.283	0.400	0.475	0.395	0.558
Impact of Each Event on 12 months ahead inflation												
Event_200801	-2.075***	-0.953	-1.734***	-2.952***	-2.513***	-0.017	-3.087***	-1.944***	-2.839***	-1.748*	-1.310***	-2.251***
GFC_Episode	7.549	-9.937	-6.659**	-4.430	4.999	-3.664	-7.366	-12.135***	3.527	-28.927***	-19.082	-15.143**
GDC_Episode	4.293***	3.633**	1.642	-1.736	5.608***	5.743***	1.502**	0.596	-0.621	0.653	2.820*	5.091***
SDC_Episode	4.112*	0.580	-1.536	0.204	13.010***	7.176***	1.595*	3.321*	0.828	8.111***	7.225***	5.476**
SBC_Episode	1.717**	-1.442*	-0.293	0.794	3.678**	0.549	-0.064	-0.442	-0.572	4.656***	-0.335	1.150
BM_Episode	-3.579***	-0.709	-2.773***	-0.448	-3.392*	-0.813	-0.345	-3.330**	-2.788***	-2.250***	-2.815***	-0.969*
Event_201602	-1.200*	0.629	0.250	1.543***	1.316	-0.035	0.623***	0.160	0.884	0.244	-0.918**	0.117
Event_201606	0.129	-0.764**	0.328	0.178	0.303	-0.948*	-0.372	-0.0538	-0.386	-0.491	-2.233***	-0.494
Covid_Episode	10.287**	-14.790	3.716	-12.452***	2.716	-0.149	-8.748	-7.308***	32.979***	-11.076*	1.556	-14.446**
USelect_Episode	2.847**	3.944	8.302***	1.544	7.009***	3.385***	2.297	4.949***	3.402	2.793	9.041***	0.162
War_Episode	15.533***	4.320	12.096***	5.006*	2.084	8.969***	9.284***	15.354***	-4.011	6.580	9.842***	9.749***

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: In the above regressions, we control for demographic characteristics (age, gender, income, education, and occupation), month fixed effects (not reported in the tables), past prices perception, lagged fuel inflation, lagged unemployment, and lagged industrial production. Because the survey interviews are typically conducted in the first week of each month, we use the previous month's values of fuel inflation, the unemployment rate, and the annual change in industrial production to capture their influence on expectations reported in the subsequent month. To account for potential within-month correlation across multiple observations, standard errors are clustered at the monthly level. The variable Event_200801 is a dummy equal to 1 in February 2008 and zero otherwise, reflecting the January 2008 VSTOXX event that is observed in the February survey (see Section 2.3). Similarly for Event_201602 and Event_201606. The variables GFC_Episode, GDC_Episode, SDC_Episode, SBC_Episode, BM_Episode, Covid_Episode, USelect_episode and War_episode correspond to the cumulative impact of events during the Global Financial Crisis, the Greek Debt Crisis, the European Sovereign Debt Crisis, the Spanish Banking Crisis and Bailout, Black Monday, the COVID-19 pandemic, the US Presidential Election / New Covid Lockdowns and the Russian invasion of Ukraine, respectively. For each of these episodes and events, the effect on 12-month-ahead realized inflation is estimated using the local projection method of Jorda (2005), as detailed in Appendix A.2. Missing data for Luxembourg, the Netherlands, Ireland and Portugal for specific sub-periods, preclude estimating the impact of some of these events.

Table A4: Inflation Expectation Forecast Error Formation across the Eurozone (Markov switching identification)

Variable	AT	BE	DE	EL	ES	FI	FR	IT	LU	NL	IE	PT
Event_200801	0.219	0.0209	0.821*	-3.071***	1.287	-0.110	-1.866***	-1.994***	-1.466***		-0.365	
	(0.490)	(0.642)	(0.479)	(0.601)	(0.780)	(0.438)	(0.468)	(0.763)	(0.349)		(0.501)	
GFC_episode	-11.544**	8.920	-12.426**	-24.036***	-9.126	-6.054	-11.414**	-29.418***	13.932**		13.202***	
	(5.091)	(6.526)	(5.974)	(7.272)	(10.660)	(4.284)	(5.046)	(9.506)	(6.937)		(1.645)	
GDC_episode	-4.777***	-1.978	-0.490	1.320	-1.524	3.686***	-4.293***	-1.349	-8.370***		-8.000***	
	(0.917)	(1.363)	(1.196)	(2.067)	(1.438)	(0.877)	(0.900)	(1.454)	(1.209)		(1.219)	
SDC_Episode	-4.381***	1.773	5.617***	22.979***	14.462***	3.959***	4.108***	-0.029	2.447*	-19.255***	-1.229	
	(1.181)	(1.639)	(1.429)	(2.105)	(2.656)	(0.934)	(1.382)	(2.385)	(1.459)	(3.676)	(1.893)	
SBC_episode	1.089	-0.050	1.567**	8.663***	-0.443	2.973***	1.233*	0.238	-0.084	-3.414**	3.033***	
	(0.695)	(1.036)	(0.710)	(1.209)	(1.391)	(0.609)	(0.670)	(1.339)	(0.852)	(1.599)	(0.828)	
BM_episode	-2.559***	-5.830***	-2.202**	-5.458***	-2.746**	-1.412**	-2.338***	-2.538*	-1.512*	-10.338***		1.004
	(0.832)	(1.070)	(1.004)	(1.352)	(1.269)	(0.666)	(0.749)	(1.378)	(0.799)	(2.016)		(2.018)
Event_201602	-2.290***	-3.491***	-2.186***	-4.514***	-2.893***	-2.027***	-1.698***	-2.759***	-1.188***	-4.682***		-0.152
	(0.460)	(0.705)	(0.523)	(0.783)	(0.866)	(0.353)	(0.452)	(0.763)	(0.345)	(1.022)		(1.298)
Event_201606	-1.618***	-0.569	-2.064***	-3.219***	-3.764***	-1.645***	-1.249**	-1.653**	-3.246***	1.950*	-1.017**	-1.720**
	(0.613)	(0.876)	(0.682)	(0.815)	(1.181)	(0.470)	(0.523)	(0.729)	(0.602)	(0.989)	(0.494)	(0.811)
Covid_episode	-32.067***	-34.350***	-34.803***	-17.925***	-36.574***	-19.390***	-34.572***	-29.072***		-28.370***	0.744	-45.967***
	(3.603)	(5.020)	(3.897)	(3.982)	(7.157)	(2.507)	(4.019)	(4.555)		(3.794)	(1.704)	(4.520)
USelect_episode	-6.193***	-7.478***	-8.645***	1.252	-7.338***	-5.125***	-8.171***	-7.585***		-2.737**	-2.351***	-9.478***
	(0.997)	(1.497)	(1.305)	(1.059)	(1.560)	(0.983)	(1.042)	(1.580)		(1.184)	(0.897)	(1.832)
War_Episode	-7.648***	-11.830***	-8.173***	-13.025***	-3.642	-3.627***	-8.995***	-20.651***		-10.603***	1.768	-15.767***
	(1.254)	(1.764)	(1.897)	(1.935)	(2.235)	(1.092)	(1.252)	(2.152)		(2.343)	(1.709)	(2.470)
Past Prices Perception	-0.512***	-0.457***	-0.602***	-0.539***	-0.443***	-0.515***	-0.549***	-0.318***	-0.474***	-0.487***	-0.536***	-0.537***
	(0.00785)	(0.00943)	(0.0109)	(0.0137)	(0.00984)	(0.0129)	(0.00838)	(0.00905)	(0.0113)	(0.0179)	(0.0165)	(0.0128)
LagFuelInflation	-0.0464***	-0.0409**	-0.0657***	-0.0750***	-0.102***	-0.0708***	-0.104***	-0.127***	-0.0808***	-0.101***	-0.0295**	-0.211***
	(0.0116)	(0.0161)	(0.0146)	(0.0168)	(0.0235)	(0.0129)	(0.0123)	(0.0271)	(0.0188)	(0.0331)	(0.0114)	(0.0229)
LagUnemployment	-1.091***	-1.314***	0.173***	-0.0417	-0.0506	-0.524***	-1.535***	-0.667***	-2.016***	-1.953***	-0.217***	-0.627***
	(0.248)	(0.219)	(0.0454)	(0.0277)	(0.0331)	(0.125)	(0.136)	(0.0973)	(0.314)	(0.278)	(0.0391)	(0.142)
LagIndustrialProduction	-0.154***	-0.160***	-0.0938***	-0.184***	-0.135***	-0.120***	-0.0357	-0.0859**	-0.108***	-0.432***	-0.00127	-0.0587
	(0.0293)	(0.0336)	(0.0293)	(0.0446)	(0.0403)	(0.0212)	(0.0278)	(0.0404)	(0.0204)	(0.103)	(0.00969)	(0.0368)
Constant	6.566***	12.06***	-0.720	-1.364	0.0674	4.827***	15.25***	7.006***	11.63***	15.14***	1.501**	5.115***
	(1.416)	(1.886)	(0.582)	(0.852)	(0.889)	(1.101)	(1.357)	(1.233)	(1.710)	(2.136)	(0.626)	(1.842)
Observations	282,987	265,292	315,857	223,785	247,305	261,339	224,216	239,081	58,595	107,972	139,348	72,651
R-squared	0.398	0.330	0.526	0.349	0.317	0.439	0.458	0.196	0.381	0.370	0.392	0.482
Impact of Each Event on 12 months ahead inflation												
Event_200801	-2.075***	-0.953	-1.734***	-2.952***	-2.513***	-0.017	-3.087***	-1.944***	-2.839***	-1.748*	-1.310***	-2.251***
GFC_Episode	7.549	-9.937	-6.659**	-4.430	4.999	-3.664	-7.366	-12.135***	3.527	-28.927***	-19.082	-15.143**
GDC_Episode	4.293***	3.633**	1.642	-1.736	5.608***	5.743***	1.502**	0.596	-0.621	0.653	2.820*	5.091***
SDC_Episode	4.112*	0.580	-1.536	0.204	13.010***	7.176***	1.595*	3.321*	0.828	8.111***	7.225***	5.476**
SBC_Episode	1.717**	-1.442*	-0.293	0.794	3.678**	0.549	-0.064	-0.442	-0.572	4.656***	-0.335	1.150
BM_Episode	-3.579***	-0.709	-2.773***	-0.448	-3.392*	-0.813	-0.345	-3.330**	-2.788***	-2.250***	-2.815***	-0.969*
Event_201602	-1.200*	0.629	0.250	1.543***	1.316	-0.035	0.623***	0.160	0.884	0.244	-0.918**	0.117
Event_201606	0.129	-0.764**	0.328	0.178	0.303	-0.948*	-0.372	-0.0538	-0.386	-0.491	-2.233***	-0.494
Covid_Episode	10.287**	-14.790	3.716	-12.452***	2.716	-0.149	-8.748	-7.308***	32.979***	-11.076*	1.556	-14.446**
USelect_Episode	2.847**	3.944	8.302***	1.544	7.009***	3.385***	2.297	4.949***	3.402	2.793	9.041***	0.162
War_Episode	15.533***	4.320	12.096***	5.006*	2.084	8.969***	9.284***	15.354***	-4.011	6.580	9.842***	9.749***

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: In the above regressions, we control for demographic characteristics (age, gender, income, education, and occupation), month fixed effects (not reported in the tables), past prices perception, lagged fuel inflation, lagged unemployment, and lagged industrial production. Because the survey interviews are typically conducted in the first week of each month, we use the previous month's values of fuel inflation, the unemployment rate, and the annual change in industrial production to capture their influence on expectations reported in the subsequent month. To account for potential within-month correlation across multiple observations, standard errors are clustered at the monthly level. The variable Event_200801 is a dummy equal to 1 in February 2008 and zero otherwise, reflecting the January 2008 VSTOXX event that is observed in the February survey (see Section 2.3). Similarly for Event_201602 and Event_201606. The variables GFC_Episode, GDC_Episode, SDC_Episode, SBC_Episode, BM_Episode, Covid_Episode, USelect_episode and War_episode correspond to the cumulative impact of events during the Global Financial Crisis, the Greek Debt Crisis, the European Sovereign Debt Crisis, the Spanish Banking Crisis and Bailout, Black Monday, the COVID-19 pandemic, the US Presidential Election / New Covid Lockdowns and the Russian invasion of Ukraine, respectively. For each of these episodes and events, the effect on 12-month-ahead realized inflation is estimated using the local projection method of Jorda (2005), as detailed in Appendix A.2. Missing data for Luxembourg, the Netherlands, Ireland and Portugal for specific sub-periods, preclude estimating the impact of some of these events.

Table A5: Inflation Expectation Absolute Forecast Error Formation across the Eurozone (including interactions with High Income)

Variable	AT	BE	DE	EL	ES	FI	FR	IT	LU	NL	IE	PT
HighInco	-0.141***	-0.334***	-0.103***	-1.686***	-0.0403	-0.121***	-0.154***	-0.322***	-0.183***	-0.145***	-0.291***	-0.170***
	(0.0310)	(0.0444)	(0.0332)	(0.206)	(0.0592)	(0.0202)	(0.0260)	(0.0456)	(0.0495)	(0.0336)	(0.0599)	(0.0620)
Event_200801	0.0474	0.0169	0.209	2.954***	-0.976***	0.239	0.0642	0.607	-0.408**		0.299	
	(0.208)	(0.220)	(0.223)	(0.456)	(0.347)	(0.175)	(0.145)	(0.368)	(0.200)		(0.332)	
HighInco#Event_200801	-0.359***	0.0227	-0.727***	-0.814***	-0.816***	0.278***	0.671***	0.553***	0.0182		0.583***	
	(0.0337)	(0.0620)	(0.0346)	(0.194)	(0.0658)	(0.0206)	(0.0259)	(0.0482)	(0.0583)		(0.0715)	
GFC_episode	3.358***	-2.948**	-1.794	13.572***	-1.358	2.603*	2.339	6.077***	7.222***		3.243***	
	(1.217)	(1.146)	(1.902)	(2.766)	(3.160)	(1.346)	(2.092)	(2.179)	(1.472)		(0.383)	
HighInco#GFC_Episode	3.889***	12.102***	2.058***	9.144***	7.939***	4.685***	2.164***	-0.033	8.070***		1.246***	
	(0.262)	(0.434)	(0.246)	(1.516)	(0.518)	(0.227)	(0.212)	(0.413)	(0.403)		(0.066)	
GDC_episode	3.133***	2.109***	1.600***	-1.148	-0.008	-0.389	1.757***	-1.732***	2.693***		3.929***	
	(0.266)	(0.269)	(0.394)	(0.885)	(0.561)	(0.271)	(0.291)	(0.509)	(0.345)		(0.700)	
HighInco#GDC_episode	-0.615***	1.734***	-0.496***	12.033***	0.293**	-0.036	-0.041	1.348***	0.202**		-0.062	
	(0.063)	(0.107)	(0.060)	(0.422)	(0.122)	(0.044)	(0.060)	(0.093)	(0.097)		(0.140)	
SDC_episode	4.102***	-1.829***	-2.254***	-4.920***	-3.644***	-3.150***	-0.729	-0.588	-0.696*	1.805*	-2.603*	
	(0.568)	(0.595)	(0.727)	(1.199)	(1.020)	(0.421)	(0.490)	(1.166)	(0.411)	(1.078)	(1.559)	
HighInco#SDC_episode	-2.734***	0.370	-0.519***	6.827***	-0.252	-0.155	0.521***	0.566**	-0.495**	-1.005***	-0.454	
	(0.177)	(0.265)	(0.149)	(0.981)	(0.323)	(0.124)	(0.128)	(0.256)	(0.227)	(0.212)	(0.523)	
Event_201508	0.755***	0.905***	0.484*	1.562***	-0.168	0.566***	0.423*	0.648	0.191	0.289		-0.931**
	(0.203)	(0.238)	(0.248)	(0.570)	(0.344)	(0.184)	(0.218)	(0.420)	(0.161)	(0.439)		(0.433)
HighInco#Event_201508	-0.0490	-0.279***	-0.0890***	-0.369*	0.676***	0.182***	-0.0663**	-0.189***	-0.355***	-0.269***		0.611***
	(0.0322)	(0.0531)	(0.0292)	(0.199)	(0.0661)	(0.0241)	(0.0257)	(0.0446)	(0.0468)	(0.0430)		(0.0618)
Event_201606	-0.498**	0.391*	0.373	1.910***	0.0608	0.268	-0.186	-0.568	1.219***	0.262	-1.009*	1.469***
	(0.220)	(0.224)	(0.273)	(0.442)	(0.330)	(0.162)	(0.194)	(0.360)	(0.215)	(0.329)	(0.517)	(0.436)
HighInco#Event_201606	0.199***	-0.523***	0.127***	-2.555***	-0.437***	-0.0997***	-0.292***	-0.0850*	-0.681***	-0.373***	0.0745	0.0728
	(0.0293)	(0.0568)	(0.0290)	(0.211)	(0.0620)	(0.0312)	(0.0321)	(0.0451)	(0.0623)	(0.0433)	(0.0714)	(0.0670)
Covid_episode	8.560***	6.573***	9.746***	2.601*	6.570***	4.406***	6.024***	1.380		5.039***	2.708***	6.152***
	(0.922)	(0.806)	(0.910)	(1.399)	(1.666)	(0.566)	(1.464)	(1.025)		(0.832)	(0.912)	(1.232)
HighInco#Covid_episode	-1.361***	-1.433***	-3.422***	4.559***	-1.040***	-0.609***	-1.486***	1.708***		-1.939***	2.402***	1.396***
	(0.131)	(0.222)	(0.143)	(0.818)	(0.246)	(0.143)	(0.133)	(0.134)		(0.210)	(0.212)	(0.241)
Event_202203	2.972***	2.076***	2.052***	4.100***	-1.505**	1.220***	2.254***	3.561***		1.595***	-0.257	3.327***
	(0.287)	(0.302)	(0.468)	(0.665)	(0.612)	(0.253)	(0.279)	(0.564)		(0.433)	(0.583)	(0.494)
HighInco#Event_202203	-0.963***	-0.674***	-0.128***	-2.843***	-0.418***	0.624***	0.0309	-1.124***		-1.329***	0.511***	0.931***
	(0.0319)	(0.0509)	(0.0328)	(0.207)	(0.0640)	(0.0344)	(0.0349)	(0.0519)		(0.0495)	(0.0562)	(0.0866)
Past Prices Perception	0.496***	0.463***	0.570***	0.508***	0.458***	0.490***	0.518***	0.332***	0.433***	0.488***	0.481***	0.523***
	(0.00844)	(0.00784)	(0.0114)	(0.0123)	(0.00810)	(0.0119)	(0.00979)	(0.00792)	(0.0130)	(0.0175)	(0.0179)	(0.0159)
LagFuelInflation	0.0150***	0.000462	0.0329***	0.0442***	0.0379***	0.0236***	0.0226***	0.0730***	-0.0103**	0.0347***	0.00748	0.0937***
	(0.00533)	(0.00499)	(0.00726)	(0.00947)	(0.00884)	(0.00473)	(0.00549)	(0.0141)	(0.00472)	(0.0115)	(0.00794)	(0.0125)
LagUnemployment	0.363***	0.0947	-0.0542**	-0.0279	-0.0117	0.235***	0.305***	0.109***	0.0499	0.215**	0.143***	-0.0684
	(0.0955)	(0.0660)	(0.0247)	(0.0176)	(0.0198)	(0.0477)	(0.0460)	(0.0348)	(0.0804)	(0.101)	(0.0279)	(0.0679)
LagIndustrialProduction	0.0134	0.0214**	-0.0371**	0.0695**	-0.00157	-0.0205**	-0.0129	-0.0289***	-0.0113	-0.0320	-0.00774	-0.0320*
	(0.0149)	(0.0105)	(0.0153)	(0.0307)	(0.0194)	(0.0102)	(0.0208)	(0.0110)	(0.00897)	(0.0315)	(0.00609)	(0.0179)
Observations	282,987	265,292	315,857	223,785	247,305	261,339	224,216	239,081	58,595	107,972	139,348	72,651
R-squared	0.445	0.405	0.555	0.380	0.402	0.477	0.516	0.278	0.398	0.472	0.389	0.553
Impact of Each Event on 12 months ahead inflation												
Event_200801	-2.189**	-1.008	-1.727***	-3.059***	-2.761***	-0.098	-3.159***	-1.958***	-2.722***	-1.823**	-1.481**	-2.292***
GFC_Episode	1.154	-11.413***	-7.862***	-9.137***	-4.135	-5.415	-10.052***	-10.052***	-0.484	-22.441***	-18.854**	-15.174***
GDC_Episode	2.364***	1.590	0.674	-1.255	3.007**	3.312***	0.957**	0.644	0.275	-0.466	2.445**	3.634***
SDC_Episode	2.783	0.324	-1.943	0.015	11.319***	6.843***	1.374	2.946*	1.049	8.393***	7.752***	5.340**
Event_201508	-2.206***	-0.620	-1.652***	0.192	-2.083**	-0.422	-0.266	-1.893**	-2.214***	-1.211***	-1.805***	-0.319
Event_201606	0.009	-0.826**	0.182	0.130	0.077	-0.924*	-0.364*	-0.145	-0.626	-0.556*	-2.421***	-0.532
Covid_Episode	4.329	-10.213	0.278	-11.300***	-2.622	-1.870	-7.591**	-5.105***	9.969**	-9.145**	-2.420	-10.903**
Event_202203	4.301***	1.311	4.488***	1.802**	-0.155	2.945***	2.951***	3.603**	-1.483	-0.664	3.961***	3.884***

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: In the above regressions, we control for demographic characteristics (age, gender, income, education, and occupation), month fixed effects (not reported in the tables), past prices perception, lagged fuel inflation, lagged unemployment, and lagged industrial production. Because the survey interviews are typically conducted in the first week of each month, we use the previous month's values of fuel inflation, the unemployment rate, and the annual change in industrial production to capture their influence on expectations reported in the subsequent month. To account for potential within-month correlation across multiple observations, standard errors are clustered at the monthly level. The variable Event_200801 is a dummy equal to 1 in February 2008 and zero otherwise, reflecting the January 2008 VSTOXX event that is observed in the February survey (see Section 2.3). Similarly for Event_201508, Event_201606 and Event_202203. The variables GFC_Episode, GDC_Episode, SDC_Episode and Covid_Episode correspond to the cumulative impact of events during the Global Financial Crisis, the Greek Debt Crisis, the European Sovereign Debt Crisis, and the COVID-19 pandemic, respectively. For each of these episodes and events, the effect on 12-month-ahead realized inflation is estimated using the local projection method of Jorda (2005), as detailed in Appendix A.2. Missing data for Luxembourg, the Netherlands, Ireland and Portugal for specific sub-periods, preclude estimating the impact of some of these events.

Table A6: Inflation Expectation Forecast Error Formation across the Eurozone (including interactions with High Income)

Variable	AT	BE	DE	EL	ES	FI	FR	IT	LU	NL	IE	PT
HighInco	-0.0844	0.553***	-0.338***	1.677***	-0.189**	0.281***	0.214***	0.357***	-0.123*	0.382***	0.364***	0.213***
	(0.0603)	(0.0746)	(0.0836)	(0.276)	(0.0834)	(0.0280)	(0.0365)	(0.0610)	(0.0649)	(0.0595)	(0.0711)	(0.0737)
Event_200801	-0.138	0.0592	0.150	-3.859***	0.633	-0.184	-1.675***	-2.053***	-1.242***		-0.274	
	(0.494)	(0.633)	(0.473)	(0.636)	(0.772)	(0.428)	(0.450)	(0.760)	(0.341)		(0.501)	
HighInco#Event_200801	0.297***	-0.196***	1.078***	0.817***	1.115***	-0.341***	-0.895***	-0.251***	-0.286***		-0.125*	
	(0.0608)	(0.0648)	(0.0788)	(0.245)	(0.0880)	(0.0275)	(0.0345)	(0.0537)	(0.0693)		(0.0638)	
GFC_episode	-5.239	5.918	-2.182	-14.576***	-0.308	-4.800*	-1.558	-20.111***	18.028***		3.893***	
	(3.320)	(4.128)	(3.664)	(4.079)	(5.569)	(2.591)	(4.513)	(5.061)	(3.620)		(0.455)	
HighInco#GFC_episode	-0.407	-5.256***	3.222***	-9.638***	-4.730***	2.056***	0.365	9.236***	1.953***		0.835***	
	(0.484)	(0.503)	(0.590)	(1.995)	(0.677)	(0.221)	(0.269)	(0.469)	(0.546)		(0.061)	
GDC_episode	-3.584***	-2.219**	-1.843**	1.365	-2.075*	3.330***	-3.123***	-0.706	-5.369***		-5.579***	
	(0.705)	(1.005)	(0.836)	(1.379)	(1.103)	(0.716)	(0.680)	(1.042)	(0.993)		(0.842)	
HighInco#GDC_episode	1.149***	-1.769***	1.112***	-10.708***	0.375**	-0.317***	-0.226***	-1.226***	0.259		-0.628***	
	(0.116)	(0.127)	(0.148)	(0.529)	(0.156)	(0.055)	(0.068)	(0.118)	(0.160)		(0.127)	
SDC_episode	-6.326***	2.125	3.609**	23.438***	13.444***	3.417***	3.495**	-0.127	1.091	-19.125***	-1.197	
	(1.207)	(1.659)	(1.403)	(2.089)	(2.672)	(0.943)	(1.391)	(2.336)	(1.435)	(3.620)	(1.851)	
HighInco#SDC_episode	3.387***	0.073	2.377***	-10.839***	2.014***	1.106***	-0.109	-1.307***	3.219***	1.614***	-0.290	
	(0.321)	(0.325)	(0.371)	(1.302)	(0.405)	(0.134)	(0.168)	(0.342)	(0.378)	(0.296)	(0.439)	
Event_201508	-1.346**	-3.053***	-1.297*	-2.691***	-1.478*	-0.821*	-1.473***	-1.871**	-0.809	-6.101***		0.152
	(0.524)	(0.616)	(0.659)	(0.792)	(0.756)	(0.448)	(0.501)	(0.786)	(0.608)	(1.364)		(1.302)
HighInco#Event_201508	0.343***	0.236***	0.438***	0.331	-0.334***	0.143***	0.0517	-0.160***	0.680***	-0.0159		-0.533***
	(0.0585)	(0.0663)	(0.0719)	(0.265)	(0.0830)	(0.0280)	(0.0342)	(0.0545)	(0.0661)	(0.0603)		(0.0711)
Event_201606	-1.198**	-0.835	-1.922***	-3.376***	-3.465***	-1.492***	-1.113**	-1.404**	-3.734***	1.793*	-1.532***	-1.828**
	(0.569)	(0.848)	(0.656)	(0.784)	(1.057)	(0.431)	(0.500)	(0.686)	(0.551)	(0.961)	(0.501)	(0.847)
HighInco#Event_201606	0.00742	0.504***	0.162***	2.341***	0.267***	-0.310***	0.0748*	0.0558	0.817***	0.252***	0.128	-0.104
	(0.0555)	(0.0685)	(0.0610)	(0.278)	(0.0752)	(0.0458)	(0.0400)	(0.0591)	(0.0780)	(0.0629)	(0.0824)	(0.0918)
Covid_episode	-22.672***	-24.222***	-21.943***	-10.106***	-21.118***	-12.220***	-18.806***	-15.907***		-18.531***	1.162	-22.687***
	(2.436)	(3.319)	(2.370)	(2.431)	(3.959)	(1.600)	(3.349)	(2.573)		(2.543)	(1.135)	(3.752)
HighInco#Covid_episode	3.641***	3.186***	4.592***	-4.794***	5.879***	1.200***	1.564***	-1.514***		4.709***	0.957***	-2.435***
	(0.236)	(0.265)	(0.256)	(1.089)	(0.296)	(0.194)	(0.156)	(0.172)		(0.269)	(0.247)	(0.326)
Event_202203	-3.547***	-2.980***	-2.716***	-4.245***	3.385***	-0.384	-1.896***	-5.327***		-3.578***	1.894**	-3.391***
	(0.543)	(0.755)	(0.841)	(0.881)	(1.044)	(0.538)	(0.581)	(0.945)		(1.172)	(0.745)	(1.237)
HighInco#Event_202203	1.024***	0.285***	0.177***	3.343***	0.156**	-1.080***	-0.357***	0.707***		0.818***	-0.813***	-0.926***
	(0.0585)	(0.0679)	(0.0663)	(0.274)	(0.0759)	(0.0484)	(0.0383)	(0.0602)		(0.0681)	(0.0666)	(0.0872)
Past Prices Perception	-0.512***	-0.456***	-0.601***	-0.540***	-0.442***	-0.513***	-0.547***	-0.317***	-0.473***	-0.483***	-0.537***	-0.530***
	(0.00802)	(0.0101)	(0.0113)	(0.0140)	(0.0103)	(0.0132)	(0.00875)	(0.00934)	(0.0117)	(0.0179)	(0.0164)	(0.0138)
LagFuelInflation	-0.0456***	-0.0366**	-0.0612***	-0.0708***	-0.0951***	-0.0669***	-0.0978***	-0.121***	-0.0777***	-0.0982***	-0.0339***	-0.212***
	(0.0115)	(0.0149)	(0.0135)	(0.0149)	(0.0215)	(0.0125)	(0.0122)	(0.0255)	(0.0175)	(0.0335)	(0.0106)	(0.0254)
LagUnemployment	-1.241***	-1.162***	0.138***	-0.0324	-0.0483	-0.531***	-1.447***	-0.640***	-2.003***	-1.896***	-0.212***	-0.565***
	(0.263)	(0.214)	(0.0430)	(0.0265)	(0.0322)	(0.123)	(0.141)	(0.0923)	(0.300)	(0.277)	(0.0376)	(0.140)
LagIndustrialProduction	-0.132***	-0.167***	-0.0497*	-0.167***	-0.102***	-0.117***	0.0117	-0.0655**	-0.103***	-0.416***	-0.00365	0.0175
	(0.0288)	(0.0332)	(0.0279)	(0.0411)	(0.0327)	(0.0179)	(0.0423)	(0.0294)	(0.0183)	(0.104)	(0.00901)	(0.0519)
Constant	7.653***	10.56***	-0.236	-1.237	0.494	5.025***	14.63***	7.068***	11.77***	14.79***	1.630***	4.632**
	(1.496)	(1.791)	(0.573)	(0.812)	(0.867)	(1.080)	(1.382)	(1.183)	(1.609)	(2.093)	(0.603)	(1.818)
Observations	282,987	265,292	315,857	223,785	247,305	261,339	224,216	239,081	58,595	107,972	139,348	72,651
R-squared	0.394	0.323	0.520	0.345	0.312	0.433	0.451	0.188	0.378	0.359	0.388	0.467
Impact of Each Event on 12 months ahead inflation												
Event_200801	-2.189**	-1.008	-1.727***	-3.059***	-2.761***	-0.098	-3.159***	-1.958***	-2.722***	-1.823**	-1.481**	-2.292***
GFC_Episode	1.154	-11.413***	-7.862***	-9.137***	-4.135	-5.415	-10.052***	-10.052***	-0.484	-22.441***	-18.854**	-15.174***
GDC_Episode	2.364***	1.590	0.674	-1.255	3.007**	3.312***	0.957**	0.644	0.275	-0.466	2.445**	3.634***
SDC_Episode	2.783	0.324	-1.943	0.015	11.319***	6.843***	1.374	2.946*	1.049	8.393***	7.752***	5.340**
Event_201508	-2.206***	-0.620	-1.652***	0.192	-2.083**	-0.422	-0.266	-1.893**	-2.214***	-1.211***	-1.805***	-0.319
Event_201606	0.009	-0.826**	0.182	0.130	0.077	-0.924*	-0.364*	-0.145	-0.626	-0.556*	-2.421***	-0.532
Covid_Episode	4.329	-10.213	0.278	-11.300***	-2.622	-1.870	-7.591**	-5.105***	9.969**	-9.145**	-2.420	-10.903**
Event_202203	4.301***	1.311	4.488***	1.802**	-0.155	2.945***	2.951***	3.603**	-1.483	-0.664	3.961***	3.884***

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: In the above regressions, we control for demographic characteristics (age, gender, income, education, and occupation), month fixed effects (not reported in the tables), past prices perception, lagged fuel inflation, lagged unemployment, and lagged industrial production. Because the survey interviews are typically conducted in the first week of each month, we use the previous month's values of fuel inflation, the unemployment rate, and the annual change in industrial production to capture their influence on expectations reported in the subsequent month. To account for potential within-month correlation across multiple observations, standard errors are clustered at the monthly level. The variable Event_200801 is a dummy equal to 1 in February 2008 and zero otherwise, reflecting the January 2008 VSTOXX event that is observed in the February survey (see Section 2.3). Similarly for Event_201508, Event_201606 and Event_202203. The variables GFC_Episode, GDC_Episode, SDC_Episode and Covid_Episode correspond to the cumulative impact of events during the Global Financial Crisis, the Greek Debt Crisis, the European Sovereign Debt Crisis, and the COVID-19 pandemic, respectively. For each of these episodes and events, the effect on 12-month-ahead realized inflation is estimated using the local projection method of Jorda (2005), as detailed in Appendix A.2. Missing data for Luxembourg, the Netherlands, Ireland and Portugal for specific sub-periods, preclude estimating the impact of some of these events.

A.2 Impact of identified Events on Realized Inflation

For each country in our sample, we estimate the adverse events impact on realized inflation, $\pi_{c,t}$, using the local projection method of Jorda (2005). Specifically, we estimate the following regression for horizons, h, ranging from zero to twelve months:

$$\pi_{c,t+h} = a_{c,h} + \sum_{j=1}^{3} \delta c, j\pi_{c,t-j} + + \sum_{j=1}^{3} \gamma_{c,j} Unemployment_{t-j} + \sum_{j=1}^{n} \beta_{c,j,h} Event_j + u_{c,t+h} \tag{A1}$$

where $\pi_{c,t+h}$ denotes realized inflation in country c at horizon h, $Event_j$ is an indicator for event j taking the value 1 on the event date and zero otherwise, and $\beta_{c,j,h}$ measures the response of inflation to event j at horizon h for country c. The total number of events, n, is equal to 23 under the Bloom (2009) approach and 37 under the Markov Regime Switching approach. All specifications include lagged inflation and the unemployment rate as control variables. Standard errors are computed using the NeweyWest estimator with automatic bandwidth selection as in Newey and West (1994). To measure the aggregate impact of consecutive events, such as Covid or the Global Financial Crisis, it is necessary to compute a linear combination of the estimated coefficients, $\beta_{c,j,h}$ from each relevant regression event dummy.

Figure A1: Event Jan 08: Local projections (Inflation)

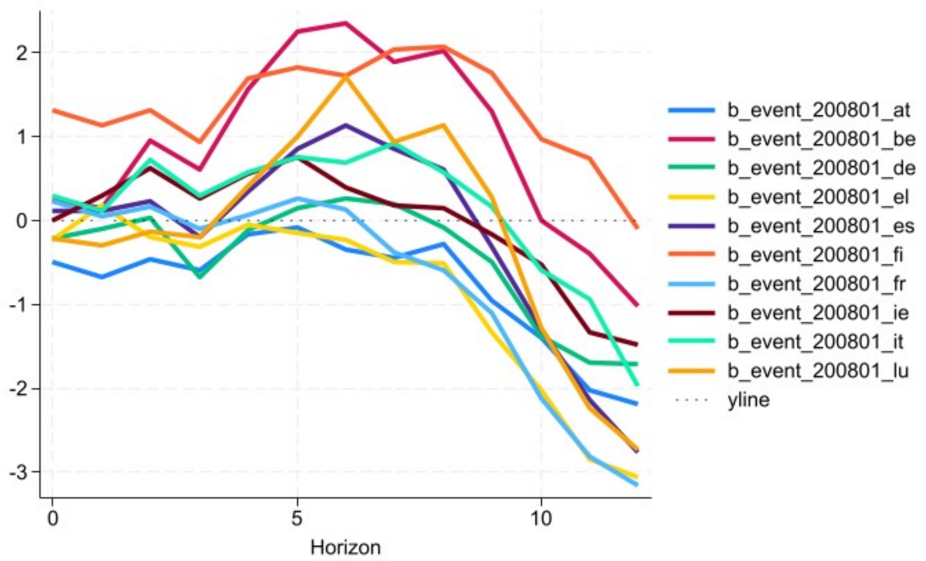

Figure A2: Episode 1 (Sep 08 to Apr 09): Local projections (Inflation)

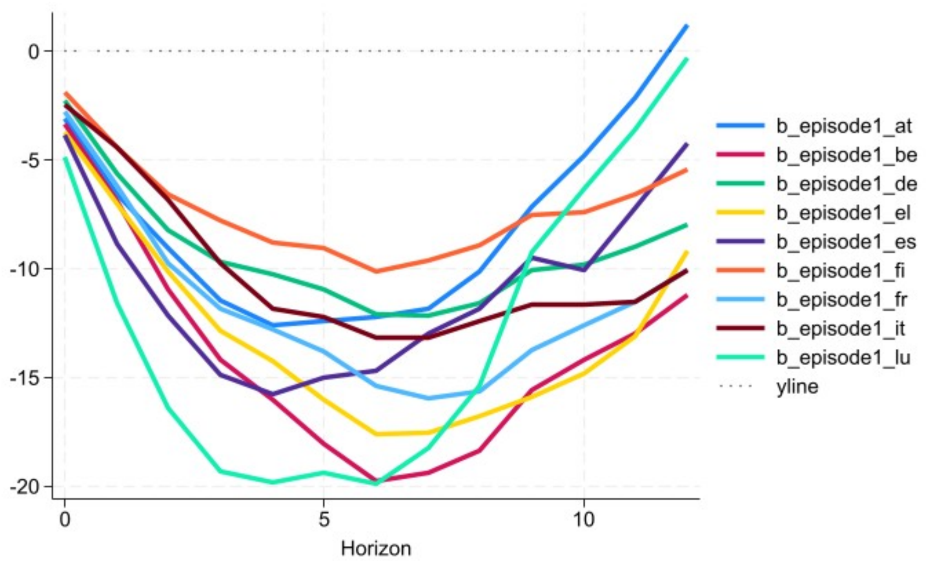

Figure A3: Episode 2 (May 10 to Jun 10): Local projections (Inflation)

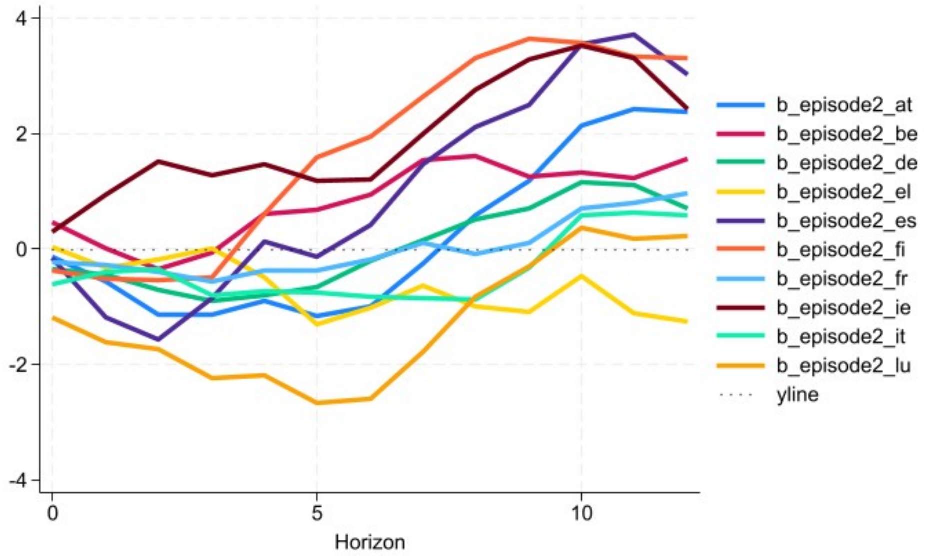

Figure A4: Episode 3 (Aug 11 to Dec 11): Local projections (Inflation)

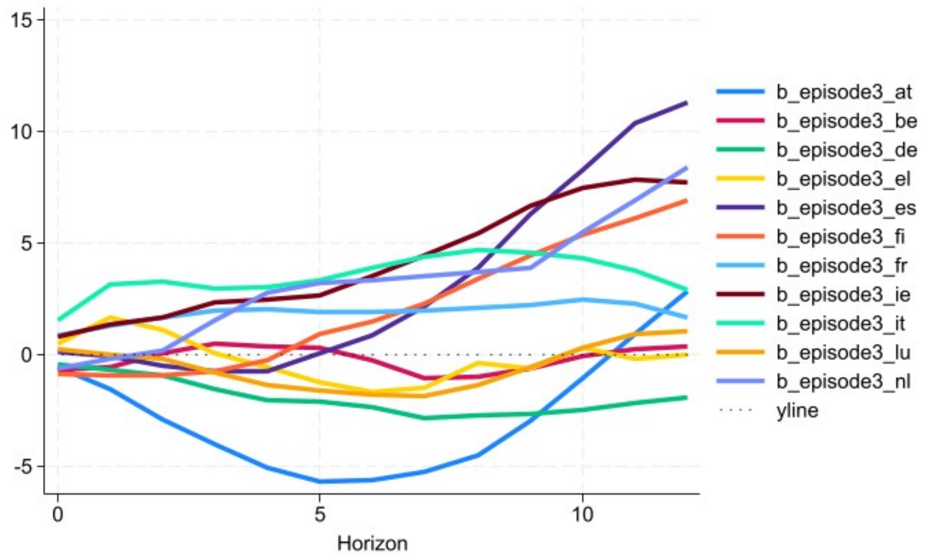

Figure A5: Event Aug 15: Local projections (Inflation)

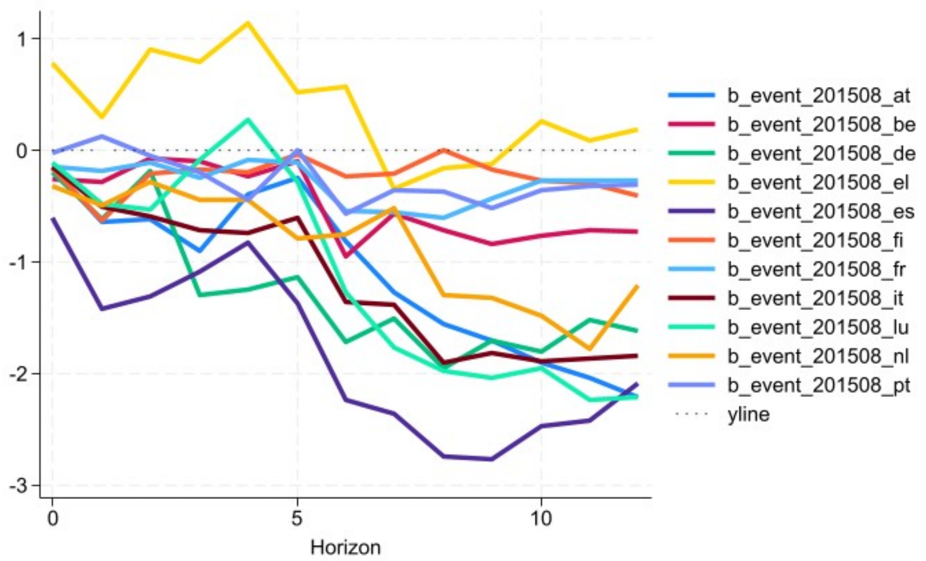

Figure A6: Event Jun 16: Local projections (Inflation)

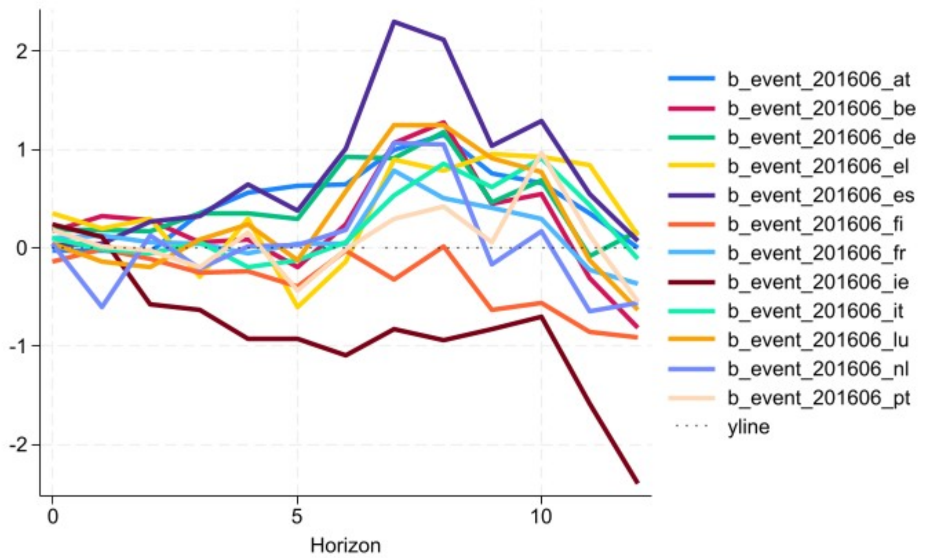

Figure A7: Episode 4 (Feb 20 to Apr 20, and Jun 20): Local projections (Inflation)

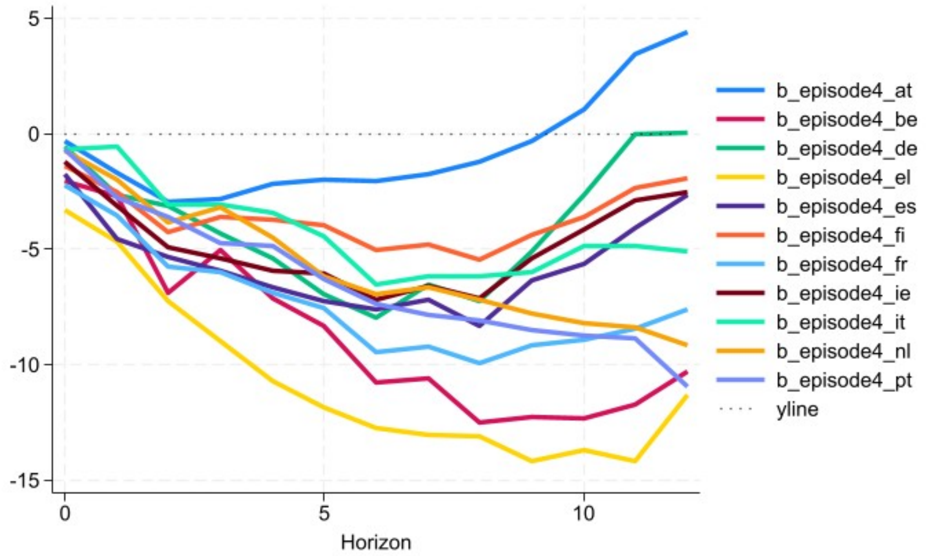

Figure A8: Event Mar 22: Local projections (Inflation)