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What makes Monetary Policy more powerful?

A Big Data Approach

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This paper contains research conducted within the network "Challenges for Monetary Policy Transmission in a Changing World Network" (ChaMP). It consists of economists from the European Central Bank (ECB) and the national central banks (NCBs) of the European System of Central Banks (ESCB).

ChaMP is coordinated by a team chaired by Philipp Hartmann (ECB), and consisting of Diana Bonfim (Banco de Portugal), Margherita Bottero (Banca d'Italia), Emmanuel Dhyne (Nationale Bank van België/Banque Nationale de Belgique) and Maria T. Valderrama (Oesterreichische Nationalbank), who are supported by Gonzalo Paz-Pardo and Jean-David Sigaux (both ECB), 7 central bank advisers and 8 academic consultants.

ChaMP seeks to revisit our knowledge of monetary transmission channels in the euro area in the context of unprecedented shocks, multiple ongoing structural changes and the extension of the monetary policy toolkit over the last decade and a half as well as the recent steep inflation wave and its reversal. More information is provided on its website.

Non-Technical Summary

We have a great deal of evidence that the effects of monetary policy are not constant across time-periods, and can vary at different stages of the economic cycle. In order to conduct policy effectively, central banks need to understand when their actions have larger or smaller effects. If a monetary policymaker knew in advance that policy rate changes had strong effects at a particular stage of the business cycle, they would be more cautious about forceful action at these times. On the other hand, if central banks observed they were in a state associated with weak transmission, they could take stronger and more forceful actions to compensate. It is therefore of great interest to learn when monetary policy is more (or less) effective.

Previous research has emphasised many different mechanisms by which the impact of monetary policy can be amplified, or weakened. An influential body of work dating back to Keynes argues that monetary policy is less effective in recessions. Other work has emphasised that the strength of transmission can change when interest rates approach zero (the so-called "Zero Lower Bound"). The state of the financial cycle, which summarises the overall level of borrowing and indebtedness in an economy, has also been emphasised. Other studies have found transmission to weaken when uncertainty is high.

However, while many channels have been documented, the majority of previous studies have emphasised one or two effects in isolation. We lack an overall picture of which amplification channels are most important for monetary policy transmission, and which are less important. Our work contributes by taking a "big data" approach to the factors that influence the strength of monetary policy. We study the case of the US Federal Reserve (Fed) and the European Central Bank (ECB). Given the potential for a large number of active channels, we keep our overall research design as simple as possible. We study the case of transmission to financial variables during times when the Fed and ECB communicate. Our paper is therefore part of the "event study" literature. We construct large datasets of macroeconomic and financial variables to allow for a (potentially large) number of active channels. In order to estimate models with a large number of variables, we need to use specialised techniques, often called "data reduction" methods. We use a straightforward factor-based approach, whereby we summarise our data as a smaller number of components, and interact these with our policy variables.

Our first contribution is to assess the number of interaction effects that are relevant, when searching broadly over a large dataset, while reducing variation using our factors. We first focus on the case of the US. We find that monetary policy transmission is characterised by a small number of important interaction effects. Importantly, we could equally have found evidence for a highly complex process. However, our findings indicate that the large number of mechanisms discussed in the previous literature can be summarised by a much smaller number of non-linear states.

For the US, when studying transmission to long-term interest rates (US Treasuries), we find one factor to be particularly important for model performance – this factor relates to credit growth, and the level of interest rates. We call this the "interest rate cycle" factor. When this factor is low, monetary policy is more effective. Many of the factors we test, that relate to often discussed mechanisms (e.g. involving uncertainty), are not found to be relevant. We do find some evidence that transmission is stronger in recessions, though this effect is less robust than the effects relating to interest rates. For the euro area, we find the most important source of amplification relates to whether sovereign debt markets are stressed or not. Overall, our results isolate a small number of factors, mostly relating to financial variables, that indicate whether central bank statements will have strong (or weak) effects on asset prices.

What Makes Monetary Policy More Powerful? A Big Data Approach*

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Abstract

A large literature on monetary policy transmission has emphasised many potential non-linear drivers. Transmission strength has been shown to vary with the business cycle, financial frictions, and uncertainty, amongst other mechanisms. However, most studies focus on a small number of channels at a time. Our study takes a "big data" approach to non-linearity, allowing us to rank the relative importance of a wide range of non-linear transmission channels. We focus on asset price responses to central bank statements. Using a large, mixed-frequency macro-financial dataset, we show that US monetary policy surprises feature a small number of important non-linear drivers, relating especially to financial variables. Monetary transmission to long-term interest rates is weaker at times of high interest rates and high credit growth, consistent with diminishing effectiveness over a hiking cycle. While non-linearity over the interest rate cycle appears to dominate other channels, we find some evidence that monetary policy is weaker in booms. Using euro area data, we find a prominent role for sovereign risk in state-dependent transmission.

JEL Codes: E52, E33, C32, C11.

Keywords: Monetary policy, state-dependence, non-linearity, event study, big data.

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1 Introduction

The idea that the effectiveness of monetary policy changes with the state of the world can be traced back at least as far as Keynes (1936). Keynes posited that if the interest rate were sufficiently low, the monetary authority could not stimulate the economy by easing rates further (so-called "pushing on a string"). The question of whether the impact of monetary policy is state-dependent is an important one. Policymakers cannot calibrate their stance appropriately without knowing whether the effects of their tools are stronger (or weaker) in given situations.

As the macroeconomic literature developed in the wake of Keynes' work, a plethora of additional sources of state-dependent monetary policy have been proposed. With respect to transmission to macroeconomic variables, monetary policy effectiveness has been found to depend upon the business cycle (Tenreyro and Thwaites, 2016; Mumtaz and Surico, 2015), financial cycle (Alpanda et al., 2021; Rünstler and Bräuer, 2020), inflation (Gargiulo et al., 2025), proximity to the Zero Lower Bound (Krugman et al., 1998; Kiley and Roberts, 2017) and the level of interest rates (Berger et al., 2021; Eichenbaum et al., 2025), amongst many other mechanisms. Researchers have also investigated non-linear transmission to financial variables, documenting non-linearities at the Zero Lower Bound (Swanson and Williams, 2014; King, 2019), across the business cycle (Bauer et al., 2024), and levels of uncertainty (De Pooter et al., 2021; Bauer et al., 2022; Tillmann, 2020). In practice, therefore, it seems monetary policymakers must grapple simultaneously with a potentially large number of sources of state-dependence.

An important limitation of the previous literature is the use of primarily *low-dimensional* approaches to evaluate non-linearity. These approaches typically estimate a few non-linear channels, and frequently focus only on a single channel. Low-dimensional approaches suffer from two important drawbacks, however. First, the variables chosen to represent potential state-dependent channels may be correlated with others, leading both to a lack of clarity as to which channel matters, and to omitted variable bias concerns. Second, the use of low-dimensional specifications makes it difficult to establish the economic importance of any given channel relative to others. To date, researchers have tended to employ somewhat *ad hoc* approaches to evaluate the role of different channels, for example by simply substituting one state-variable for potential alternatives and conducting a horse race exercise across models.

This paper takes a *high-dimensional*, "big data" approach. We systematically evaluate which sources of state-dependence matter most for monetary policy transmission to asset prices. For the US and the euro area, we construct mixed-frequency datasets incorporating large numbers of financial and macro-economic variables. We specifically design these datasets to incorporate non-linear mechanisms that have previously been emphasised in the literature. We reduce the dimensionality of these large datasets using factor models, with each factor representing a linear component of the information available to market participants prior to a central bank communication event. We then create a series of "factor interaction effects", by multiplying our factors by high-frequency monetary policy surprises (Jarociński and Karadi, 2020). The use of these factor interaction effects will allow us to survey sources of non-linearity across a large number of potential macroeconomic and financial drivers, while keeping our specification as parsimonious as possible.

We incorporate our factor interaction effects into standard non-linear event study regressions. We use data from high-frequency asset price movements around meeting days of the Federal Open Market Committee (FOMC) and European Central Bank (ECB) as our dependent variables. We therefore focus on transmission to financial variables, and leave transmission to the macroeconomy for future work. In particular, we focus on transmission to yields on long-term government bonds and equities. The former is a key metric of monetary policy's power to control financial conditions and signal a future policy path. The latter is a key channel through which monetary policy affects financial conditions. We also study the transmission of policy to sovereign spreads for the euro area case. Following Cloyne et al. (2023), we use the Kitagawa-Oaxaca-Blinder decomposition to summarise state-dependent effects.

Although we allow for many state-dependent effects using data reduction methods, we do so in the context of a research design that is deliberately kept parsimonious. Firstly, we study transmission of monetary policy to financial variables only, using simple event study regressions. Transmission to macroeconomic variables is left for future work. Secondly, we summarise state-dependence through the use of continuous interaction terms, meaning our model is linear in parameters. Finally, the focus of our paper is on state-dependence, and we do not study other forms of non-linearity, such as sign- and size-dependent effects.

Our first contribution is to assess the number of non-linear states that are active for monetary policy transmission. We do so by applying model selection criteria to the factor interaction effects in our event study regression, as well as by testing for their statistical significance. We are therefore able to quantify the "dimensionality" of state-dependent transmission for the first time. We first focus on the case of the US. We find that monetary transmission is characterised by a small number of important non-linearities. Importantly, we do so in a setting where we have allowed for a broad range of potential sources of non-linear transmission. We could equally have found evidence for a highly complex process. Our findings indicate that the large number of mechanisms discussed in previous literature can be empirically summarised by a much smaller number of non-linear states.

For the US, when studying transmission to long-term interest rates, we find that the strongest model performance comes when allowing for more than one non-linear state, highlighting the limitations of the lowest dimensional investigations in the literature. When we allow up to 10 distinct and competing economic channels to operate, we find only two channels have statistically significant effects. These stem from the interaction of monetary policy with the first and second principal components from our data. The first factor we interpret as a summary measure of the business cycle, while the second we interpret as indicating the state of the monetary/financial cycle. It is notable that many factors that more closely relate to financial frictions and uncertainty, for example, are *not* selected as useful predictors, nor are they statistically significant. Our findings suggest that these factors are either of limited empirical relevance, or their effects are summarised linearly by the business cycle and monetary/financial cycle factors.

Our second contribution is to show that the non-linear effects are economically large and have clear economic interpretations. For the case of transmission down the yield curve, we find that the strongest evidence is for non-linear transmission according to the state of the monetary/financial cycle. The relevant factor loads most strongly on private sector leverage, measures of inflation, nominal wages and the Federal Funds Rate. The factor is orthogonal to the business cycle factor (the first principal component) by construction. The factor introduces countercyclicality to monetary policy transmission, with transmission stronger when interest rates and credit growth are lower. This indicates that monetary policy transmission should weaken over the course of an interest rate cycle. The magnitude of the non-linear effect is economically large—the transmission of a 10 basis point monetary policy shock is reduced by 38% when the monetary/financial cycle factor is one standard deviation above its mean.

We also find evidence for counter-cyclical transmission related to the business cycle—a tightening shock transmits 27% more strongly to long-term yields when the business cycle is one standard deviation below its mean. This aligns with the results in Bauer et al. (2024), who found that transmission to Treasury yields is stronger when the economy is in a weak state. However, with respect to our model selection exercises, the evidence in support of the monetary/financial factor is considerably stronger than the evidence for the business cycle factor. Given also that the estimated magnitude of the monetary/financial factor is the larger of the two effects, we conclude that the monetary/financial channel of transmission is the dominant one in the US data.

Our third contribution is to assess the extent to which our findings for the US generalise, by conducting a comparative exercise. We study non-linear transmission in the euro area based on another large, mixed-frequency dataset designed to incorporate non-linearities, and to be comparable to the US dataset. We find robust evidence for non-linear transmission to long-term German sovereign yields, to Italian yields, to the spread between these, and to equities. We again find evidence for a parsimonious representation of non-linear transmission, with a relatively small number of effects proving useful for predicting asset price responses. The most robust source of non-linear euro area transmission is a factor related to sovereign risk and uncertainty. This factor loads positively upon the yields of Italian and Spanish debt and on a measure of economic uncertainty. This factor amplifies the transmission of a tightening shock to the spread between Italian and German debt, with a sizeable 78% increase at one standard deviation above the mean of the factor.

The euro area monetary cycle factor also affects the transmission of ECB announcement surprises, as did the similar factor extracted for the US case. However, an increase in the monetary cycle factor strengthens transmission in the euro area, whereas we found the opposite dynamic for the US. The results for the euro area are affected by the multi-year crisis period in the euro area. During this period there were intra-euro area capital flows into the German

Bund with a "flight-to-safety" motive. Only the sovereign risk/uncertainty non-linear estimated effect is robust to the removal of the crisis period from the sample. Future research based on a longer sample, in which the crisis period is not as dominant, may find more robust evidence for non-linear transmission in the euro area deriving from other macro/financial channels than sovereign risk/uncertainty.

Overall, our results indicate that the transmission of high-frequency monetary policy surprises to asset prices is non-linear, but that the number of active states can be summarised parsimoniously by a small number of factors. For the case of the US, the factor relating to the monetary/financial cycle appears dominant, even relative to the business cycle itself. For the case of the euro area, the effect of sovereign spreads is the most robust across specifications. While many other channels have been emphasised in the literature, our findings indicate that non-linear transmission is best understood through the study of a small number of latent states.

A key interpretive question is whether state-dependence in our results reflects differences in how monetary policy transmits to markets, or instead reflects differences in the composition of central bank surprises across states. Although we use monetary policy shocks isolating policy surprises, central bank events may still embed different mixtures of policy news and information effects depending on macro-financial conditions, particularly during crises. Our baseline interpretation emphasises transmission: the same policy shock produces different market responses depending on the prevailing monetary/financial cycle in the US or sovereign spreads in the euro area.

The paper is organised as follows. Section 2 provides a review of the existing approaches to non-linearity in the macroeconomic literature. Section 3 explains our methodology. Section 4 discusses the data used in this study. Section 6 discusses the empirical results for the US and euro area. Section 7 concludes.

2 Literature Review

When quantifying non-linear transmission, researchers typically make two important steps. The first step is to defend theoretically a mechanism that may lead to non-linear transmission and to locate empirical proxies for the source of non-linearity. For example, a researcher may posit that monetary policy decisions are less impactful in an uncertain environment and proxy uncertainty using financial market or survey data. Often, a number of different empirical proxies are available, and it is incumbent on the researcher to establish the robustness of the results across this set of proxies. The second step is the specification of the non-linear model. In macroeconomic applications, various methods are used including structural models directly incorporating the non-linear channel (e.g., Kiley and Roberts, 2017), VAR models incorporating thresholds (Balke, 2000), Markov-switching regime shifts (Sims and Zha, 2006), or time-varying parameters (Primiceri, 2005), and state-dependent local projections (Tenreyro and Thwaites, 2016). Recent literature has also incorporated machine learning methods—such as random forests (Errico et al., 2025) to capture non-linearity in macroeconomic models. In this paper, rather than treating state-variable selection and model specification as two sequential steps, we adopt a systematic approach: we assemble a broad set of candidate state variables motivated by the literature, before embedding each directly into the same non-linear estimation framework. This allows us to rank the importance of states, and to guard against results driven by the idiosyncratic behaviour of certain proxies.

The literature has documented a vast array of state-dependent channels of monetary policy transmission. As summarised in Appendix Table 8, most of these papers mainly investigate a single state variable of interest. In relation to the business cycle, Tenreyro and Thwaites (2016) and Mumtaz and Surico (2015) find that monetary policy is weaker in recessions. Bauer et al. (2024) show that time-varying perceived Fed responsiveness rises during hiking cycles, implying that interest rate increases in recessions have an additional effect on term-premia. Focusing on the role of the financial sector in transmission, Li (2022) reports evidence that the transmission of monetary policy is non-linear in the leverage ratio of primary dealers, ultimately resulting in monetary policy being less effective in recessions. Rünstler and Bräuer (2020) find evidence for state-dependence in the effects of monetary policy shocks on GDP for a panel of euro area countries, depending on the leverage cycle. There is substantial evidence that higher uncertainty weakens monetary policy transmission, as investors put less weight on central bank signals and adjust their interest rate positions by less when confidence in the policy outlook is low (Pellegrino, 2021; Bauer et al., 2022; De Pooter et al., 2021; Tillmann, 2020; Aastveit et al., 2017).

Several recent contributions allow for the simultaneous activation of multiple non-linear transmission channels, yet typically remain low-dimensional by examining just two or three drivers. For instance, Alpanda et al. (2021) show that the impact of monetary policy shocks on output and other macroeconomic and financial variables is attenuated during periods of economic downturn, high household debt and elevated interest rates. Jordà et al. (2020) also examine three dimensions, finding that transmission is stronger when growth, inflation and mortgage credit are elevated. Unlike most studies that limit attention to a low-dimensional set of state variables, El-Shagi (2021) examines a much larger set of state variables using a sparse LASSO-based approach.

In this paper, we lean on the literature to provide potential channels of non-linear transmission, and our *high-dimensional* approach allows us to examine them in a systematic way.

3 Methodology

Our approach to examining the degree of state-dependence in monetary policy transmission is to combine "big data" methods, extracting factors from a large dataset, with a standard event study regression (Kuttner, 2001). A regression of this type can be expressed as follows:

$$y_t = \alpha + \beta MPS_t + \upsilon_t, \quad t \in \{1, \ldots, T\}, \tag{1}$$

where y_t is the high-frequency change in some asset price on meeting day t. MPS_t is a monetary policy surprise, constructed from changes in interest rate futures prices around communication events. υ_t is an exogenous and serially uncorrelated disturbance term.

In the high-frequency identification literature, the event study window is usually set to be between 10 and 20 minutes before and after the communication event (Gürkaynak et al., 2005). Under the assumption of efficient markets, interest rate futures should incorporate all publicly available information immediately prior to the meeting. The change in interest rates during the event study window therefore represents the policy surprise component. We can treat such movements as reflecting exogenous monetary policy surprises, conditional on the assumption that no other news event affecting interest rates took place during this narrow window of time. Given this assumption, the coefficient β reflects the causal effect of the monetary policy surprise on asset prices.

The relationship in equation 1 is linear and therefore state-independent. As discussed in Section 2, a comprehensive literature has found that there may be important state variables that affect the transmission of monetary policy. A simple way to capture non-linear relationships would be simply to augment equation 1 with an interaction term,

$$y_t = \alpha + \beta MPS_t + \gamma MPS_t \times z_t + \upsilon_t, \quad t \in \{1, \dots, T\}, \tag{2}$$

where z_t is a potential source of state-dependence. Here z_t is indexed at time t but represents information available prior to the event window. The total effect of a monetary policy surprise on the change in asset prices is given by the sum of β and γz_t.

One can think of equation 2 as being "representative" of many forms of low-dimensional non-linear investigations, where z_t can be substituted for alternative drivers. Our approach is to simply extend equation 2 to allow for a *large* number of potential sources of non-linearity. In the case that we have a set of N alternative drivers, we could simply replace the scalar variable z_t with a N-dimensional vector $\mathbf{Z}_t = [z_{1,t}, z_{2,t}, \dots, z_{N,t}]'$. However, as N becomes large, such an approach would raise concerns regarding over-fitting. The number of observations in a high-frequency event-study regression is usually low. An additional concern is that many of the potential drivers within $\mathbf{Z}_t$ would be correlated with each other, making the interpretation of the coefficients challenging. Coefficient size and statistical significance could be affected by the inclusion or exclusion of one or more correlated drivers. Our baseline approach to reduce the dimensionality of our model is therefore to extract factors from a large dataset of financial and macroeconomic variables using Principal Component Analysis (PCA). We use the extracted factors as potential driving variables, rather than the underlying data series themselves. These factors are orthogonal by construction.

Alternative approaches to estimating a multi-dimensional non-linear process are possible. We favour using factors for their combination of parsimony and ease of interpretation. In on-going work by the present authors we apply machine learning algorithms to the estimation of a multi-dimensional version of equation 2. Evidence from a LASSO approach is presented in Aydın Yakut et al. (2024).

Our baseline specification is given by:

$$y_t = \alpha + \beta MPS_t + \sum_{k=1}^{K} \gamma_k MPS_t \times f_{k,t} + \upsilon_t, \tag{3}$$

$$z_{i,t} = \sum_{k=1}^{K} \lambda_{i,k} f_{k,t} + \varepsilon_{i,t}, \quad \forall i \in \{1,\ldots,N\}, \forall t \in \{1,\ldots,T\}. \tag{4}$$

We do not interact the N data series directly with the monetary policy shock, instead we interact a smaller set of K factors $\{f_{k,t}\}_{k=1}^{K}$, where $K < N$, as per Equation 3. To estimate the factors, we reduce the dimensionality of our macro-financial dataset $\{z_{i,t}\}_{i=1}^{N}$ according to Equation 4. Here $\varepsilon_{i,t}$ is an exogenous and serially uncorrelated idiosyncratic factor. As before, each of the series $\{z_{i,t}\}_{i=1}^{N}$ are appropriately lagged to ensure they represent information available prior to the intraday window. This implies that the factors used for interactions represent linear combinations of lagged data.

One can interpret our specification as a high-dimensional extension of the Kitagawa-Oaxaca-Blinder decomposition, used to examine state-dependence in causal relationships (Kitagawa, 1955; Oaxaca, 1973; Blinder, 1973). Cloyne et al. (2023) employ the Kitagawa-Oaxaca-Blinder decomposition and emphasise the importance of expressing state variables as deviations from their means, since this ensures the parameter β and vector of parameters $\{\gamma_k\}_{k=1}^{K}$ have clear economic interpretations. Our factors have zero mean by construction, since we standardise $z_{i,t}$ prior to estimation. The parameter β represents the state-independent effect of the monetary policy surprise. Termed by Cloyne et al. (2023) the "direct effect", this is the effect of monetary policy on asset prices at the mean of the state variables. If we do not find any evidence for non-linearity, the sole operative effect of monetary policy is this direct effect, and transmission is reducible to the state-independent specification in equation 1. Meanwhile, the "indirect effect" represents the contribution of the state variables to transmission. A statistically significant estimate for parameter γ_k would indicate non-linear transmission, while the relative sizes of β and $\gamma_k f_{k,t}$ allow us to determine whether any such non-linearity is economically meaningful, for given realisations of the interaction variable $k \in \{1,\ldots,K\}$. Transmission of monetary policy is the sum of the two—the "total effect". This combination of coefficients is the effect of a unit monetary policy surprise, and can be evaluated at different values of the state variables, $\{f_{k,t}\}_{k=1}^{K}$.

In equation 3, we do not include a vector of main effects of the state variables, meaning $\{f_{k,t}\}_{k=1}^{K}$ do not enter the relationship directly, only through their interaction with the surprise. Much of the high-frequency event study literature has operated on the basis that the monetary policy surprise should not be predictable by information that was publicly available before the monetary policy meeting. For this reason, our baseline regressions do not contain control variables. However, recent studies (Miranda-Agrippino, 2016; Bauer and Swanson, 2022) have documented a level of predictability of these surprises, i.e., that they are not orthogonal to all real and financial information available before the meeting. Therefore, we show robustness to specifications that include lagged data as control variables.

A regression such as equation 3 can be estimated using ordinary least squares (OLS) if the sample size is relatively large and the state-variables are observable. However, in our set-up, the state variables are not observable, but are estimated factors. In this study we follow a two-step approach, estimating factors using PCA, before entering them into our main non-linear regression equation. We therefore need to account for the problem of generated regressors. Inference in this setup is not straightforward. Bai and Ng (2006) show that if the cross-sectional dimension, i.e., the number of variables used to estimate the factors, is asymptotically large compared to the time series dimension then inference based on the standard OLS estimators can remain valid. More specifically, for a given time-series T of N data-series, they require $\sqrt{T}/N \rightarrow 0$, in addition to other regularity conditions. Gonçalves and Perron (2014) show that the asymptotic distribution of the OLS estimators can be affected such that a bias term arises if this condition fails. They propose a flexible bootstrap approach using a residual-based, two-stage wild algorithm in factor-augmented regressions. We follow the approach of Gonçalves and Perron (2014), as detailed in Appendix C.

4 Data

To study the effects of monetary policy on asset prices, we need a series of high-frequency policy surprises (Kuttner, 2001; Bernanke and Kuttner, 2005; Gürkaynak et al., 2005). Our baseline measures are the monetary policy surprise series of Jarociński and Karadi (2020), which are available for both the US and euro area. These surprises control for "information effects" through the application of an algorithm that places sign-restrictions on the response of equities.[1] We standardise these shocks such that they produce 10 basis point changes in the first Eurodollar futures contract (ED1) for the US and the three-month Overnight Index Swap rate for the euro area, respectively. Other forms of monetary policy surprise have been used in the literature to decompose the role of conventional and unconventional policies (Swanson, 2021; Altavilla et al., 2019; Jarociński, 2024). We use these series to examine robustness to the role of quantitative easing policies. For the US, we source data on high-frequency asset price responses from the dataset made available on the website of Marek Jarocínski. For the euro area, we use the EA-MPD (Altavilla et al., 2019). Summary statistics for the event study data are available in Appendix Table 12.

We construct a large dataset of real and financial variables to allow us to examine many simultaneous potential sources of non-linear monetary policy transmission, for both the US and euro area. The US dataset is an extended version of the widely-used macro-financial FRED-MD dataset of McCracken and Ng (2016). In addition to the core macroeconomic and financial time series in FRED-MD, we incorporate variables that have been previously emphasised in the literature on state-dependent monetary policy transmission, but are not present in FRED-MD. These relate to uncertainty (emphasised in De Pooter et al. 2021) and the financial cycle (Adrian and Shin, 2014). For the euro area, we construct our own dataset using information from Eurostat, the ECB, Refinitiv, and Bloomberg, among other sources (as detailed in Appendix D).[2] For the US, the dataset comprises 233 observations from 5 February 1997 to 18 December

[1]Note that we use the updated surprise series made available on the GitHub page of Marek Jarociński. These surprises are constructed using the first principal component of interest rate futures contracts of up to a one-year horizon. This differs slightly from the treatment in Jarociński and Karadi (2020), where contracts at the 3-month horizon are used.

[2]Appendix Table 14 lists the different transformations we can apply to the data, and the groups in the data. Appendix Tables 15 and 16 provide each variable's name, its interpretation, group, source, frequency, and the transformation applied, if any, for the US and euro area datasets.

2024, while for the euro area the span is 211 observations from 5 February 2004 to 12 December 2024.[3]

Table 1 summarises our two datasets, which are mixed-frequency, including daily, weekly, monthly and quarterly variables. The dataset incorporates 129 variables for the US and 125 for the euro area. To illustrate the range of non-linear channels we will examine, we outline groups of real and financial data to which the variables could be assigned, such as interest rates, the yield curve, prices, and so on. We extract our factors from the whole dataset without segregating the data according to these groups.

Table 1: Numbers of Macro-financial Variables by Group and Frequency

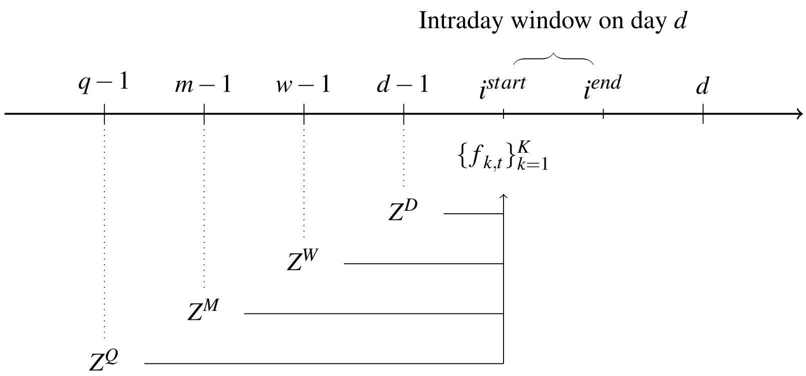
	US					EA			
Section	M	D	Q	W	Total	M	Q	D	Total
Activity	26				26	29	1		30
Labour	31				31	1	13		14
Money and Credit	9			4	13	9			9
Interest Rates		4			4			3	3
Yield Curve		2			2			2	2
Exchange Rates	1	4			5			5	5
Prices	20				20	28		1	29
Stock Market	2	2			4			6	6
Uncertainty	6	4			10	2		2	4
Financial Frictions	2	4		1	7	10		8	18
Financial Cycle	2		5		7	1	4		5
Total	99	20	5	5	129	80	18	27	125

Notes: Table shows the number of variables in our macro-financial datasets for US and the euro area, subdivided by group and frequency—daily ("D"), weekly ("W"), monthly ("M"), quarterly ("Q").

For each variable in our dataset, we use the highest frequency version that is available. For example, we replace monthly interest rate data in FRED-MD with equivalents at daily frequency. Figure 1 shows how we align the highest-frequency versions of the variables of different frequencies to the meeting day. The meeting takes place on day d in week w, month m, and quarter q. We gather all series into vectors Z^s, where the index s represents their frequency of measurement: daily (D), weekly (W), monthly (M), or quarterly (Q). Each vector is aligned so the data are the closest to the meeting day but preceding and not including the meeting, so the data are not affected by the monetary policy surprise at that meeting. Hence the daily data

[3]Our euro area dataset starts only in 2004 due to shorter availability of euro area financial variables.

Figure 1: Event study window and the structure of the mixed-frequency dataset



are measured on the preceding day, $d-1$, the weekly data are measured on the preceding week, $w-1$, and so on. This procedure ensures that our measure of the information set of market participants prior to the meeting does not include data that could be affected by the surprise itself.

From this aligned mixed-frequency dataset of dimension N, we extract K factors, $\{f_{k,t}\}_{k=1}^{K}$ using PCA, as described in Section 3. One issue is that the Covid-19 shock leads to very large movements in many of the series, and is in many respects a "unique case". During this sub-period, new factors relating to the pandemic itself likely became relevant. We prefer to remove such effects from our factor model. We do this by estimating our factors by PCA on the dataset prior to 2020. Keeping the estimated loadings constant, we extrapolate our factors forward into the period after 2020. This has the advantage of ensuring our factor definitions are not affected by the pandemic period. However, the use of extrapolated factors does introduce a small amount of correlation between the factors in the full sample (which is not present by definition in the sample on which they were estimated).

Table 2 displays the largest six loadings for the first six factors of the data. In the US data, the first factor loads most strongly on industrial production and employment numbers, giving a clear real economy interpretation. We will refer to this factor as the "business cycle factor". The second factor loads most strongly on the financial cycle as measured by the private sector credit-to-GDP gap, services Consumer Price Index (CPI) inflation, average hourly earnings of goods-producing employees, the CPI for all urban consumers, and the Federal Funds Rate. We refer to this factor as the "monetary/financial cycle factor". Appendix Table 13 displays the cumulative variance explained by the respective principal components. The first factor explains 30% of the variance. The second factor explains an additional 12.6% of the variance. Figure 2 displays the time-series evolution of the business cycle and monetary/financial cycle factors for the US. As expected, the business cycle factor tracks the US business cycle closely (especially the evolution of industrial production). The monetary/financial cycle factor is markedly elevated in the pre-GFC period, but then falls sharply with interest rates as the Fed encountered the effective lower bound.

With respect to the euro area data, we will also refer to the first factor as the "business cycle" factor given its loadings on series related to industrial production, retail sales and business confidence. We refer to the second factor as the "monetary cycle" factor, as its highest loadings are on measures of inflation and euro area short-term interest rates. This differs from the second factor in the US, which also loads strongly upon private sector credit. We call the third factor the "sovereign risk/uncertainty factor" as it loads positively upon Italian and Spanish sovereign bond spreads and the Baker et al. (2019) measure of Economic Policy Uncertainty, but negatively upon a German bond spread.[4] Figure 2 displays the first three factors for the euro area data.

5 Non-Linear Transmission: Some Stylised Facts

Before employing our novel high-dimensional approach to non-linearity, we take a simple, low-dimensional approach to document certain stylised facts about monetary policy transmission in the US and euro area. These facts are useful for interpreting later results. Our main finding is that while transmission of monetary policy surprises to long-rates appears to strengthen during recessions in the US (as reported by Bauer et al. 2024), the opposite is the case for the euro area, with transmission strengthening during booms. In an overall sense, transmission down the yield curve is countercyclical in the US, but procyclical in the euro area. In the sections that follow, we will apply our high-dimensional approach to track the channels that drive such differences.

[4] The Italian and Spanish spreads are computed with respect to German yields, while the German spread is computed with respect to the Deposit Facility Rate, the main policy rate of the ECB during the majority of the period of interest.

Table 2: Factor Loadings

United States

Factor 1		**Factor 2**		**Factor 3**	
Ind Prod: Final	0.15	Credit Gap (BIS)	0.20	ISRATIOx (Inv/Save)	-0.21
Emp: TTU	0.15	CPI: Services	0.18	PPI: Consumption Gds.	0.20
Emp: Total Nonfarm	0.15	Avg. Earnings Goods	0.18	CPI: Transp.	0.20
Ind Prod: Final Prod	0.15	CPI: All Items	0.17	PPI: Finished Gds	0.20
Ind Prod: Mfg	0.15	Fed Funds Rate	0.17	PCE: Nondurable Exp	0.20
Ind Prod (Total)	0.15	CPI: Less Med Care	0.17	CPI: Commodities	0.19
Factor 4		**Factor 5**		**Factor 6**	
Fin Crisis Equity Vol	0.23	Fiscal Equity Vol	0.21	CPI: Durables	-0.29
M2 Money Supply	0.20	Ind Prod: Dur. Cons Gds	0.20	5-Year Spread	0.25
Canada/U.S. FX	0.19	Ind Prod: Cons Gds	0.20	Leverage (BSS)	0.23
Nondur Emp (Goods)	0.17	VIX (Vol Index)	0.19	10-Year Spread	0.22
MPOL Equity Vol	0.17	Macro Equity Vol	0.19	AAA Spread	0.22
World EPU Adj PPPGDP	0.16	Ind Prod: Mat’l Dur. Gds	0.18	PCE: Durables Exp	-0.21

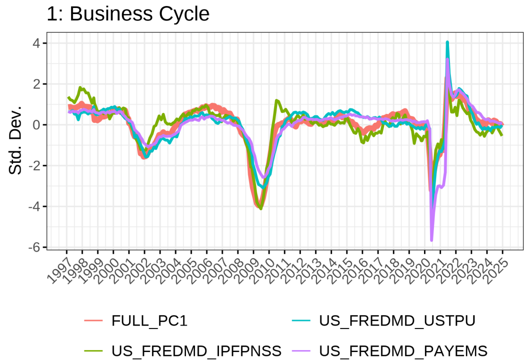
Euro Area

Factor 1		**Factor 2**		**Factor 3**	
Services Confidence	0.15	HICP: Ex Energy & Unproc. Food	0.18	Italy 10Y Spread	0.20
Industrial Confidence	0.15	HICP: Ex Energy	0.17	Italy 2Y Spread	0.20
Retail Sales	0.14	PPI: Durable Cons. Gds	0.17	Germany 5Y Spread	-0.19
Turnover: Dur. Cons. Gds	0.14	Euribor 3M	0.16	Econ. Policy Uncertainty	0.19
Industrial Production	0.14	HICP: Ex Energy & Food	0.16	Spain 10Y Spread	0.19
Services New Business	0.14	ECB Deposit Rate	0.16	Spain 2Y Spread	0.18
Factor 4		**Factor 5**		**Factor 6**	
Germany 10Y Spread	0.23	JPY/EUR FX Rate	0.21	HICP: Communication	0.26
Credit-to-GDP Gap (BIS)	0.20	Euro Stoxx 50	0.21	Euro Stoxx 50	0.21
Corp. AAA 2Y Spread	0.20	Euro Stoxx Banks	0.21	FR CAC 40	0.21
Employment	-0.19	FR CAC 40	0.20	IT FTSE MIB	0.21
Germany 5Y Spread	0.19	IT FTSE MIB	0.20	DE DAX	0.20
ECB Commodity Price Index	0.18	HICP: Communication	-0.20	Euro Stoxx Banks	0.20

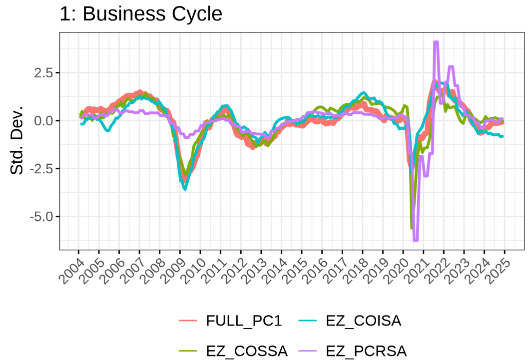
Notes: Table shows the variable loadings for the first six factors from the US and euro area datasets. Displayed are the first six loadings by the size of the loadings. Variables were standardised prior to the application of principal component analysis.

Figure 2: Examples of Estimated Factors

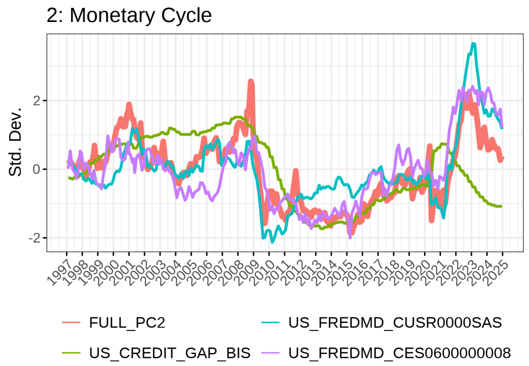
(a) US Factor 1: Business Cycle



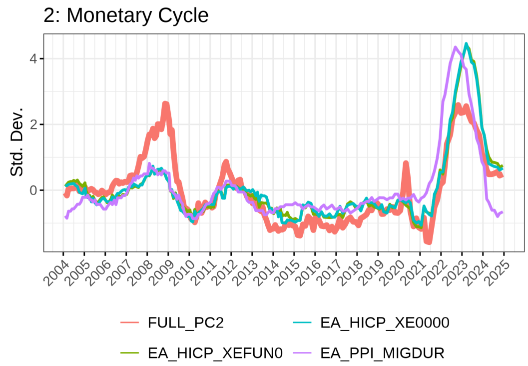
(b) EA Factor 1: Business Cycle



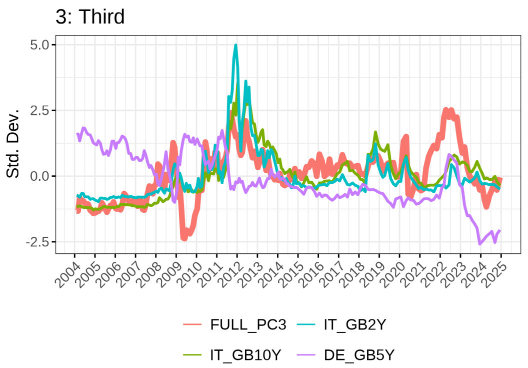
(c) US Factor 2: Monetary/Financial Cycle



(d) EA Factor 2: Monetary Cycle



(e) EA Factor 3: Sovereign Risk/Uncertainty



Notes: Figure shows the time-series evolution of key factors of interest: the first two factors extracted for US, and the first three factors for the euro area. The frequency of the factors reflects that of the central bank communication events in our sample. We also plot the three variables with the largest loadings by size for each of the factors. We represent the magnitudes in this figure in terms of the standard deviation of each variable (including the factor).

Table 3 looks at transmission to the US Treasury 10 year futures rate and the German 10 year Bund yield using four models, where different real economy variables are used as interaction effects.[5] First, we follow Bauer et al. (2024) in defining a "weak growth" dummy variable, which takes a value of one if the output gap is below its median.[6] We also use the unemployment rate, the GDP growth rate, and a Smooth Transition state-dependent model with expansionary and recessionary states (Tenreyro and Thwaites, 2016). For the US, we find evidence in each model that transmission to long-term bond yields is stronger when the economy is weaker. In columns (1) to (3) we find that transmission of the monetary policy shock is stronger when the output gap is below its median and when the unemployment rate is higher, but is weaker with a higher GDP growth rate. The smooth transmission model in column (4) shows that the transmission of the 10 basis point tightening shock is over four times higher in the recessionary state than in the expansionary one.

The findings for the US are in line with the results in Bauer et al. (2024). These authors argue that countercyclical transmission relates to amplification effects on term premia that are active when market participants revise their perceptions regarding the Fed policy rule. This result nevertheless contradicts the spirit of the contributions of Keynes (1936) and Tenreyro and Thwaites (2016), since transmission strength is stronger in recessions, not weaker.

When we study the euro area case, however, we find quite different results. In column (5) of Table 3 we observe that the coefficient on the interaction with the weak dummy, defined based on euro area output gap, is negative. While not statistically significant, the signs of the interactions in columns (6) and (7) again suggest that transmission to the German long-term yields is weaker when the economy is weaker, and in column (8), transmission is only significant when the economy is in the expansionary state.

One rationalisation for the differences in results between the US and euro area relates to the nature of sovereign risk in a monetary union. Our sample spans the Global Financial Crisis and the euro area Sovereign Debt Crisis. During the period of market stress, substantial "flight-

[5] We source the US data from Jarociński and Karadi (2020), who provide information on Treasury futures rates, while the Altavilla et al. (2019) report yields.

[6] We construct an output gap estimate for the US based on the Real Potential Gross Domestic Product series produced by the Congressional Budget Office. The output gap for the euro area is based on the Hamilton filter measure provided in the updated Euro Area-Wide Model Database (İpek and Kısacıkoğlu, 2025).

Table 3: Transmission to 10 Year Yields: Low-dimensional Stratification Approach

	US: Treasury Future 10Y				EA: German 10Y			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MPS	2.586^{***}	6.040^{***}	4.148^{***}		8.352^{***}	6.764^{***}	6.659^{***}	
	(0.574)	(0.566)	(0.562)		(1.289)	(1.038)	(1.042)	
Weak × MPS	7.554^{***}				-4.446^{**}			
	(1.152)				(2.128)			
Unemp. Rate × MPS		4.297^{***}				-1.023		
		(0.705)				(1.006)		
GDP × MPS			-1.640^{*}				1.014	
			(0.897)				(1.327)	
Expansion × MPS				2.771^{***}				8.098^{***}
				(0.632)				(1.212)
Recession × MPS				11.778^{***}				-1.966
				(1.654)				(4.149)
Main Effects	Y	Y	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.351	0.329	0.238	0.290	0.180	0.168	0.154	0.178
N	233	233	233	233	211	211	211	211

Notes: Table shows results from OLS regressions of changes in yields on event days on the Jarociński and Karadi (2020) monetary policy surprise, for the US and euro area. Each model includes non-linear interaction terms. *Weak* takes a value of one if the output gap is below its median. *Unemp. Rate* is the unemployment rate. *GDP* is the annual GDP growth rate for that quarter. *Expansion* and *Recession* are defined using a logistic function of a seven-quarter trailing moving average of the GDP growth rate, normalised by its standard deviation, and with the recessionary state calibrated to hold 20% of the time following Tenreyro and Thwaites (2016). Columns (1) - (3) and (5 - 7) are single interaction estimations as in equation 2, while columns (4) and (8) are Smooth Transition models. The main effect of the respective state variable is included in each case. Statistical significance is denoted by $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$. Standard errors are in parentheses.

to-safety" effects were observed, resulting in large cross-border capital flows that compressed yields on the main safe asset, the German Bund (Lane, 2013). In this environment, contractionary monetary policy surprises may have increased the demand for Bunds, increasing safe asset premia and thereby lowering yields. To the extent these capital flows coincided with a weak economy, this mechanism could account for the signs on the monetary policy interaction effect coefficient reported in Table 3. In support of this interpretation, we find that the positive weak growth interaction effect in Table 3 turns negative when the crisis period is dropped from the sample, though the estimate is not statistically significant.[7] Our high-dimensional investigations of transmission to German bonds will also be affected by safe asset premia responses during 2009-13.

6 Empirical Results

Moving to our high-dimensional approach, we first focus on the US, exploring the number of dimensions and the magnitude of non-linear transmission. We then turn to the euro area.

6.1 Non-Linear Transmission in the US

In order to assess the dimensionality of non-linear monetary policy transmission we test for the number of active interaction effects in our event study setup. While the literature has suggested many potential non-linear channels of transmission, our study is the first to survey many mechanisms systematically. Given the number of proposed channels, one might expect to find numerous dimensions of state-dependence. On the other hand, our approach may equally reveal that non-linearity is reducible to a few channels, or even a single overall channel. As we shall see, our estimates favour a low-dimensionality of non-linear transmission in the US case, with at most two factors being relevant robustly.

We apply model selection criteria to our baseline equation 3. Our preferred selection criterion is a pseudo-out-of-sample K-fold cross-validation (CV) exercise. We include or exclude different factor interaction effects from equation 3. We divide the dataset into 10 folds randomly,

[7] These results are omitted for brevity and available on request.

estimate the model over nine of the folds, and compute the root mean-squared error (RMSE) over the remaining fold. We average the RMSE over the held-out folds, repeat this process 10 times, and average again. Note that this exercise is not a fully out-of-sample criterion. The reason is that the factors themselves were estimated over the full-sample, and are not re-estimated within the cross-validation exercise. Since we aim to interpret our factors, we prefer to keep their loadings (and therefore their interpretations) fixed across different models for equation 3.

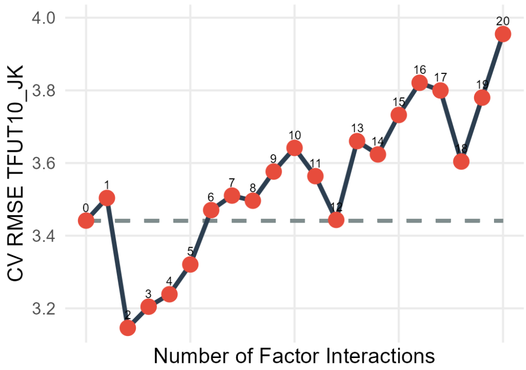
The results of this exercise are displayed in Figure 3. In our first investigation, displayed in panel (a), we consider nested models. Here, we incrementally increase the number of non-linear terms by one as we add factors to the model. Under this approach, models that incorporate information from less relevant factors (which explain a lower share of the variance of the data) will be penalised, in the sense that they will also need more parameters to estimate. We observe that a five-factor model will perform better than the linear case, but this is due to the fact that the second factor is very useful at explaining non-linearity. In Appendix Figure 6, we show that the results in panels (a) and (b) are robust to the inclusion of the unconventional monetary policy surprise for the US from Jarociński (2024).

In a second investigation, displayed in panel (b), we add each of the first 20 estimated factors from our macro-financial dataset individually to the model as non-linear interaction terms. Each model contains only a single factor interaction. We report the RMSE expressed in differences relative to the RMSE of a linear model. We can see that the majority of the non-linear interaction terms do not improve the RMSE. The clear exception is the second factor, which reduces the RMSE by 0.3bp relative to the linear case. This suggests that the factor most closely associated with non-linear transmission of monetary policy is the monetary/financial cycle factor. This factor can be interpreted as a mixture of the debt cycle and interest rate cycle states examined in Alpanda et al. (2021), and our results therefore emphasise the relative importance of these channels. We also document that factors 16, 17, and 18 reduce the RMSE, however each of these factors explains a very low fraction of the variance of our dataset, so we do not focus on the effects of these.

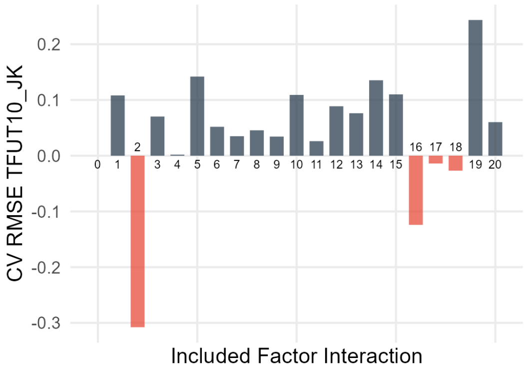
As discussed previously, the second factor is closely related to an interest rate cycle. It is also notable from the RMSE results that the data do not suggest a strong non-linear relationship

Figure 3: Non-Linear Model Selection Criteria—Treasury Future 10-Year Rate

(a) Nested Non-Linear Models



(b) Individual Non-Linear Models



Notes: Figure shows the average root mean squared error (RMSE) out-of-sample from OLS estimation of our non-linear model, computed according to 10-fold cross validation (repeated 10 times). The dependent variable is the Treasury Futures 10 Year rate, and the monetary policy surprise comes from Jarociński and Karadi (2020). The x-axis represents different models. In panel (a) the non-linear models are nested, with the label representing the number of non-linear terms. The *n*th non-linear interaction is the *n*th factor from our macro-financial dataset. The dashed line represents the RMSE from the baseline linear case. In panel (b) the models are not nested, and a different non-linear interaction is included in each case. In this panel RMSE is expressed having subtracted the RMSE of the baseline linear case.

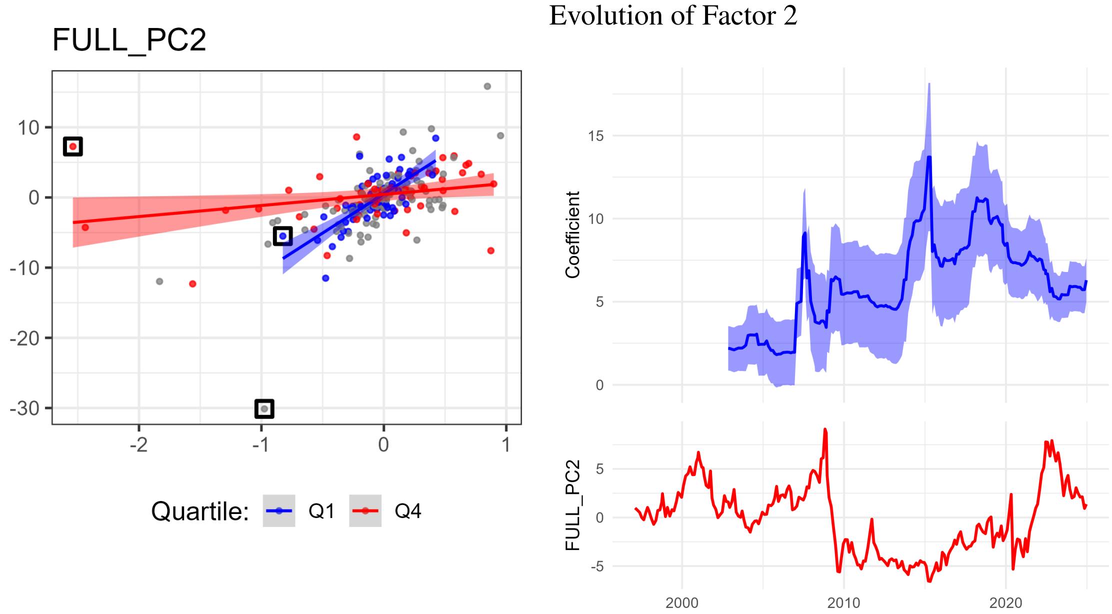
related to the business cycle factor (the first principal component). This is surprising, given the emphasis placed on the business cycle in earlier work (Tenreyro and Thwaites, 2016; Alpanda et al., 2021; Bauer et al., 2024). These results instead point to the dominant role of the interest rate cycle, relative to the business cycle, for explaining the non-linear response of long-rates.

In Figure 4 we examine more closely the non-linear transmission mechanism relating to the financial/monetary cycle factor. In panel (a) we plot the scatter relationship between changes in the 10 Year Treasury futures rate, and the monetary policy shock from Jarociński and Karadi (2020). We also highlight the upper and lower quartiles of the distribution of the monetary cycle factor in red and blue, respectively. This provides a simple representation of the non-linear relation we document. The figure demonstrates that the transmission mechanism weakens when the monetary cycle factor is high (i.e., when credit, inflation, or the Federal Funds Rate is high). We also highlight the three most influential observations for a full sample regression. This establishes that the non-linear relationship does not appear to be driven by outliers, since the most influential observations do not congregate in either the high- or low-state for the second factor.

In Figure 4 panel (b) we document variation in the strength of transmission over time, by

Figure 4: The Role of the Monetary Cycle Factor—Treasury Futures 10Y Rate

(a) Scatter and Non-Linear State (in Factor 2) (b) Rolling Regression Estimates and the Evolution of Factor 2



Notes: Panel (a) shows a scatter plot, with the change in the Treasury Future 10 Year rate on the y-axis, and the change in the Jarociński and Karadi (2020) shock on the x-axis. Observations when the second factor is in its highest quartile are shown in red. Observations when the second factor is in its lowest quartile are shown in blue. Separate regression lines are plotted according to whether the second factor is in the highest or lowest quartile. Also highlighted are the three most influential observations in the full sample regression by DFBETA. Panel (b) shows the time-series evolution of the coefficient estimated from a rolling bivariate regression between the US 10-year rate and the JK shock. The rolling window is set to equal 50 observations. The time-series evolution of the second factor is displayed for reference. Confidence bands are displayed at 95%.

running a simple rolling regression of the 10 year Treasury futures rate on the monetary policy surprise. We notice from this figure that the relation strengthens over our sample period, before moderating somewhat in the wake of the Covid-19 pandemic. We can observe that the rolling coefficient estimates are at their lowest when the monetary cycle factor was high, prior to the Global Financial Crisis. The sharp fall in the financial/monetary cycle factor in the wake of the crisis, and during the ELB period, occurs during the period for which the relation between the Jarociński and Karadi (2020) surprise and long-rates is stronger. These shifts can explain why we found the second factor useful for explaining periods of stronger and weaker transmission in our RMSE exercises discussed above.

The previous investigations, based on model selection criteria, suggest there is an important non-linearity related to the monetary/financial cycle factor. In Table 4 we test statistically for non-linear transmission using our baseline model, estimated with 10 factors. Although our previous analysis indicated a five-factor model to be the largest model that improves relative to the linear case in terms of RMSE, the factors are orthogonal by construction, so coefficient estimates are stable as the number of factors increases.[8] We present two sets of estimates for each dependent variable. The first is over the full sample, with the second ending before 2020. Inference in Table 4 is based on the bootstrap algorithm from Gonçalves and Perron (2014), given the factors are generated regressors (see Appendix C).

Table 4: Non-Linear Event Study Regression—US

	Full Sample		Pre-Covid Sample	
Variables	TFUT10	S&P500	TFUT10	S&P500
Intercept	0.29***	−0.02***	0.20*	−0.03***
MPS	7.63***	−1.38***	7.10***	−1.46***
Interaction Effects				
Factor 1	−0.37*	0.00	−0.44**	−0.01
Factor 2	−0.82***	0.01	−0.81***	0.02
Factor 3	0.18	−0.02	−0.40	−0.04*
Factor 4	0.30	0.01	−0.44	−0.04**
Factor 5	−0.19	0.02	0.21	0.03
Factor 6	0.37	0.02	0.50	0.11**
Factor 7	0.14	0.00	0.04	0.02
Factor 8	0.20	−0.02	0.19	0.02
Factor 9	−0.04	0.06	−0.32	0.02
Factor 10	−0.06	0.01	−0.06	0.00
Main Effects	N	N	N	N
Adj. R2	0.53	0.87	0.58	0.88
N	233	233	192	192

Notes: Event study regressions of the changes in 10 Year Treasury Future and the S&P500 index on the monetary policy surprise from Jarociński and Karadi (2020), interacted with 10 factors from our dataset. Statistical significance is denoted by *p<0.1; **p<0.05; ***p<0.01, based on percentiles of the distribution generated by bootstrap algorithm from Gonçalves and Perron (2014), with 5,000 repetitions.

Table 5: Magnitude of Non-Linearities—US

	Direct Effect	State Dependence	Low	High
TFUT10	7.63	Business Cycle	9.70	5.56
		Monetary/Financial Cycle	10.56	4.71

Notes: Direct effect and interaction effects from the full sample event study regression of 10 Year Treasury Future in Table 4. "Low" and "High" represent one standard deviation below and above the mean of the associated factor. The values are in basis points and are relative to a shock that raises ED1 by 10 basis points.

[8] The extrapolation step to cover the Covid-19 period does introduce a small amount of correlation in our factors when the full sample is considered, as discussed above.

The coefficients in Table 4 show that the average transmission of a 10 basis point monetary policy shock to the 10 Year Treasury futures rate is 7.6 basis points. Only the coefficients on the first two factors are statistically significant, and both are negative. This suggests that non-linear transmission is largely counter-cyclical in the US, with transmission stronger when growth is lower and interest rates/leverage are lower. The finding of stronger transmission in a lower growth period is consistent with the findings of Bauer et al. (2024). Weaker transmission in periods of high interest rates/high debt aligns with results from Alpanda et al. (2021), though interest rates and debt were separately studied in that paper whereas they are combined in a single factor in our study. Table 4 also shows that these findings are robust to using the shorter sample. On the other hand, evidence for non-linear transmission to equities appears only in the Pre-Covid sample and not in the full sample. In results available upon request, we have found that non-linear models for transmission to equities do not improve the RMSE relative to the baseline linear case. We therefore conclude that transmission to equities is broadly linear in the US.

In Table 5, we summarise the magnitudes of the non-linear effects by comparing state-independent transmission with transmission when at ± 1 standard deviation of the business cycle and monetary/financial cycle factors. Transmission of the 10 basis point shock drops to 4.7 basis points when the monetary/financial cycle is one standard deviation above its mean—a sizeable 38% reduction. The effect of the business cycle is somewhat smaller, with a 27% reduction when the factor is one standard deviation above the mean.

One channel for which we do not find strong evidence relates to uncertainty, a channel emphasised in De Pooter et al. (2021). Our dataset includes both measures of financial uncertainty, such as the VIX, and uncertainty shocks from the literature, such as from Davis (2016) and Bauer et al. (2022). We cannot exclude the possibility that uncertainty plays a role in the non-linear transmission mechanism, since the first two factors also correlate with uncertainty variables. However, to the extent they play a role, these uncertainty effects may be summarised linearly by factor(s) more closely related to the financial and interest rate cycles. Our results therefore suggest that future research would benefit from focusing on the relationship between transmission and the interest rate cycle rather than uncertainty mechanisms *per se*.

In summary, despite allowing for up to 10 distinct channels of non-linear transmission, we only find evidence for the role of two: the business cycle and monetary/financial cycle factors. Taken in conjunction with Figure 3, showing that the business cycle factor lacked robustness in the out-of-sample prediction exercises, the stronger evidence is for the monetary/financial cycle as the main source of non-linearity in US transmission. In Appendix Table 9, we show that the inclusion of a QE surprise control does not materially change the results.

6.2 Non-linear Transmission in the Euro Area

Having established the dominant sources of non-linear transmission for the case of the US, we now take a comparative approach, and study transmission in the euro area. Figure 5 shows the results of our RMSE exercise to compare non-linear models with the linear benchmark, now applied to European data. Panel (a) represents the German 10 Year Bund yield. In panel (b) we study the spread between the yields on 10 year sovereign bonds for Italy relative to Germany. In the former case, there is evidence for a number of non-linearities, while in the latter case, the only important non-linearity relates to the third factor, the sovereign risk/uncertainty factor. Figure 5 includes the QE surprise from Altavilla et al. (2019) as a control in both cases. In Appendix Figure 7, we show the same exercise omitting the QE control. For the German 10 year yield, model performance is noticeably worse even in the linear case, and is worse and more volatile across the range of included factor interactions. We conclude that in the euro area, controlling for QE is essential and we include this control in our baseline investigations.

In Table 6, we display the results from the high-dimensional non-linear approach outlined in equation 3 for the euro area. We estimate our regression using the response of 10 year yields in Germany and Italy, the Italian-German spread, and equities as dependent variables using the full sample.[9] Our estimates show that a 10 basis point monetary policy surprise, on average, increases German and Italian yields by 7.4 and 10.2 basis points, respectively. Italian spreads respond more than one to one (17.6 basis points) to the same magnitude of surprise conditional on the other factors. The monetary policy tightening surprise also reduces equities, as expected.

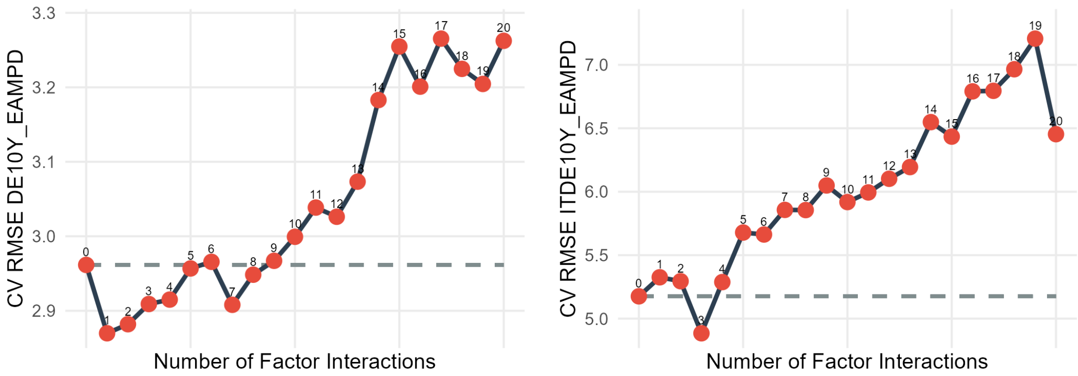
For German yields, we find that the only statistically significant interaction is with the mon-

[9]These estimates include the QE control on the baseline. We report estimates omitting the control in Appendix Table 10.

Figure 5: Non-Linear Model Selection Criteria—Euro Area

(a) Nested Non-Linear Models: German 10 Year

(b) Nested Non-Linear Models: Italian-German 10 Year Spread



Notes: Figure shows the average root mean squared error (RMSE) out-of-sample from OLS estimation of our non-linear model, computed according to 10-fold cross validation (repeated 10 times). In panel (a) the dependent variable is the German 10 Year yield, in panel (b) the dependent variable is the 10 year Italian-German yield spread. The independent variable is the Jarociński and Karadi (2020) monetary policy surprise. All specifications include the QE surprise of Altavilla et al. (2019) as a control variable. The x-axis represents different models. The non-linear models are nested, with the label representing the number of non-linear terms. The *n*th non-linear interaction is the *n*th factor from our macro-financial dataset. The dashed line represents the RMSE from the baseline linear case.

Table 6: Non-Linear Event Study Regression—Euro Area

Variables	DE10Y	IT10Y	ITDE10Y	STOXX50
Intercept	−0.27***	−0.78***	−0.52***	−0.03***
MPS	7.41***	17.58***	10.19***	−2.65***
QE control	0.90***	0.56*	−0.33	0.01
Interaction Effects				
Factor 1	0.46	−0.05	−0.49	0.05
Factor 2	0.55**	−0.07	−0.60**	0.17***
Factor 3	−0.21	2.08***	2.30***	−0.06
Factor 4	−0.33	−2.01	−1.68	0.07
Factor 5	0.51	1.24	0.73	0.03
Factor 6	0.97	0.26	−0.69	−0.05
Factor 7	0.93	0.84	−0.10	0.07
Factor 8	0.47	2.45	1.91	−0.10
Factor 9	−0.95	−0.48	0.50	0.11
Factor 10	−1.12	−1.81	−0.74	0.15
Main Effects	N	N	N	N
Adj. R2	0.51	0.58	0.50	0.75
N	211	211	211	211

Notes: Event study regressions of the changes in German 10 Year yield, Italian 10 Year yield, the spread between the Italian and German 10 Year yields, and the STOXX50 stock index on the monetary policy shock from Jarociński and Karadi (2020), interacted with 10 factors from our dataset. These regressions also include the QE surprise from Altavilla et al. (2019) as a control. Statistical significance is denoted by $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$, based on percentiles of the distribution generated by bootstrap algorithm from Gonçalves and Perron (2014), with 5,000 repetitions.

etary cycle factor. The positive sign aligns with the results in Table 3, and is the opposite sign to the equivalent high-dimensional result for the US. We demonstrated the overall counter-cyclicality of transmission in the US, relative to pro-cyclicality in the euro area, in Section 5. We again find that the positive and significant coefficient is not robust to the exclusion of the crisis period in the euro area, as shown in Appendix Table 11. This underscores how transmission of monetary policy to German yields appears to be affected in our sample by "flight-to-safety" dynamics affecting German government debt (Lane, 2013).

For Italian yields and spreads, we find that the sovereign risk and uncertainty factor is the most important driver of state-dependent transmission. The positive coefficient indicates that higher sovereign risk/economic uncertainty amplifies the transmission of a tightening shock. In Appendix Table 11 we show that non-linear transmission to spreads due to this factor is robust to omission of the crisis period for the euro area, contrary to our findings for the monetary factor and German yields. Table 7 shows that the magnitude of the non-linear effect in sovereign spreads is large. When the sovereign risk factor is one standard deviation above its mean, transmission of a 10 basis point monetary policy shock to the Italian-German spread is 18.1 basis points, a 78% increase relative to the effect at the mean. Fanelli and Marsi (2022) identify a separate channel of transmission related to sovereign spread shocks. Our work complements this by showing sovereign spreads to be a form of state-dependence in transmission of conventional monetary policy shocks.

Table 7: Magnitude of Non-Linearities—Euro Area

	Direct Effect	State Dependence	Low	High
DE10Y	7.41	Monetary Cycle	4.92	9.90
IT10Y	17.58	Sovereign Risk	10.38	24.77
ITDE10Y	10.19	Monetary Cycle	12.89	7.49
		Sovereign Risk	2.25	18.13
STOXX50	−2.65	Monetary Cycle	−3.39	−1.90

Notes: Direct effect and interaction effects from the full sample event study regressions in Table 6. "Low" and "High" represent one standard deviation below and above the means of the associated factor. The values are in basis points and are relative to a shock that raises the 3 Month Overnight Index Swap rate by 10 basis points.

The coefficient on the monetary cycle factor interaction in the spreads regression is negative and significant, the opposite to the effect on German yields. This is in keeping with the findings of Lengyel and Giuliodori (2022) in which "flight-to-safety" effects that increase demand for German debt compress German yields and increase the Italian-German spread. This interaction is also not robust to omitting the crisis period (Table 11), highlighting the special and dominant dynamics of the 2009-13 period.

For equities, we find that the monetary cycle factor dampens transmission. Further, the magnitude of the effect is large, with a 28% reduction when the monetary cycle factor is high, as shown in Table 7. This result is in keeping with Eichenbaum et al. (2025), who find transmission to equities is dampened in a high interest rate environment. However, Table 11 shows that the monetary factor effect is not robust to omission of the crisis period, as was the case with the German 10 Year yield.

Overall, the euro area sample is affected by its relatively shorter length, and by the prolonged period of crisis that it contains. Certain of the drivers of non-linear transmission we uncover appear to have effects that are confined to specifications that include the crisis sub-period. Nonetheless, we find strong evidence for state-dependent transmission to the spread between the yields on Italian and German long-term government debt, and to euro area equities.

7 Conclusion

The extent to which monetary policy transmission is non-linear is a key question for monetary policymakers. If important non-linear channels are active, policymakers cannot take for granted that the same actions would give the same outcomes in all states of the world.

To date, the literature has mostly addressed the question of non-linear transmission through *low-dimensional* approaches. We argue that these approaches suffer from important drawbacks: the chosen state variable may be correlated with other potential drivers of non-linearity, the state variable may not be chosen in a systematic manner, and the estimates may suffer from omitted variable bias. Low-dimensional approaches make it difficult to establish the economic importance of any channel of non-linearity relative to others that may matter.

This paper contributes by taking a *high-dimensional* approach. Using large, mixed-frequency datasets for the US and euro area that are designed to incorporate many sources of non-linearity highlighted in the literature, we systematically evaluate which channels of non-linear transmission to asset prices matter. We show strong evidence for the superiority of non-linear models over a linear approach, and for models incorporating multiple sources of non-linearity over the *low-dimensional* approach common in the literature. Nonetheless, the number of active channels of non-linearity remains tractable—we find two sources of non-linearity in the US. Extension to a systematic study of non-linearity thus does not come at the expense of interpretability.

The strongest evidence in the US is for a monetary/financial factor driving non-linear transmission, with counter-cyclical effects. These effects are also economically significant with a 38% difference in the transmission of a 10 basis point monetary policy tightening shock for a one standard deviation change in the monetary/financial factor. For policymakers, this result has a clear message. As the monetary/financial factor increases, in other words as the central bank progresses through an interest rate hiking cycle, we should expect the transmission of further monetary policy tightening shocks to diminish.

In the case of the euro area, our investigations are hampered by the presence of financial crisis and sovereign debt crisis periods. Nonetheless, we find strong evidence for non-linear transmission, especially with respect to sovereign risk and economic uncertainty. Promising avenues for future research include examining how state-dependence interacts with other forms of non-linearity such as sign-dependence of the monetary policy surprise, and examining the dynamic transmission of monetary policy to macroeconomic variables in high-dimensional specifications.

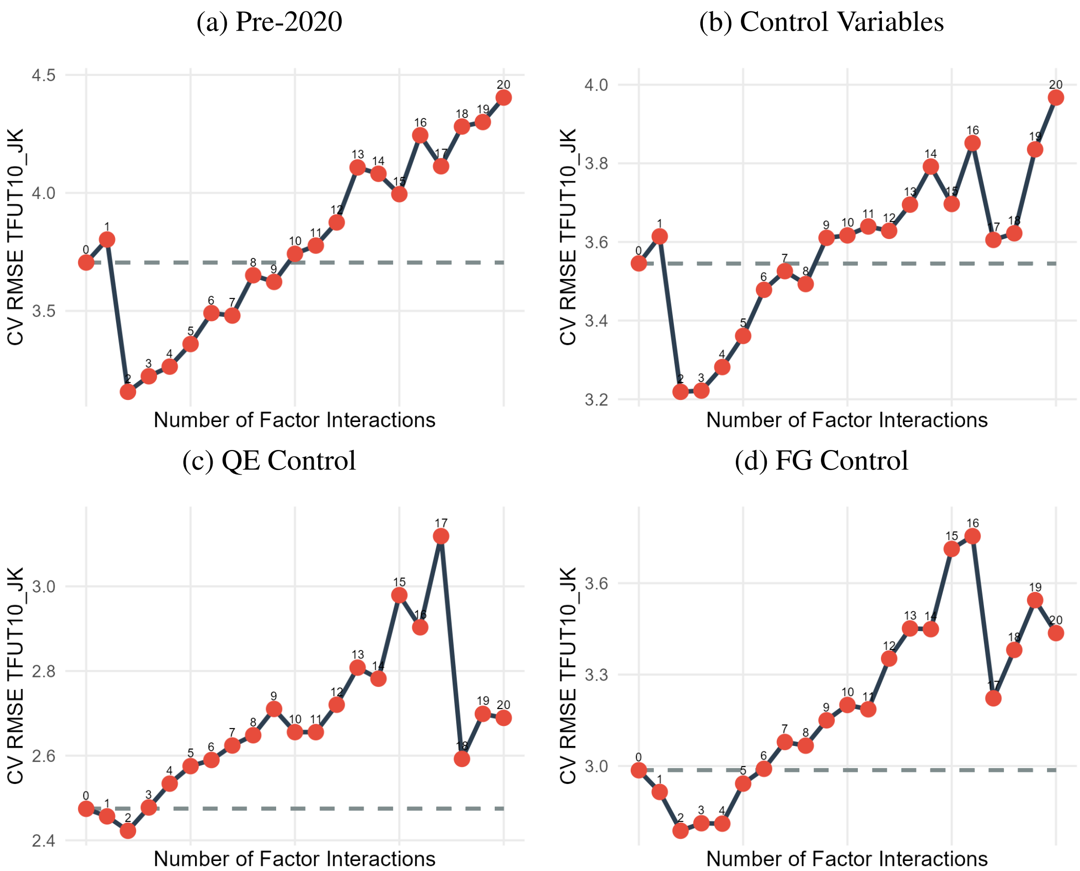
A Extended Literature Review

Table 8: Review of Non-linear Monetary Policy Transmission in the Literature

State Variable(s)	Key References	Main Findings
Zero Lower Bound	Krugman et al. (1998); Kiley and Roberts (2017); Sims and Wu (2021); Swanson (2018); Debortoli et al. (2019)	Some studies find transmission to be weaker at the ZLB (Krugman et al., 1998). Others find little evidence for non-linear transmission (Swanson, 2018).
Business Cycle	Tenreyro and Thwaites (2016); Mumtaz and Surico (2015); Jordà et al. (2020); Alpanda et al. (2021); Bauer et al. (2024)	Transmission to real variables may be stronger in expansions (e.g., Tenreyro and Thwaites (2016)). Transmission to financial variables may be stronger in a weak economy (Bauer et al., 2024).
Financial Cycle; Leverage; Financial Conditions; Stress	Rünstler and Bräuer (2020); Jordà et al. (2020); Alpanda et al. (2021); Bernanke et al. (1999); Kashyap and Stein (2000); Kishan and Opiela (2000); Li (2022)	Transmission may be less effective when there is high household leverage (Jordà et al., 2020), or more effective (Alpanda et al., 2021). The leverage and liquidity of financial intermediaries may also affect transmission. Transmission is weaker in times of financial stress (Saldías, 2017).
Uncertainty	Pellegrino (2021); De Pooter et al. (2021); Bauer et al. (2022); Tillmann (2020); Aastveit et al. (2017)	Weaker transmission when uncertainty is high.
Inflation	Jordà et al. (2020); Ascari and Haber (2022)	Real transmission may be weaker in low inflation environments, but price level transmission may be stronger when trend inflation is high.

B Robustness Checks and Additional Results

Figure 6: Individual Non-Linear Models for the US—10 Year Treasury Futures Rate—Robustness



Notes: Figure shows the average root mean squared error (RMSE) out-of-sample from OLS estimation of our non-linear model, computed according to (repeated) 10-fold cross validation. The x-axis represents different models. The non-linear models are nested, with the label representing the number of non-linear terms. The *n*th non-linear interaction is the *n*th factor from our macro-financial dataset. The dashed line represents the RMSE from the baseline linear case. Panel (a) restricts the sample to the pre-Covid period. Panel (b) includes the first 7 principal components as control variables (main effects) for all specifications. Panel (c) includes the Jarociński (2024) QE surprise as a control variable. Panel (d) adds the Odyssean forward guidance from the same paper as a control.

Table 9: The US Non-Linear Event Study Regression: Including QE Control

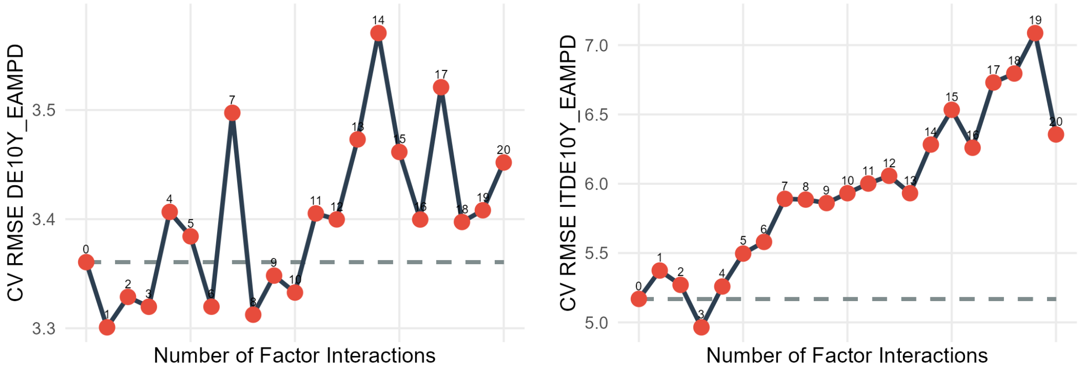
Variables	TFUT10	S&P500
Intercept	0.01	-0.01*
MPS	5.16***	-1.30***
QE Control	0.86***	-0.03***
Interaction Effects		
Factor 1	-0.01	-0.01
Factor 2	-0.44***	0.00
Factor 3	-0.02	-0.02
Factor 4	0.30	0.01
Factor 5	-0.06	0.02
Factor 6	0.43	0.02
Factor 7	-0.06	0.00
Factor 8	-0.03	-0.02
Factor 9	0.15	0.05
Factor 10	0.10	0.01
Main Effects	N	N
Adj. R2	0.73	0.87
N	233	233

Notes: Event study regressions of the changes in 10 Year Treasury Future and the S&P500 index on the monetary policy surprise from Jarociński and Karadi (2020), interacted with 10 factors from our dataset. These regressions also include the QE surprise from Jarociński (2024) as a control. Statistical significance is denoted by $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$, based on percentiles of the distribution generated by bootstrap algorithm from Gonçalves and Perron (2014), with 5,000 repetitions.

Figure 7: Non-Linear Model Selection Criteria—Euro Area—Excluding QE Control

(a) Nested Non-Linear Models: German 10 Year

(b) Nested Non-Linear Models: Italian-German 10 Year Spread



Notes: Figure shows the average root mean squared error (RMSE) out-of-sample from OLS estimation of our non-linear model, computed according to 10-fold cross validation (repeated 10 times). In panel (a) the dependent variable is the German 10 Year yield, in panel (b) the dependent variable is the 10 year Italian-German yield spread. The independent variable is the Jarociński and Karadi (2020) monetary policy surprise. The x-axis represents different models. The non-linear models are nested, with the label representing the number of non-linear terms. The *n*th non-linear interaction is the *n*th factor from our macro-financial dataset. The dashed line represents the RMSE from the baseline linear case.

Table 10: The EA Non-Linear Event Study Regression: Excluding QE control

Variables	DE10Y	IT10Y	ITDE10Y	STOXX50
Intercept	-0.27***	-0.78***	-0.51***	-0.03***
MPS	8.17***	18.04***	9.93***	-2.64***
Interaction Effects				
Factor 1	0.46	-0.04	-0.50	0.05
Factor 2	0.38	-0.18	-0.53*	0.16***
Factor 3	-0.42	1.96***	2.37***	-0.06
Factor 4	-0.61	-2.20	-1.59	0.07
Factor 5	0.53	1.26	0.71	0.03
Factor 6	0.80	0.16	-0.61	-0.05
Factor 7	1.04	0.90	-0.17	0.08
Factor 8	-0.33	1.98	2.19	-0.11
Factor 9	-1.14	-0.59	0.57	0.11
Factor 10	-1.69	-2.11	-0.56	0.15
Main Effects	N	N	N	N
Adj. R2	0.33	0.55	0.49	0.75
N	211	211	211	211

Notes: Event study regressions of the changes in German 10 year yield, Italian 10 year yield, the spread between the Italian and German 10 year yields, and the STOXX50 stock index on the monetary policy shock from Jarociński and Karadi (2020), interacted with 10 factors from our dataset. Statistical significance is denoted by *p<0.1; **p<0.05; ***p<0.01, based on percentiles of the distribution generated by bootstrap algorithm from Gonçalves and Perron (2014), with 5,000 repetitions.

Table 11: The EA Non-Linear Event Study Regression: Excluding 2009-01 to 2013-06

Variables	DE10Y	IT10Y	ITDE10Y	STOXX50
Intercept	−0.47***	−0.91***	−0.44***	0.00
MPS	8.57***	16.59***	8.02***	−2.64***
QE control	0.87***	0.65**	−0.23	0.01
Interaction Effects				
Factor 1	−0.33	−0.46	−0.13	−0.08
Factor 2	−0.19	0.59	0.79	−0.15
Factor 3	0.43	3.73***	3.32***	−0.12**
Factor 4	0.63	−0.08	−0.72	0.11*
Factor 5	0.68	1.75	1.15	−0.01
Factor 6	0.55	0.2	−0.39	−0.06
Factor 7	0.25	1.01	0.74	0.00
Factor 8	0.16	−0.19	−0.31	−0.01
Factor 9	−0.02	0.31	0.30	−0.06
Factor 10	0.50	0.39	−0.04	−0.06
Main Effects	N	N	N	N
Adj. R2	0.62	0.60	0.61	0.85
N	157	157	157	157

Notes: Event study regressions of the changes in German 10 year yield, Italian 10 year yield, the spread between the Italian and German 10 year yields, and the STOXX50 stock index on the monetary policy shock from Jarociński and Karadi (2020), interacted with 10 factors from our dataset. These regressions also include the QE surprise from Altavilla et al. (2019) as a control. Statistical significance is denoted by *p<0.1; **p<0.05; ***p<0.01, based on percentiles of the distribution generated by bootstrap algorithm from Gonçalves and Perron (2014), with 5,000 repetitions.

C Bootstrap Algorithm

We apply the two-stage residual-based wild bootstrap of Gonçalves and Perron (2014).

Bootstrap Steps:

1. Estimate equations 3 and 4 by Ordinary Least Squares, to obtain the OLS coefficients, $(\hat{\lambda}, \hat{\alpha}, \hat{\beta}, \hat{\gamma})$, the estimated factors, $\{\hat{f}_{k,t}\}_{k=1}^{K}$, and the estimated error terms $\hat{e}_{it}$ and $\hat{\upsilon}_t$.

2. Re-sample $\hat{e}_{it}$ and $\hat{\upsilon}_t$ using the wild bootstrap to create the error terms e^*_{it} and υ^*_t:

$$e^*_{it} = \hat{e}_{it}\zeta_{it}$$

$$\upsilon^*_t = \hat{\upsilon}_t\xi_t$$

   where ζ_{it} and ξ_t are both independently and identically distributed random variables with zero mean and unit variance.

3. Generate the bootstrap samples z^*_{it} and y^*_t by using e^*_{it}, υ^*_t, and fitted values derived from

the estimated OLS coefficients ($\hat{\lambda}$, $\hat{\alpha}$, $\hat{\beta}$, $\hat{\gamma}$), the estimated factors $\{\hat{f}_{k,t}\}_{k=1}^{K}$ and the fixed regressor MPS_t.

$$z_{it}^{*} = \sum_{k=1}^{K} \hat{\lambda}_{i,k}\hat{f}_{k,t} + e_{it}^{*}, \tag{5}$$

$$y_t^{*} = \hat{\alpha} + \hat{\beta}MPS_t + \sum_{k=1}^{K} \hat{\gamma}_k MPS_t \times \hat{f}_{k,t} + \upsilon_t^{*}, \tag{6}$$

for $\forall i \in \{1,\ldots,N\}$, $\forall t \in \{1,\ldots,T\}$.

4. Estimate the bootstrap factors $\{\hat{f}_{k,t}^{*}\}_{k=1}^{K}$ using the generated sample z_{it}^{*},

$$z_{it}^{*} = \sum_{k=1}^{K} \hat{\lambda}_{i,k}^{*}\hat{f}_{k,t}^{*} + \hat{e}_{it}^{*}. \tag{7}$$

5. Estimate the bootstrapped OLS coefficients ($\hat{\alpha}^{*}$, $\hat{\beta}^{*}$, $\hat{\gamma}^{*}$) by regressing y_t^{*} on the fixed regressor MPS_t and its interactions with the bootstrap factors $\{\hat{f}_{k,t}^{*}\}_{k=1}^{K}$.

6. Repeat steps 2 to 5 by $B = 5,000$ times.

D Factor Dataset

Table 12: Event Study Data Summary Statistics

Variable	Mean	SD	Min	Max
United States				
TFUT10 *(bp.)*	-0.16	4.05	-30.13	15.84
SP500 *(pp.)*	0.04	0.63	-1.77	4.51
Euro Area				
DE 10Y *(bp.)*	-0.10	3.68	-14.65	16.25
IT 10Y *(bp.)*	-0.08	7.14	-23.70	45.60
IT SPRD. 10Y *(bp.)*	0.02	6.07	-22.90	45.80
STOXX50 *(pp.)*	-0.10	0.71	-3.98	2.01

Notes: Table shows summary statistics from the event study data. US data are sourced from the updated dataset of Jarociński and Karadi (2020). Our sample extends from 5th February 1997 to 18th December 2024 and comprises 233 observations. EA data are sourced from the EA-MPD of Altavilla et al. (2019). Our sample extends from 5th February 2004 to 12th December 2024 and comprises 211 observations.

Table 13: Summary Statistics Cumulative Variance Explained

Full Factors:	1	2	3	4	5	6	7	8	9	10
US	27.97	40.56	51.54	59.32	63.46	66.56	69.07	71.49	73.65	75.61
EA	30.09	50.87	61.50	69.01	74.35	77.87	80.29	82.36	84.13	85.61

Notes: Table shows the cumulative variance explained by each factor when Principal Component Analysis is applied to the full dataset.

Table 14: Group and Transformation Keys

Transformation		Groups	
TC†	Operation	GC†	Name
1	No transformation	1	Activity
2	First difference	2	Labour
3	Second difference	3	Money and Credit
4	Log	4	Interest Rates
5	Log difference	5	Yield Curve
6	Log second difference	6	Exchange Rates
7	Change in percentage growth	7	Prices
8	12 weeks change	8	Stock Market
9	3 months change	9	Uncertainty
10	90 days change	10	Financial Frictions
11	Second difference of six-month change	11	Financial Cycle
12	YoY change for monthly data		
13	YoY change for quarterly data		

Notes: † TC: transformation code, and GC: group code.

Table 15: The US Dataset Variable Definitions

	GC	Section	Dataset Name	Freq.	TC	Description
1	1	Activity	US_FREDMD_RPI[a]	M	12	Real Personal Income
2	1	Activity	US_FREDMD_W875RX1[a]	M	12	Real Personal Income ex transfer receipts
3	1	Activity	US_FREDMD_INDPRO[a]	M	12	IP Index
4	1	Activity	US_FREDMD_IPFPNSS[a]	M	12	IP: Final Products and Nonindustrial Supplies
5	1	Activity	US_FREDMD_IPFINAL[a]	M	12	IP: Final Products (Market Group)
6	1	Activity	US_FREDMD_IPCONGD[a]	M	12	IP: Consumer Goods
7	1	Activity	US_FREDMD_IPDCONGD[a]	M	12	IP: Durable Consumer Goods
8	1	Activity	US_FREDMD_IPNCONGD[a]	M	12	IP: Nondurable Consumer Goods
9	1	Activity	US_FREDMD_IPBUSEQ[a]	M	12	IP: Business Equipment
10	1	Activity	US_FREDMD_IPMAT[a]	M	12	IP: Materials
11	1	Activity	US_FREDMD_IPDMAT[a]	M	12	IP: Durable Materials
12	1	Activity	US_FREDMD_IPNMAT[a]	M	12	IP: Nondurable Materials
13	1	Activity	US_FREDMD_IPMANSICS[a]	M	12	IP: Manufacturing (SIC)
14	1	Activity	US_FREDMD_IPB51222S[a]	M	12	IP: Residential Utilities
15	1	Activity	US_FREDMD_IPFUELS[a]	M	12	IP: Fuels
16	1	Activity	US_FREDMD_CUMFNS[a]	M	12	Capacity Utilization: Manufacturing
17	1	Activity	US_FREDMD_DPCERA3M086SBEA[a]	M	5	Real personal consumption expenditures
18	1	Activity	US_FREDMD_CMRMTSPLx[a]	M	5	Real Manu. and Trade Industries Sales
19	1	Activity	US_FREDMD_RETAILx[a]	M	5	Retail and Food Services Sales
20	1	Activity	US_FREDMD_ACOGNO[a]	M	5	New Orders for Consumer Goods
21	1	Activity	US_FREDMD_AMDMNOx[a]	M	5	New Orders for Durable Goods
22	1	Activity	US_FREDMD_ANDENOx[a]	M	5	New Orders for Nondefense Capital Goods
23	1	Activity	US_FREDMD_AMDMUOx[a]	M	5	Unfilled Orders for Durable Goods
24	1	Activity	US_FREDMD_BUSINVx[a]	M	5	Total Business Inventories
25	1	Activity	US_FREDMD_ISRATIOx[a]	M	1	Total Business: Inventories to Sales Ratio

26	1	Activity	US_FREDMD_UMCSENTx[a]	M	1	Consumer Sentiment Index
27	2	Labour	US_FREDMD_HWI[a]	M	12	Help-Wanted Index for United States
28	2	Labour	US_FREDMD_HWIURATIO[a]	M	1	Ratio of Help Wanted/No. Unemployed
29	2	Labour	US_FREDMD_CLF16OV[a]	M	12	Civilian Labor Force
30	2	Labour	US_FREDMD_CE16OV[a]	M	12	Civilian Employment
31	2	Labour	US_FREDMD_UNRATE[a]	M	1	Civilian Unemployment Rate
32	2	Labour	US_FREDMD_UEMPMEAN[a]	M	12	Average Duration of Unemployment (Weeks)
33	2	Labour	US_FREDMD_UEMPLT5[a]	M	12	Civilians Unemployed - Less Than 5 Weeks
34	2	Labour	US_FREDMD_UEMP5TO14[a]	M	12	Civilians Unemployed for 5-14 Weeks
35	2	Labour	US_FREDMD_UEMP15OV[a]	M	12	Civilians Unemployed - 15 Weeks & Over
36	2	Labour	US_FREDMD_UEMP15T26[a]	M	12	Civilians Unemployed for 15-26 Weeks
37	2	Labour	US_FREDMD_UEMP27OV[a]	M	12	Civilians Unemployed for 27 Weeks and Over
38	2	Labour	US_FREDMD_CLAIMSx[a]	M	12	Initial Claims
39	2	Labour	US_FREDMD_PAYEMS[a]	M	12	All Employees: Total nonfarm
40	2	Labour	US_FREDMD_USGOOD[a]	M	12	All Employees: Goods-Producing Industries
41	2	Labour	US_FREDMD_CES1021000001[a]	M	12	All Employees: Mining and Logging: Mining
42	2	Labour	US_FREDMD_USCONS[a]	M	12	All Employees: Construction
43	2	Labour	US_FREDMD_MANEMP[a]	M	12	All Employees: Manufacturing
44	2	Labour	US_FREDMD_DMANEMP[a]	M	12	All Employees: Durable goods
45	2	Labour	US_FREDMD_NDMANEMP[a]	M	12	All Employees: Nondurable goods
46	2	Labour	US_FREDMD_SRVPRD[a]	M	12	All Employees: Service-Providing Industries
47	2	Labour	US_FREDMD_USTPU[a]	M	12	All Employees: Trade, Transportation & Utilities
48	2	Labour	US_FREDMD_USWTRADE[a]	M	12	All Employees: Wholesale Trade
49	2	Labour	US_FREDMD_USTRADE[a]	M	12	All Employees: Retail Trade
50	2	Labour	US_FREDMD_USFIRE[a]	M	12	All Employees: Financial Activities
51	2	Labour	US_FREDMD_USGOVT[a]	M	12	All Employees: Government
52	2	Labour	US_FREDMD_CES0600000007[a]	M	1	Avg Weekly Hours : Goods-Producing
53	2	Labour	US_FREDMD_AWOTMAN[a]	M	12	Avg Weekly Overtime Hours : Manufacturing

54	2	Labour	US_FREDMD_AWHMAN[a]	M	1	Avg Weekly Hours : Manufacturing
55	2	Labour	US_FREDMD_CES0600000008[a]	M	12	Avg Hourly Earnings : Goods-Producing
56	2	Labour	US_FREDMD_CES2000000008[a]	M	12	Avg Hourly Earnings : Construction
57	2	Labour	US_FREDMD_CES3000000008[a]	M	12	Avg Hourly Earnings : Manufacturing
58	3	Money and Credit	US_FREDMD_M1SL[b]	W	10	M1 Money Stock
59	3	Money and Credit	US_FREDMD_M2SL[b]	W	10	M2 Money Stock
60	3	Money and Credit	US_FREDMD_M2REAL[a]	M	5	Real M2 Money Stock
61	3	Money and Credit	US_FREDMD_BOGMBASE[a]	M	6	Monetary Base
62	3	Money and Credit	US_FREDMD_TOTRESNS[a]	M	6	Total Reserves of Depository Institutions
63	3	Money and Credit	US_FREDMD_NONBORRES[a]	M	6	Reserves Of Depository Institutions
64	3	Money and Credit	US_FREDMD_BUSLOANS[b]	W	10	Commercial and Industrial Loans
65	3	Money and Credit	US_FREDMD_REALLN[a]	M	6	Real Estate Loans at All Commercial Banks
66	3	Money and Credit	US_FREDMD_NONREVSL[a]	M	6	Total Nonrevolving Credit
67	3	Money and Credit	US_FREDMD_CONSPI[a]	M	2	Nonrevolving consumer credit to Personal Income
68	3	Money and Credit	US_FREDMD_DTCOLNVHFNM[a]	M	6	Consumer Motor Vehicle Loans Outstanding
69	3	Money and Credit	US_FREDMD_DTCTHFNM[a]	M	6	Total Consumer Loans and Leases Outstanding
70	3	Money and Credit	US_FREDMD_INVEST[b]	W	10	Securities in Bank Credit at All Commercial Banks
71	4	Interest Rates	US_FREDMD_FEDFUNDS[b]	D	1	DFF: Federal Funds Effective Rate
72	4	Interest Rates	US_FREDMD_TB3MS[b]	D	1	DTB3: 3-Month Treasury Bill Secondary Market Rate
73	4	Interest Rates	US_FREDMD_TB6MS[b]	D	1	DTB6: 6-Month Treasury Bill Secondary Market Rate
74	4	Interest Rates	US_FREDMD_GS1[b]	D	1	DGS1: Market Yield on Treasury Securities at 1Y Constant Maturity
75	5	Yield Curve	US_FREDMD_T5YFFM[b]	D	1	T5YFF: 5Y Treasury Constant Maturity Minus Federal Funds Rate
76	5	Yield Curve	US_FREDMD_T10YFFM[b]	D	1	T10YFF: 10Y Treasury Constant Maturity Minus Federal Funds Rate
77	6	Exchange Rates	US_FREDMD_EXSZUSx[b]	D	10	DEXSZUS: Swiss Francs to U.S. Dollar Spot Exchange Rate
78	6	Exchange Rates	US_FREDMD_EXJPUSx[b]	D	10	DEXJPUS: Japanese Yen to U.S. Dollar Spot Exchange Rate
79	6	Exchange Rates	US_FREDMD_EXUSUKx[b]	D	10	DEXUSUK: U.S. Dollars to U.K. Pound Sterling Spot Exchange Rate
80	6	Exchange Rates	US_FREDMD_EXCAUSx[b]	D	10	DEXCAUS: Canadian Dollars to U.S. Dollar Spot Exchange Rate
81	6	Exchange Rates	US_FREDMD_TWEXAFEGSMTHx[b]	M	9	Trade Weighted U.S. Dollar Index

82	7	Prices	US_FREDMD_WPSFD49207[a]	M	12	PPI: Finished Goods
83	7	Prices	US_FREDMD_WPSFD49502[a]	M	12	PPI: Finished Consumer Goods
84	7	Prices	US_FREDMD_WPSID61[a]	M	12	PPI: Intermediate Materials
85	7	Prices	US_FREDMD_WPSID62[a]	M	12	PPI: Crude Materials
86	7	Prices	US_FREDMD_OILPRICEx[a]	M	12	Crude Oil, spliced WTI and Cushing
87	7	Prices	US_FREDMD_PPICMM[a]	M	12	PPI: Metals and metal products
88	7	Prices	US_FREDMD_CPIAUCSL[a]	M	12	CPI : All Items
89	7	Prices	US_FREDMD_CPIAPPSL[a]	M	12	CPI : Apparel
90	7	Prices	US_FREDMD_CPITRNSL[a]	M	12	CPI : Transportation
91	7	Prices	US_FREDMD_CPIMEDSL[a]	M	12	CPI : Medical Care
92	7	Prices	US_FREDMD_CUSR0000SAC[a]	M	12	CPI : Commodities
93	7	Prices	US_FREDMD_CUSR0000SAD[a]	M	12	CPI : Durables
94	7	Prices	US_FREDMD_CUSR0000SAS[a]	M	12	CPI : Services
95	7	Prices	US_FREDMD_CPIULFSL[a]	M	12	CPI : All Items Less Food
96	7	Prices	US_FREDMD_CUSR0000SA0L2[a]	M	12	CPI : All items less shelter
97	7	Prices	US_FREDMD_CUSR0000SA0L5[a]	M	12	CPI : All items less medical care
98	7	Prices	US_FREDMD_PCEPI[a]	M	12	Personal Cons. Expend.: Chain Index
99	7	Prices	US_FREDMD_DDURRG3M086SBEA[a]	M	12	Personal Cons. Exp: Durable goods
100	7	Prices	US_FREDMD_DNDGRG3M086SBEA[a]	M	12	Personal Cons. Exp: Nondurable goods
101	7	Prices	US_FREDMD_DSERRG3M086SBEA[a]	M	12	Personal Cons. Exp: Services
102	8	Stock market	US_SPX_SX[f]	D	10	S&P 500 Index Composite
103	8	Stock market	US_SPX_SX_INDU[f]	D	10	S&P 500 Index Industrials
104	8	Stock market	US_FREDMD_S.P.div.yield[a]	M	5	S&P 500 Index Dividend Yield
105	8	Stock market	US_FREDMD_S.P.PE.ratio[a]	M	5	S&P 500 Index Price Earnings Ratio
106	9	Uncertainty	US_FREDMD_VIXCLSx[b]	D	1	VIXCLS: CBOE Volatility Index: VIX
107	9	Uncertainty	US_EPU[c]	D	1	Economic Policy Uncertainty
108	9	Uncertainty	US_MOVE3M_IX[f]	D	1	BofA ML MOVE Index Treasury Volatility
109	9	Uncertainty	WW_JPM_FX_VOL[f]	D	1	JP Morgan Global FX Volatility Index

110	9	Uncertainty	US_EPU_CAT_MPOL[c]	M	1	Monetary Policy Uncertainty
111	9	Uncertainty	WW_EPU_ADJPPPGDP[e]	M	1	Global Economic Policy Uncertainty
112	9	Uncertainty	US_EMVOLTK_MACRO[c]	M	1	Equity Market Vol. Tracker: Macro News/Outlook
113	9	Uncertainty	US_EMVOLTK_FINCRIS[c]	M	1	Equity Market Vol. Tracker: Financial crises
114	9	Uncertainty	US_EMVOLTK_FISCAL[c]	M	1	Equity Market Vol. Tracker: Fiscal Policy
115	9	Uncertainty	US_EMVOLTK_MPOL[c]	M	1	Equity Market Vol. Tracker: Monetary policy
116	10	Financial Frictions	US_EBP_FGLZ[d]	M	1	Excess Bond Premium
117	10	Financial Frictions	US_CISS[g]	D	1	United States, Systemic Stress Composite Indicator.
118	10	Financial Frictions	US_FINSTRESS_STLF[b]	W	1	St. Louis Fed Financial Stress Index.
119	10	Financial Frictions	US_FINSTRESS_KCF[b]	M	1	Kansas City Financial Stress Index
120	10	Financial Frictions	US_FREDMD_AAAFFM[b]	D	1	AAAFF: Moody's Seasoned Aaa Corp. Bond Minus Fed Funds Rate
121	10	Financial Frictions	US_FREDMD_BAAFFM[b]	D	1	BAAFF: Moody's Seasoned Baa Corp. Bond Minus Fed Funds Rate
122	10	Financial Frictions	US_FREDMD_COMPAPFFx[b]	D	1	CPFF: 3-Month Commercial Paper Minus Fed Funds Rate
123	11	Financial Cycle	US_LEVERAGE_BSS[b]	Q	1	Bruno and Shin (2015) Leverage of Security Brokers and Dealers
124	11	Financial Cycle	US_CREDIT_GAP_BIS[h]	Q	1	Credit to GDP Gap
125	11	Financial Cycle	US_RES_PRICE_GAP[b]	Q	1	Residential Price Gap[10]
126	11	Financial Cycle	US_CRDTTIGHT_LRG2LRG[b]	Q	1	Net (%) of Large Dom. Banks Tight. Stds. for Large&Middle Firms
127	11	Financial Cycle	US_CREDTTIGHT_LRG2SML[b]	Q	1	Net (%) of Large Dom. Banks Tight. Stds. for Small Firms
128	11	Financial Cycle	US_FREDMD_HOUST[a]	M	4	Housing Starts: Total New Privately Owned
129	11	Financial Cycle	US_FREDMD_PERMIT[a]	M	4	New Private Housing Permits (SAAR)

Notes: a: FRED_MD; b: FRED ; c: Baker et al. (2019); d: Gilchrist et al. (2016); e: Davis (2016); f: Bloomberg; g: ECB; h: BIS.

[10] We construct a residential price gap estimate for the US based on the Residential Property Prices (QUSN628BIS) from FRED using the Hodrick-Prescott filter with $\lambda = 1600$.

Table 16: The EA Dataset Variable Definitions

	GC	Section	Dataset Name	Freq.	TC	Description
1	1	Activity	EA_COMNO	M	1	HCOB PMI: Composite - New Orders SA
2	1	Activity	EA_COMO	M	1	HCOB PMI: Composite - Output SA
3	1	Activity	EA_CONF_INFL_OECD[b]	M	1	Consumer Opinion Surveys: Inflation Future Tendency
4	1	Activity	EA_EMPMIMNOQ	M	1	HCOB PMI: Manufacturing - New Orders SA
5	1	Activity	EA_IP_CAP[a]	M	5	Industrial Production Index, MIG Capital Goods[†]
6	1	Activity	EA_IP_CONSTCT[a]	M	5	Industrial Production Index, Construction[†]
7	1	Activity	EA_IP_CSMPTN[a]	M	5	Industrial Production Index, Consumer Goods[†]
8	1	Activity	EA_IP_DUR[a]	M	5	Industrial Production Index, MIG Durable Consumer Goods[†]
9	1	Activity	EA_IP_INDU[a]	M	5	Industrial Production Index, Total Industry[†]
10	1	Activity	EA_IP_NDUR[a]	M	5	Industrial Production Index, MIG Non-durable Consumer Goods[†]
11	1	Activity	EA_IP_NRGY[a]	M	5	Industrial Production Index, MIG Energy[†]
12	1	Activity	EA_MFG	M	1	HCOB PMI: Manufacturing SA
13	1	Activity	EA_NVHC_CAR[a]	M	5	Car registration, New passenger car[†]
14	1	Activity	EA_SERBA_2	M	1	HCOB PMI: Services - Business Activity SA
15	1	Activity	EA_SERNB	M	1	EM HCOB PMI: Services - New Business SA
16	1	Activity	EA_TOVT_CAP[a]	M	5	Total Turnover Index, MIG Capital Goods[†]
17	1	Activity	EA_TOVT_CDUR[a]	M	5	Total Turnover Index, MIG Durable Consumer Goods[†]
18	1	Activity	EA_TOVT_CSMP[a]	M	5	Total Turnover Index, Consumer Goods[†]
19	1	Activity	EA_TOVT_INTMED[a]	M	5	Total Turnover Index, MIG Intermediate Goods[†]
20	1	Activity	EA_TOVT_MANU[a]	M	5	Total Turnover Index, Manufacturing[†]
21	1	Activity	EA_TOVT_NRGY[a]	M	5	Total Turnover Index, MIG Energy (exc. NACE Rev.2 Sect. D-E)[†]
22	1	Activity	EA_TOVV_RET_FD[a]	M	5	Total Turnover Index, Retail Sale of Food, Beverages and Tobacco[†]
23	1	Activity	EA_TOVV_RET_NFD[a]	M	5	Total Turnover Index, Retail Sale of Non-food Products (exc. fuel)[†]
24	1	Activity	EA_TOVV_RET_XF[a]	M	5	Total Turnover Index, Retail Trade (exc. fuel)[†⋆]
25	1	Activity	EO_PMUISA[c]	M	1	S&P Global Capacity Utilisation Index
26	1	Activity	EZ_COCSA[c]	M	1	Consumer Confidence Indicator

27	1	Activity	EZ_COISA[c]	M	1	Industrial Confidence Indicator
28	1	Activity	EZ_CORSA[c]	M	1	Retail Survey: Confidence
29	1	Activity	EZ_COSSA[c]	M	1	Services Confidence Indicator
30	1	Activity	EZ_PCRSA[c]	Q	5	Household & NPISH Final Consumption Expenditure
31	2	Labour	EA_UNEMP[a]	M	1	Unemployment Rate, Total: Age 15 to 74[†]
32	2	Labour	EA_HOURS[a]	Q	5	Hours Worked, All Activities, Total Employment[†]
33	2	Labour	EA_HOURS_INDU[a]	Q	5	Hours Worked, Industry (exc. construction), Total Employment[†]
34	2	Labour	EA_HOURS_SERV[a]	Q	5	Hours Worked, Services, Total Employment[†]
35	2	Labour	EA_LABCOST[a]	Q	5	Labour Cost Index, Total Labour Costs[†]
36	2	Labour	EA_LABCOST_WAG[a]	Q	5	Labour Cost Index, Wages and Salaries[†]
37	2	Labour	EA_NEG_WAGES[a]	Q	1	Indicator of Negotiated Wage Rates[†]
38	2	Labour	EZ_CPESA[c]	Q	5	Compensations per Employee
39	2	Labour	EZ_EMCP[c]	Q	5	Total Employment: Construction (voln)
40	2	Labour	EZ_EMMP[c]	Q	5	Total Employment: Manufacturing (voln)
41	2	Labour	EZ_EMPAP[c]	Q	5	Total Employment: Pub Adm., Def., Edu., Health, Sowk (voln)
42	2	Labour	EZ_EMPP[c]	Q	5	Total Employment: PS&T Act., Admins. & Sprt Svc Act. (pers)
43	2	Labour	EZ_EMTRP[c]	Q	5	Total Employment: WS&RT, Transp., ACC&FS Act. (pers)
44	2	Labour	EZ_LNNSA[c]	Q	5	Total Employment: Domestic Concept? (vol)
45	3	Money and Credit	EA_LNS_HHLD[a]	M	5	MFI Loans to HH & NPISH (Stocks, EUR, All Mat.)[‡]
46	3	Money and Credit	EA_LNS_HHLD_HOUS[a]	M	5	MFI (exc. ESCB) Loans for House Purchase to HH & NPISH (Stocks, EUR, All Mat.)[‡]
47	3	Money and Credit	EA_LNS_NFC[a]	M	5	MFI Loans to NFCs (Stocks, EUR, All Mat.)[‡]
48	3	Money and Credit	EA_LNS_NFC_GE5Y[a]	M	5	MFI Loans to NFCs, (Stocks, EUR, $>$ 5Y)[‡]
49	3	Money and Credit	EA_LNS_NFC_LE1Y[a]	M	5	MFI Loans to NFCs, (Stocks, EUR, $\leq$ 1Y)[‡]
50	3	Money and Credit	EA_M1SAF[c]	M	1	EM M1 (flows, CURA)
51	3	Money and Credit	EA_M2SAF[c]	M	1	EM M2 (flows, CURA)
52	3	Money and Credit	EA_MCGSA[c]	M	5	EM Credit to General Government (flows, EP)
53	3	Money and Credit	EA_MCOLSA[c]	M	5	EM Loans to Other EA Residents excl. Govt (EP)

54	4	Interest Rates	DE_GB2Y[d]	D	1	2 Year Government Bond - Germany
55	4	Interest Rates	EA_ECB_POL_DFR[d]	D	1	ECB DFR Rate
56	4	Interest Rates	EA_EURIBOR_3M[d]	D	1	3-month Euro Interbank Offered Rate
57	5	Yield Curve	DE_GB10Y[d]	D	1	10 Year Government Bond - Germany minus ECB DFR
58	5	Yield Curve	DE_GB5Y[d]	D	1	5 Year Government Bond - Germany minus ECB DFR
59	6	Exchange Rates	EA_REX_CH[c]	D	5	Swiss Franc to Euro (ECB)
60	6	Exchange Rates	EA_REX_GB[c]	D	5	UK £ to Euro (ECB)
61	6	Exchange Rates	EA_REX_JP[c]	D	5	Japanese Yen to Euro (ECB)
62	6	Exchange Rates	EA_REX_US[c]	D	5	US $ to Euro (ECB)
63	6	Exchange Rates	EZ_EE18[a]	D	5	ECB Nominal Effective Exc. Rate of the Euro against EER-18
64	7	Prices	WW_POE[c]	D	5	Oil Price (OILBRSV*EUDOLLR)
65	7	Prices	EA_CMDPI_UW[a]	M	5	ECB Commodity Price Index, EUR, Use-weighted, Non-energy[†]
66	7	Prices	EA_CMDPI_UW_FD[a]	M	5	ECB Commodity Price Index, EUR, Use-weighted, Food[†]
67	7	Prices	EA_CMDPI_UW_NFD[a]	M	5	ECB Commodity Price Index, EUR, Use-weighted, Non-food[†]
68	7	Prices	EA_HICP_COMM00[a]	M	5	HICP Communication Services, Index[‡]
69	7	Prices	EA_HICP_FOODPR[a]	M	5	HICP Processed Food incl. Alcohol and Tobacco, Index[‡]
70	7	Prices	EA_HICP_FOODUN[a]	M	5	HICP Unprocessed Food, Index[‡]
71	7	Prices	EA_HICP_HOUSE0[a]	M	5	HICP Housing Services, Index[‡]
72	7	Prices	EA_HICP_MISC00[a]	M	5	HICP Miscellaneous Services, Index[‡]
73	7	Prices	EA_HICP_NEIG[a]	M	5	HICP Industrial Goods exc. Energy, Index[‡]
74	7	Prices	EA_HICP_NRGY00[a]	M	5	HICP Energy, Index[‡]
75	7	Prices	EA_HICP_OVERALL[a]	M	5	HICP Overall, Index[‡]
76	7	Prices	EA_HICP_PCA_OVERALL[a]	M	5	Persistent and Common Component of Inflation[‡]
77	7	Prices	EA_HICP_RECR00[a]	M	5	HICP Recreation and Personal Services, Index[‡]
78	7	Prices	EA_HICP_TRANSP[a]	M	5	HICP Transport Services, Index[‡]
79	7	Prices	EA_HICP_TRIM30[a]	M	5	Trimmed Mean 30%, Annual rate of change[‡]
80	7	Prices	EA_HICP_WMED[a]	M	5	Weighted Median, Annual rate of change[‡]
81	7	Prices	EA_HICP_XE0000[a]	M	5	HICP exc. Energy, Index[‡]

82	7	Prices	EA_HICP_XEF000[a]	M	5	HICP exc. Energy and Food, Index[‡]
83	7	Prices	EA_HICP_XEFUN0[a]	M	5	HICP exc. Energy and Unprocessed Food, Index[‡]
84	7	Prices	EA_IMPP_CAP[a]	M	5	Import Price Index, MIG Capital Goods[†]
85	7	Prices	EA_IMPP_CDUR[a]	M	5	Import Price Index, MIG Durable Consumer Goods[†]
86	7	Prices	EA_PPI_INDXCONS[a]	M	5	Producer Price Index, Industry exc. cons, except food, bev. & tob. [†]
87	7	Prices	EA_PPI_MIGCAP[a]	M	5	Producer Price Index, MIG Capital Goods[†]
88	7	Prices	EA_PPI_MIGCONS[a]	M	5	Producer Price Index, MIG Non-durable Consumer Goods[†]
89	7	Prices	EA_PPI_MIGDUR[a]	M	5	Producer Price Index, MIG Durable Consumer Goods [†]
90	7	Prices	EA_PPI_MIGIMDTGOOD[a]	M	5	Producer Price Index, MIG Intermediate Goods Industry[†]
91	7	Prices	EA_PPI_TOTALINDXCONSMIGEN[a]	M	5	Producer Price Index, Total Industry exc. Construction and MIG Energy[†]
92	7	Prices	WW_GLOBPRC_FOOD[b]	M	5	Global Price of Food Index
93	8	Stock market	DE_DAX_SX[d]	D	5	Deutsche Boerse AG German Stock Index DAX
94	8	Stock market	EA_EUR_SX_50_PR[d]	D	5	The EURO STOXX 50 Index
95	8	Stock market	EA_EUR_SX_BANKS_PR[d]	D	5	The EURO STOXX Banks (Price) Index
96	8	Stock market	ES_IBEX_SX[d]	D	5	IBEX 35 Spain
97	8	Stock market	FR_CAC_40_SX[d]	D	5	CAC 40 Index Euronext Paris
98	8	Stock market	IT_FTSE_MIB_SX[d]	D	5	Borsa Italiana 40
99	9	Uncertainty	DE_VDAX_SX_VOL[d]	D	1	Deutsche Borse VDAX-NEW Volatility Index
100	9	Uncertainty	EA_EUR_SX_50_VOL[d]	D	1	EURO STOXX 50 Volatility Index VSTOXX
101	9	Uncertainty	EA_EPU[f]	M	1	Economic Policy Uncertainty
102	9	Uncertainty	WW_EPU_ADJCPGDP[g]	M	1	Global Economic Policy Uncertainty
103	10	Financial Frictions	EA_CORPAAA_2Y[c]	D	1	RF EU CORP BMK AAA 2Y - RED. Yield
104	10	Financial Frictions	EA_CORPBBB_2Y[c]	D	1	RF EU CORP BMK BBB 2Y - RED. Yield
105	10	Financial Frictions	EA_EONIA	D	1	Euro OverNight Index Average
106	10	Financial Frictions	EA_ICE_BAML[b]	D	1	ICE BAML EA
107	10	Financial Frictions	ES_GB10Y[d]	D	1	10 Year Government Bond - Spain
108	10	Financial Frictions	ES_GB2Y[d]	D	1	2 Year Government Bond - Spain
109	10	Financial Frictions	IT_GB10Y[d]	D	1	10 Year Government Bond - Italy

110	10	Financial Frictions	IT_GB2Y[d]	D	1	2 Year Government Bond - Italy
111	10	Financial Frictions	EA_CISS[a]	M	1	Composite Indicator of Systemic Stress
112	10	Financial Frictions	EA_CISS_BM[a]	M	1	CISS contribution from bond market subindex
113	10	Financial Frictions	EA_CISS_CO[a]	M	1	CISS contribution from cross-subindex correlations
114	10	Financial Frictions	EA_CISS_EM[a]	M	1	CISS contribution from equity market subindex
115	10	Financial Frictions	EA_CISS_FI[a]	M	1	CISS contribution from financial intermediaries subindex
116	10	Financial Frictions	EA_CISS_FX[a]	M	1	CISS contribution from foreign exchange market subindex
117	10	Financial Frictions	EA_CISS_MM[a]	M	1	CISS contribution from money market subindex
118	10	Financial Frictions	EA_IL_HHD_CONS_OTHR[a]	M	1	AAR/NDER - Consumer Credit and Other Lending to HH & NPISH (Outstanding, EUR)‡
119	10	Financial Frictions	EA_IL_HHD_HOUS[a]	M	1	AAR/NDER - Lending for House Purchase to HH & NPISH (Outstanding, EUR)‡
120	10	Financial Frictions	EA_ILNB[a]	M	1	Loans to NFCs, Cost of Borrowing (EUR, New Business, Volume-weighted MA)‡
121	11	Financial Cycle	EA_BPER[a]	M	5	Building Permits-Dwellings, All Residential exc. Community Res.†
122	11	Financial Cycle	EA_CDTDMND_FRMS_LAG1Q[a]	Q	1	BLS, Credit Standards to Firms, Loan Demand‡
123	11	Financial Cycle	EA_CDTSTND_FRMS_LAG1Q[a]	Q	1	BLS, Credit Standards to Firms, Loan Supply‡
124	11	Financial Cycle	EA_CREDIT_GAP_BIS[e]	Q	1	Credit to GDP Gap
125	11	Financial Cycle	EA_HOUSP_RES[a]	Q	1	Residential Property Transaction Value, Index (ECB)†

Notes: a: ECB; b: FRED; c: Datastream; d: Bloomberg; e: BIS; f: Baker et al. (2019); g: Davis (2016).

† : Euro area 19 - fixed. ‡ : Euro area changing composition. * : Except of motor vehicles and motorcycles.

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