When is monetary policy more powerful?

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Abstract

The idea that monetary policy may have non-linear effects has a long history in economics. The literature has provided a plethora of potential sources of non-linearity, but most previous studies have used *low dimensional* modelling approaches that allow for only one or two channels to operate simultaneously. This study takes a *high dimensional* "big data" approach, allowing us to systematically evaluate which of many non-linear channels matter for transmission. Using a large, mixed-frequency dataset designed to incorporate many sources of non-linearity in the literature, we establish that monetary policy transmission to asset prices has multi-dimensional state-dependence with economically large non-linear effects. Strong real economic conditions strengthen transmission, but this can be dominated by other effects at times, including from financial variables. As such, transmission is not reducible to low-dimensional stratification, such as recessions vs. expansions. We show that low dimensional approaches can suffer from considerable omitted variable bias.

JEL Codes: E52, E33, C32, C11.

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1 Introduction

The idea that the effectiveness of monetary policy can change with the state of the world can be traced back at least as far as Keynes (1936). Keynes made an argument for state-dependence in the power of monetary policy; if the interest rate were sufficiently low, the monetary authority would have no power to stimulate the economy by lowering the interest rate further. The metaphor of "pushing on a string" has been attributed to his argument – just as it is easier to pull on a string than to push on one, it is easier for monetary policy to curtail economic growth than to stimulate it.

The question of whether monetary policy has state-dependent effects is of the utmost importance for policymakers: do they possess a tool that is equally effective at different times, no matter the economic situation? As the macroeconomic literature has developed, a plethora of potential sources of state-dependence, or *non-linearity*, in monetary policy transmission have been proposed.[1] Monetary policy effectiveness has been found to depend upon whether the policy rate is at the Zero Lower Bound (Krugman et al., 1998; Kiley and Roberts, 2017), upon the business cycle (Tenreyro and Thwaites, 2016; Mumtaz and Surico, 2015), financial cycle (Alpanda et al., 2021; Rünstler and Bräuer, 2020), and uncertainty (De Pooter et al., 2021; Bauer et al., 2022a; Tillmann, 2020), among others.

Clearly, there are many potential state-dependent channels through which the power of monetary policy can be affected. How should one evaluate this evidence? Much of the previous literature has approached the question of non-linearity in transmission through *low dimensional* approaches, evaluating few channels, most often a single channel. Low dimensional approaches suffer from 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 one channel, relative to others. To date, researchers have tended to employ somewhat ad hoc approaches to evaluate the role of given channels, for example by simply substituting one state-variable for potential alternatives and conducting a horse race across models.

This paper takes a *high dimensional*, "big data" approach. This allows us to systematically evaluate how many, and which, sources of non-linearity might matter for monetary policy trans-

[1] In this study, we use the terms "state-dependence" and "non-linearity" interchangeably. Non-linearity can, however, encapsulate other forms of asymmetry such as sign- or size-dependence.

mission. Our first contribution is to construct a novel, large, mixed-frequency dataset of U.S. real and financial variables. We design this dataset to incorporate non-linear mechanisms that have been put forth in the literature. For the purposes of inference, we apply data reduction techniques, summarising variation across a large number of potential state-variables using a factor model. We ensure our factors have clear economic interpretations by extracting them from various sub-divisions of related variables (for example, a labour group, an uncertainty group). We define these groups a priori, according to the divisions suggested by McCracken and Ng (2016). These factors are how we represent the states that may give rise to state-dependence.

We incorporate these factors into standard non-linear event study regressions. Following Cloyne et al. (2023), we use the Kitagawa-Oaxaca-Blinder decomposition to examine potential state-dependence. As has become common in recent years, we use data from high-frequency asset price movements around meeting days of the Federal Open Market Committee (FOMC), as our dependent variables. In particular, we focus on transmission down the yield curve to the U.S. 10 year Treasury Bond yield, and to 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 intermediation. We take intraday asset price responses from FOMC meetings for the period between February 1997 and December 2019, using the dataset of Bauer and Swanson (2022).

The contributions of this paper are several-fold. First, we establish that transmission of monetary policy to asset prices has multi-dimensional state-dependence. When extracting our factors, we find the number required to summarise our real/financial dataset is more than 20. It is possible, however, that none, or few, of these factors matters for transmission. On the contrary, in our event study regressions, we find that 10 factors are statistically significant when examining transmission to yields while six are statistically significant for equities. This represents strong evidence not only that transmission is non-linear, but that low dimensional approaches are not sufficient to understand transmission.

Second, we show that the non-linearities arising from the states have economically large effects. The factor with the largest effect on transmission has a clear economic interpretation: it loads most strongly on U.S. employment levels. In our event study regression, transmission is more powerful as the real economic conditions represented by the "Labour" factor strengthen. At the mean of our dataset, a 10 basis point (bp) monetary policy surprise transmits to the 10 year yield as a 7bp increase. If the Labour factor were one standard deviation above its mean, transmission of the 10bp surprise would be 46% stronger, at almost 11bp in total. This is an economically significant increase in the strength of transmission.

Another economically significant factor loads most strongly on the spread between the U.S. 10 year Treasury yield and the Fed Funds Rate. This has a clear financial interpretation, showing that both real and financial state variables matter for transmission. The term structure of interest rates is well-known to embed predictive power about future real economic activity and inflation (Estrella and Mishkin, 1997). Expectations of future conditions may thus affect current transmission. If this "Spreads" factor were two standard deviations above the mean, i.e., if the yield curve were steep, transmission to yields would be 42% stronger.

Third, we decompose transmission of monetary policy over time, allowing us to identify periods in which monetary policy transmission was stronger or weaker, and which factors drove this. In general, we find that monetary policy transmission is "pro-cyclical" in the sense that some of the weakest periods we identify coincide with the recessions around the Dotcom bubble and the Global Financial Crisis (GFC). Using our factors, we can examine patterns in transmission in finer detail.

Looking at our Labour factor, we find that the contribution of the real economy to transmission is unambiguously pro-cyclical. This factor makes large, negative, contributions to transmission during the aforementioned two recessions. This finding aligns with arguments of Keynes (1936) and Tenreyro and Thwaites (2016), but is in contrast to Bauer et al. (2022b) in which transmission is found to be stronger when the economy is in a weaker state.

While the real economy is important for understanding transmission, it is not the only factor that matters. Intuitively, we find that the forward-looking financial spreads factor anticipates the real economy factor via the predictive power of the yield curve. As such, it weakens transmission in advance of the Dotcom and GFC recessions, and during 2019. It also begins to add positively to transmission during the "second half" of these recessions when the yield curve is steeper and anticipates the end of the recession. Because of this, there are "within recession" dynamics that are missed by simple sub-period analysis such as by stratifying one's data according to whether it is an NBER recession, or by whether there is a positive output gap.

Intriguingly, we find that some of the FOMC days on which there was the strongest transmission come during the latter portion of the GFC recession. This strong transmission is driven by the Spreads factor, and other factors, which jointly swamp the negative contribution from the real economy. Once more, this highlights how transmission is multi-dimensional in nature.

Fourth, we highlight the susceptibility of low-dimensional state-dependent approaches to Omitted Variable Bias. We repeat our event study regressions using low-dimensional approaches in which we stratify the data according to a real economy variable such as a recession dummy. When doing this, we find that transmission is "counter-cyclical", as in Bauer et al. (2022b) - weaker if the economy is stronger. Omitting any of our factors related to the real economy, we add our other factors to the event study regression one by one. As we add our factors, we find that the effect of the real economy variable changes from counter-cyclical to pro-cyclical, especially once we control for financial factors. This emphasises how transmission is multi-dimensional and how a factor approach provides a practicable method for the econometrician to summarise the multiple important economic channels that generate the transmission data.

For the monetary policymaker, understanding whether transmission is subject to non-linearity is of the utmost importance. The ultimate question for the policymaker is when is monetary policy more, or less, powerful. Non-linear transmission increases the complexity of using the available tools to achieve one's policy goals: if the effects of monetary policy cannot be assumed to be the same at all points in time, then the policymaker must carefully assess the prevailing economic and financial conditions when they move to act. One key finding of this paper is that the state-dependence in transmission is not reducible to a single summary measure, such as the business cycle. On the one hand, this finding implies still greater complexity for the policy-maker: transmission is non-linear in more than one way. On the other hand, we provide a novel and practicable approach to represent and understand the non-linearities.

The paper is organized 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 5 discusses empirical results, while Section 6 provides several robustness checks. Section 7 concludes.

2 Literature Review

The empirical and theoretical literature on monetary policy shocks has documented a vast array of potential channels through which their effects could vary in a state-dependent manner. In this section, we provide a broad overview of such channels.

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 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), non-linear VAR models (Koop et al., 1996) and state-dependent local projections (Tenreyro and Thwaites, 2016) among others.

A key drawback of conventional approaches to non-linearity is that they are *low dimensional*. Non-linear mechanisms are proposed, and typically one variable is used to quantify the non-linear transmission. However, while a researcher may establish non-linearity in a given variable, assuming this variable is correlated with other relevant factors, the true source of non-linearity will remain unclear. To establish robustness, researchers frequently substitute the non-linear variable for alternatives in order to show that results differ when other sources of non-linearity are considered. Such approaches have the disadvantage of being somewhat *ad hoc*, since all manner of alternative sources of non-linearity are not incorporated.

A number of recent studies do allow for the simultaneous activation of multiple non-linear transmission channels. These studies typically remain low-dimensional, however, in the sense that only two or three channels are considered. For example, researchers have examined whether the effects of monetary policy change at a certain point of the business cycle in conjunction with a certain point of the financial cycle (Alpanda et al., 2021). Jordà et al. (2020) establish three dimensions of non-linear transmission, based on the real economy, the inflation rate and whether there is a credit boom in mortgage markets. Our study contributes by summarising the potential contribution of a "large" number of channels, which necessitates the use of data reduction techniques.

In this study we present evidence that estimates of non-linear transmission in low dimensional settings can be strongly influenced by omitted variable bias. We establish this finding by allowing for a broad range of non-linear interactions, applying big data approaches. Our study therefore complements that of Cloyne et al. (2023), who also caution that estimates of non-linear treatment effects can be biased in cases where correlated alternative non-linear sources are not modelled. These authors advocate an alternative approach to this issue, insofar that they advise instrumenting both the treatment variable, as well as the interaction variable itself. Rather than introducing additional instruments, our approach is to greatly expand the information set being leveraged in the estimation through adding many macro-financial controls, summarised by factors. Our specifications have the advantage of allowing many different non-linear sources to be ranked ordinally in importance, and can prove useful for studying interactors for which instruments are not available.

We now discuss existing evidence on non-linear transmission. Many researchers have established that monetary policy is non-linear in the business cycle. Tenreyro and Thwaites (2016) and Mumtaz and Surico (2015) find that monetary policy is weaker in recessions. Bauer et al. (2022b) find that the perceived responsiveness of monetary policy to the economy is time-varying and rises during hiking cycles. These authors document that transmission down the yield curve is strongest during periods of economic weakness, and rationalise this effect as resulting from the influence of lower perceived responsiveness on term-premia.

Moving beyond channels relating to real activity, a number of recent papers have investigated the potential for transmission to vary with the inflation regime. Ascari and Haber (2022) show that the transmission of monetary policy shocks to the price level depends on the trend inflation regime.

In light of Keynes's arguments regarding the liquidity trap, the argument that monetary policy might be weaker at the Zero Lower Bound (ZLB) on interest rates has a long tradition (Krugman, 1998). Many studies have quantified such effects in the context of the experience of developed economies with the ZLB after the 2008 financial crisis (Kiley and Roberts, 2017; Sims and Wu, 2021). However, a number of studies have found little evidence for non-linear transmission at the ZLB (Swanson, 2018; Debortoli et al., 2019).

We have a great deal of evidence that uncertainty could affect monetary policy transmission. The level of uncertainty affects the behaviour of investors, who adjust their interest rate positions by less when uncertainty is high. As such, they put less weight on signals from the central bank when they are less confident about the expected policy rate path, and transmission is weakened. See, for example, the studies of Pellegrino (2021), Bauer et al. (2022a), De Pooter et al. (2021), Tillmann (2020) and Aastveit et al. (2017).

The role of the financial sector in transmitting and amplifying monetary shocks has been long established (Bernanke et al., 1999). A growing body of literature explores links between financial intermediary balance sheets and non-linear transmission. Kashyap and Stein (2000) and Kishan and Opiela (2000) examine the role of commercial banks, finding that the response of bank lending to monetary policy is affected by the liquidity, size and capital of banks. 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. Saldías (2017) finds that the effects of monetary policy shocks on output are non-linear in financial stress.

Finally, a number of papers study effects that are non-linear not in some external state-variable, but in the sign or size of the monetary policy shock itself. Ascari and Haber (2022) and Tenreyro and Thwaites (2016) report evidence for size-dependence in transmission. Angrist et al. (2018) and Tenreyro and Thwaites (2016) establish non-linearity in the sign of the monetary surprise, while others do not report evidence for these effects (Altavilla et al., 2019).

Whether the interest is in the monetary transmission mechanism or in some other key economic channel, what most of these studies have in common is a low-dimensional mode of representing the non-linearity or state. An exception is the study of El-Shagi (2021), who employs a sparse estimation approach (LASSO) to examine multiple potential sources of non-linear transmission of monetary policy shocks to monetary aggregates. Our study differs from El-Shagi (2021) across a number of dimensions: we focus on transmission to yields and equities rather than to monetary aggregates; we use different identification methods (high-frequency event study); we allow a greater number of potential non-linear channels to operate; and we adopt a factor approach as our baseline, as opposed to a sparse framework such as LASSO.

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:

$$y_t = \alpha + \beta MPS_t + \upsilon_t, \tag{1}$$

where y_t is the high-frequency change in some asset price, such as bonds or equities.[2] MPS_t is a monetary policy surprise identified in a narrow window around communication events, while

[2] Two-day changes, daily changes, or intraday changes are used in the literature.

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, and the monetary policy surprise is defined as the change in interest rates that takes place over this window (Gürkaynak et al., 2005). Under the assumption of efficient markets, interest rate futures should incorporate all available information up to the minutes prior to the meeting. The change in interest rates in 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 would have taken place during this narrow window of time. Given this assumption, the coefficient β reflects the causal effect of this monetary policy surprise on asset prices.

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

$$y_t = \alpha + \beta MPS_t + \delta MPS_t \times Z_{t-1} + \phi Z_{t-1} + \upsilon_t, \tag{2}$$

where Z_{t-1} is a potential source of state-dependence, measured before the event study date. The total effect of a monetary policy surprise on the change in asset prices is given by the sum of β and δZ_{t-1}. The coefficient ϕ absorbs any effect of the state variable on the change in yields that is independent of its interaction with the monetary policy surprise.

One can think of equation 2 as being "representative" of many forms of low-dimensional non-linear investigations, whereby Z_t might 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. We replace the scalar variable Z_{t-1} with a vector $\mathbf{Z}_{t-1}$. Our baseline approach to reduce the dimensionality of our large real and financial dataset is to extract factors by using Principal Component Analysis (PCA). In Section 6, we show results using alternative shrinkage approaches such as LASSO and Random Forests.

Our specification is a high-dimensional extension of the Kitagawa-Oaxaca-Blinder decomposition (Kitagawa, 1955; Oaxaca, 1973; Blinder, 1973) to examine state-dependence in macroeconomic relationships, as recently employed in the study of Cloyne et al. (2023). Our baseline investigation is given by:

$$y_t = \alpha + \beta MPS_t + \delta MPS_t \times (\mathbf{Z}_{t-1} - \bar{\mathbf{Z}}) + \phi(\mathbf{Z}_{t-1} - \bar{\mathbf{Z}}) + \upsilon_t, \tag{3}$$

where $\mathbf{Z}_{t-1} = [Z_{1,t-1}, \ldots, Z_{K,t-1}]'$ is a $(K \times 1)$ vector of factors representing potential sources of non-linearity. Cloyne et al. (2023) emphasise the importance of expressing state variables in deviation from their means ($\bar{\mathbf{Z}}$), since this ensures the parameter β and vector of parameters δ have clear economic interpretations.[3]

$$\begin{aligned} \text{Direct Effect}: &\quad \beta \\ \text{Indirect Effect}: &\quad \delta(\mathbf{Z}_{t-1} - \bar{\mathbf{Z}}) \\ \text{Total Effect}: &\quad \beta + \delta(\mathbf{Z}_{t-1} - \bar{\mathbf{Z}}) \end{aligned}$$

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 1. Meanwhile, the "indirect effect" represents the contribution of the state variables to transmission. A statistically significant estimate for parameter δ would indicate non-linear transmission, while the relative sizes of β and $\delta_i Z_{i,t-1}$ allow us to determine whether any such non-linearity is economically meaningful, for a given interactor $i \in (1, \ldots, K)$. 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, $\{Z_{i,t-1}\}_{i=1}^{K}$.

In equation 3, we estimate a vector of main effects of the state variables, ϕ. 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. However, some 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 some real and financial information available before the meeting. For this reason, we include the factors from our real and financial dataset as both controls and interaction terms in our baseline specification.

[3] Our factors have zero mean by construction, meaning $\bar{\mathbf{Z}} = 0$.

4 Data

Our investigation focuses on the transmission of monetary policy to asset prices during the 193 meetings of the FOMC that took place between February 1997 and December 2019. The event study window is 30 minutes in length. The dependent variables of interest are the changes in the 10 year Treasury yield and the S&P500 index in the same window.[4] Our data source is the dataset of Bauer and Swanson (2022).

High-frequency identification of monetary policy surprises has become popular in the literature following the seminal contributions of Kuttner (2001), Bernanke and Kuttner (2005), and Gürkaynak et al. (2005). We use the intraday change in the two year Treasury yield as a summary measure of a monetary policy surprise, in a similar manner to Hanson and Stein (2015), De Pooter et al. (2021) and Bauer et al. (2022b). The use of the two year yield allows us to consistently traverse the Zero Lower Bound period, which occurs during our sample, since two year yields continued to respond to Fed communication during this period. Other forms of monetary policy surprise have been used in the literature, including the structurally identified surprises of Swanson (2021b) and Jarociński and Karadi (2020). In Section 6, we provide robustness checks based on the use of structurally decomposed surprise series.

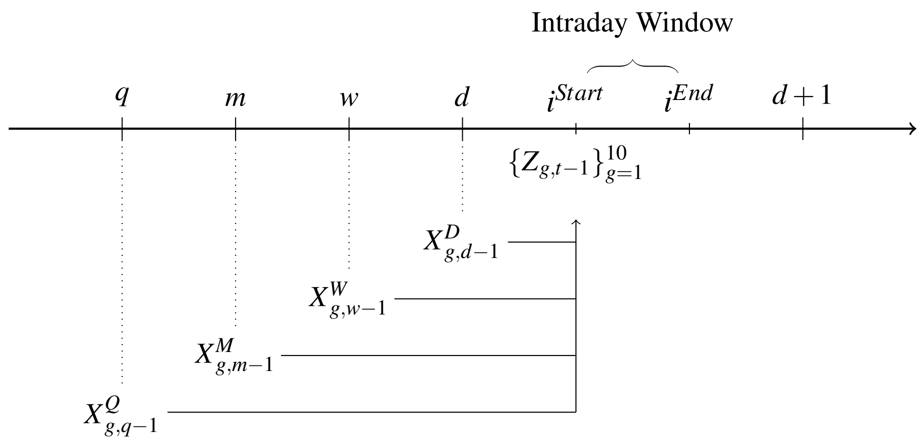
Table 1: Description of variable groups, by frequency

	Frequency				
Group Name	**D**	**W**	**M**	**Q**	**Total**
Output			16		16
Labour	2		29		31
Housing			3		3
Consumption and inventories			11		11
Money and credit		7	5		12
Interest and exchange rates	17		5		22
Prices	1		9		10
Stock market	3		2		5
Uncertainty	5		26		31
Financial cycle	1	6	2	5	14
Total	**29**	**13**	**108**	**5**	**155**

Notes: Table shows the number of variables in our dataset, subdivided by frequency – daily ("D"), weekly ("W"), monthly ("M"), quarterly ("Q").

[4] Both changes in yields and changes in instantaneous forward rates have been used in the event study literature. Nakamura and Steinsson (2018) find monetary policy transmission to be very similar between each type of dependent variable. At intraday frequency we have access to changes in yields, and proceed with these as the dependent variable for transmission down the yield curve.

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



We construct a large dataset of real and financial variables to allow us to examine a large number of potential sources of non-linear transmission. As a starting point, we use the widely-used macro-financial FRED-MD dataset of McCracken and Ng (2016). We extend these data to include additional variables that have been previously emphasised in the literature on state-dependent transmission. These include measures of uncertainty (De Pooter et al., 2021), and measures of the financial cycle and leverage (Adrian and Shin, 2014). Bauer and Swanson (2022) highlighted six macro-financial variables that can be used to predict monetary policy surprises, and we include these in our dataset. The baseline FRED-MD contains eight groups of variables separated by economic concept. We retain this structure, but add two groups relating respectively to uncertainty and the financial cycle, to make 10 groups in total. As shown in Table 1, our dataset consists of 155 variables across these 10 groups, with a mixture of data at daily, weekly, monthly, and quarterly frequencies. The full details of our dataset are made available in the Appendix.[5]

The original FRED-MD dataset is at monthly frequency. However, some of the constituent variables are available at higher frequencies. When variables are available at daily or weekly frequencies, we replace lower frequency data with higher frequency data. This ensures that our dataset incorporates information available to financial market participants at the time of the meeting.

Figure 1 outlines the structure of the mixed-frequency dataset and how it relates to a given day on which there is an FOMC meeting. The 10 data groups, indexed by g, contain vectors of

[5] Table 11 lists the different transformations we can apply to the data, and the groups in the data. Table 12 lists each variable, its interpretation, group, source, frequency, and the transformation applied, if any.

variables at frequency f, X_g^f. The index f indicates when data are monthly (M), weekly (W), or daily (D). Each variable is aligned to the meeting day to reveal the most up-to-date information that the market and the policymaker would have on that day *before* the meeting. With all the data aligned and grouped, we proceed to extract factors from each group, individually. We denote the factors within each group as Z_g. Stacking all the group factors gives us the vector Z in equation 3. To the best of our knowledge, this is the first attempt to create "meeting frequency factors" in the literature. Note also from Figure 1, as is standard in the high-frequency identification literature, the monetary policy surprise is given by $(i^{End} - i^{Start})$, the intraday change in a yield on day d.

Table 2: Bai and Ng (2002) test for the number of factors

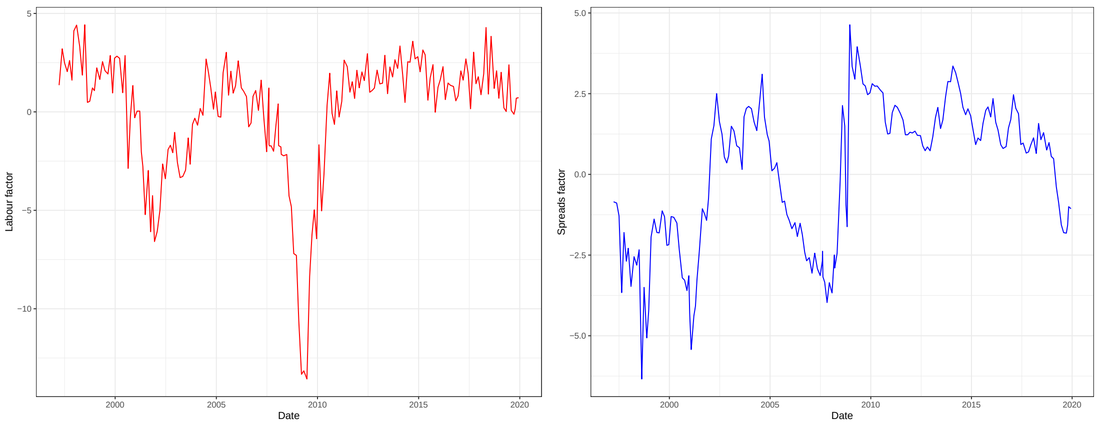
	Test value	Optimal number	Explained variation
Non-group	0.77	13	0.63
Output	0.58	3	0.72
Labour	1.03	1	0.32
Housing	1.27	1	0.94
Consumption, inventories	1.13	1	0.25
Money and credit	0.83	3	0.25
Interest and exchange rates	0.90	3	0.52
Prices	0.53	3	0.78
Stock Market	0.47	3	0.93
Uncertainty	0.91	3	0.60
Financial	0.69	3	0.77

Notes: Table shows test-statistics for the Bai and Ng (2002) tests for the number of factors, applied separately to each group.

We estimate factor models for each group of variables separately, using Principal Component Analysis (PCA). We favour the approach of extracting factors group-by-group because the factors retain direct economic interpretations. For instance, factors extracted from the Labour group are directly interpretable as relatable to the labour market, or real economy more generally. Nonetheless, one could extract the factors from the dataset as a whole without any reference to economic groups. In Section 6 we provide a robustness check using factors extracted on this basis. The benefit of this approach is to have a full set of factors that are orthogonal to each another by construction, in which case the estimated indirect effect of a given factor is insensitive to the omission or inclusion of another. However, a disadvantage of extracting factors directly from a large dataset is that we have found that many of these factors are hard to interpret, since they load on variables from multiple groups. For this reason, we prefer to estimate our factor

Figure 2: Examples of real and financial factors

(a) Labour (b) Spreads



Notes: Figure shows the time-series evolution of two factors, extracted from our dataset. The frequency of the factors reflects that of the FOMC meetings in our sample.

models by group.[6]

In order to investigate the required number of factors, we apply the Bai and Ng (2002) test, as also in McCracken and Ng (2016). Table 2 shows the optimal number of factors by group, and also for the case that we pool all data (irrespective of group) before estimating the factor model. Across the groups, the optimal number of factors is between one and three, summing to 24. In the non-group approach, we find that 13 factors is optimal, explaining 63% of the variation in the dataset. If we were to extend the number of factors to 20, we would explain 72% of the variation. The group approach does not allow a simple summary of total variation explained, but this ranges from 25% to 94% across groups. We interpret the difference in number of factors between group and non-group approaches as reflecting the greater span of the linear combination of variables when the factor is taken from the whole dataset, but this again highlights the loss of interpretability from this approach.

Table 10 from the Appendix shows the top five loading variables for each of the group factors. If a group contains more than one factor, we provide interpretations for each based on the loadings. For instance, the prices group contains three factors which, respectively, are interpreted as relating to oil prices, food and commodity prices, and consumer prices.

Figure 2 shows two examples of the factors we extract from our dataset. The first loads most strongly on U.S. employment numbers and has a clear real economy interpretation, reflecting the tightness of the labour market. The factor is negative in the early 2000s, in the wake of

[6]We find that both approaches produce similar out-of-sample prediction errors as measured by MSE.

the Dotcom bubble, and most negative in the late 2000s around the Global Financial Crisis. Thereafter, it recovers in line with the U.S. economy during the 2010s. The second factor has a financial interpretation. It loads most strongly on the spread between the U.S. 10 year Treasury yield and the Fed Funds Rate, or in other words, the slope of the yield curve. The times at which this factor is negative align with times when the U.S. yield curve was flat or inverted. For instance, the yield curve flattened and then inverted in 2000/2001 and 2006/2007, both of which are captured by this factor. Furthermore, the yield curve flattened over the course of 2018 and 2019, as also shown in this factor at the end of our sample.[7]

5 Empirical Results

In this Section, we first discuss results from our baseline specification with a high dimensional representation of state-dependence. We then provide a historical decomposition of transmission over our sample. Finally, we compare findings from our high dimensional approach with those from low dimensional approaches.

5.1 Baseline results

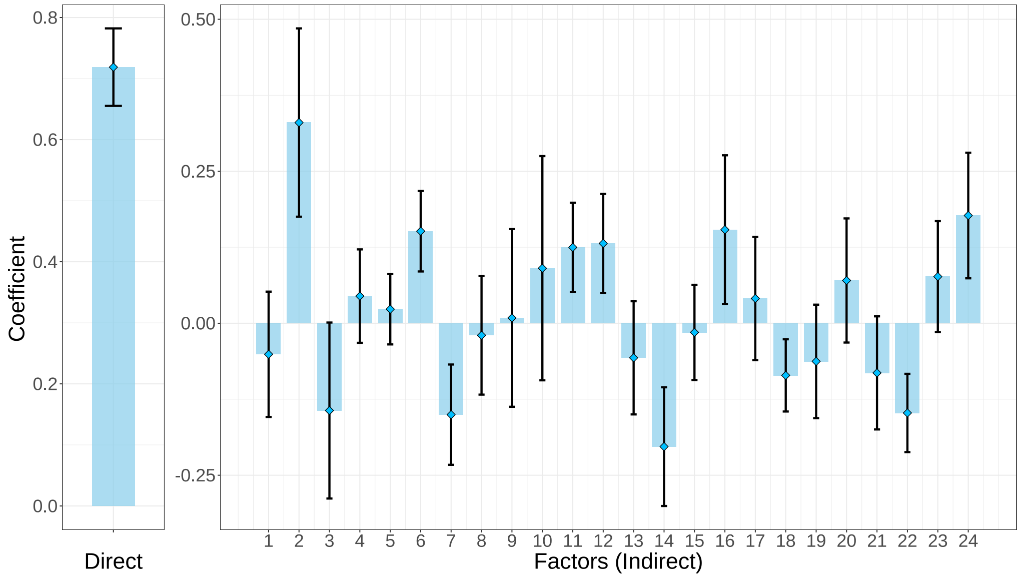
In Figure 3, we display results from the high dimensional non-linear approach outlined in equation 3. We estimate our regression using both the response of 10 year yields and equities as dependent variables. The coefficient labelled "Direct" represents our estimate of β, i.e., the state-independent effect of the monetary policy surprise on the dependent variable. This estimate represents the conditional expectation of transmission, for the case that all interaction variables are set to their averages. Our estimates imply that a 10bp surprise increase in the two year yield leads to an increase in the 10 year yield of 7.1bp, and decreases the S&P500 index by approximately 50bp. These findings are comparable in magnitude to those of related studies (Bernanke and Kuttner, 2005; Bauer and Swanson, 2022).

Figure 3 also displays coefficient estimates for the factor interactions with the monetary policy surprise, scaled by the standard deviation of the factor, and with error bands represented at 90% confidence. For the 10 year yield, we find that the Labour factor is highly statistically significant and has the largest effect. The coefficient is positive, indicating that transmission is stronger when the labour market is tight. Importantly, our research design allows us to quantify

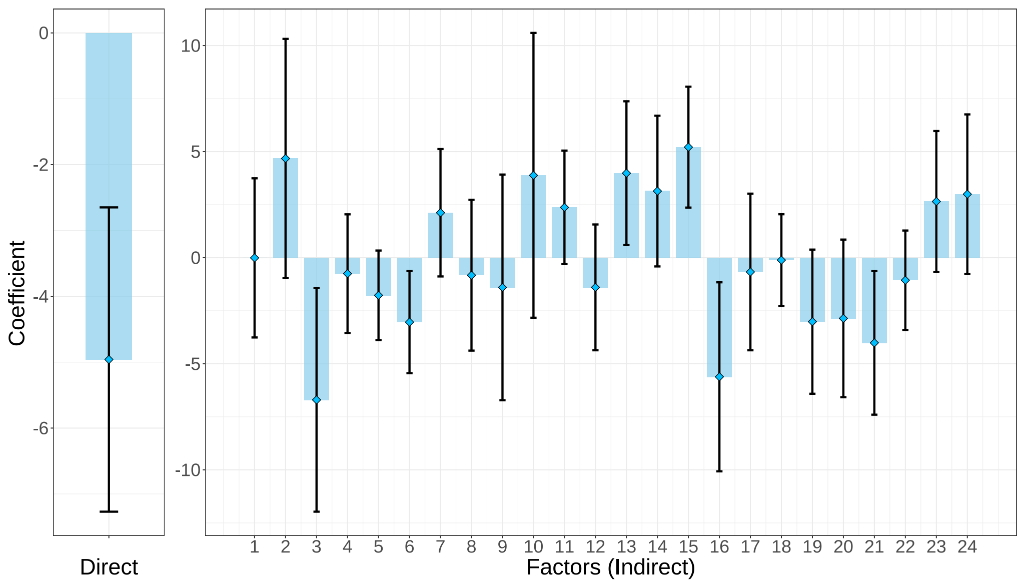
[7] The full set of factors is shown in Figure 11 in the Appendix.

Figure 3: OLS estimation results for the factor approach

(a) 10Y Yields



(b) Equities

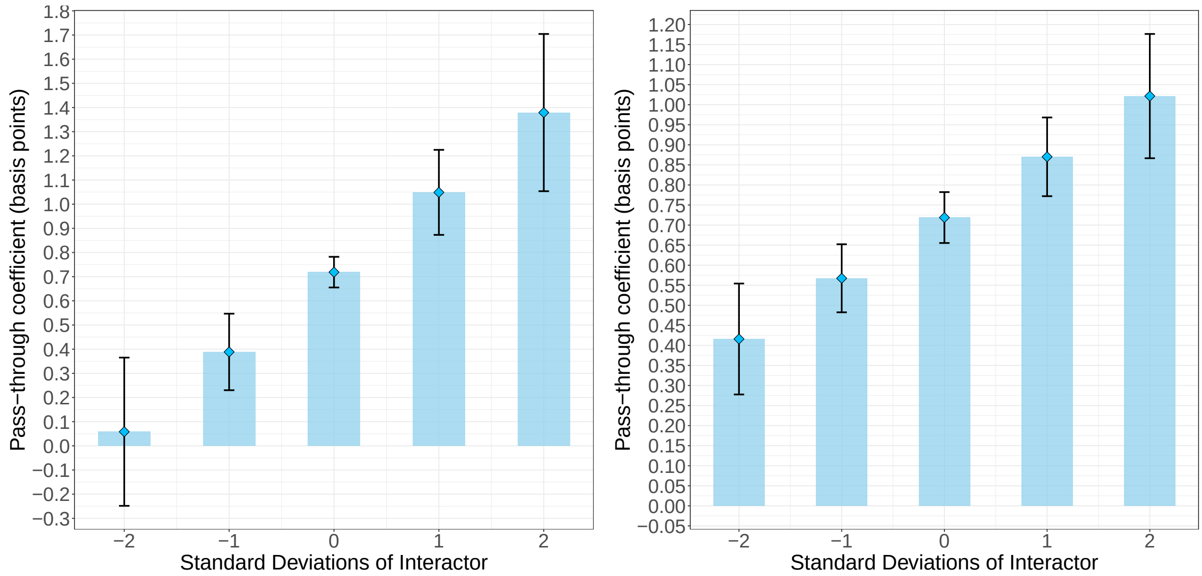


Notes: Factors are scaled to 1 S.D. increase. Error bands show 90 per cent confidence intervals.

the dimensionality of non-linear transmission. In total, we find 10 factors that are statistically significant. For equities, we find that six of the factors are statistically significant. For both of the dependent variables, we find that some of the factors amplify transmission while others dampen it. We therefore provide evidence for a transmission mechanism that is highly complex, with many relevant states influencing outcomes. We will show evidence below that a failure to account for the high dimensionality of transmission we document can lead to considerable omitted variable bias concerns.

Figure 4: Magnitude of state-dependence – Yields

(a) Labour (b) Spreads



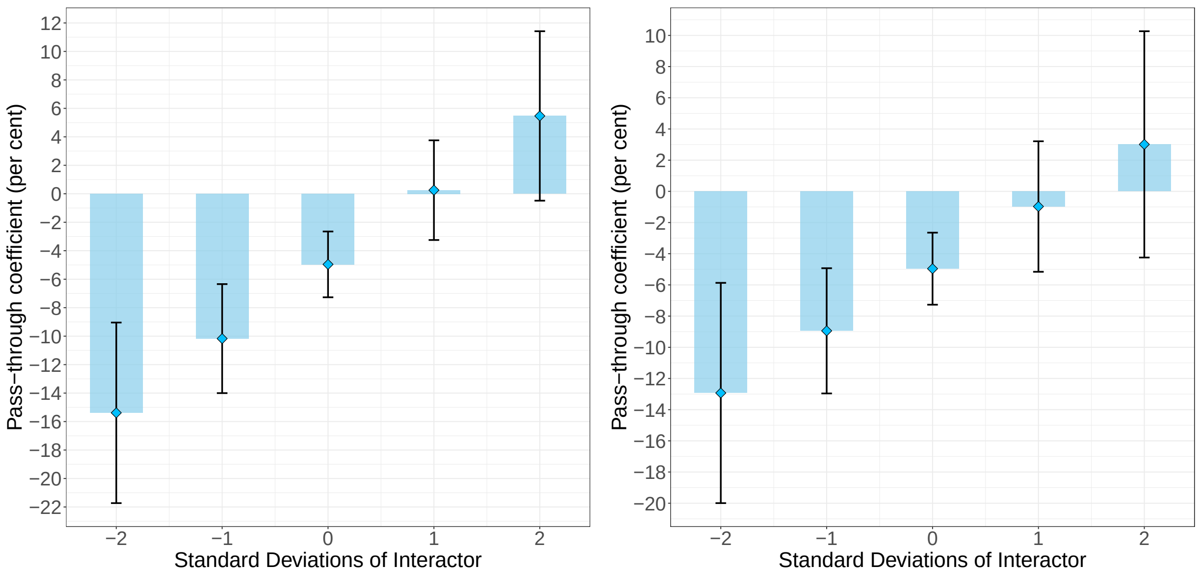
Notes: Factors are scaled to 1 S.D. increase. Error bands show 90 per cent confidence intervals.

As is well known, statistically significant interaction coefficient estimates do not imply that the non-linearities are of economically meaningful magnitudes. In other words, it is incumbent on the researcher to establish that indirect effects are "large" relative to direct effects. As noted in Section 3, one must choose some value of the state variable at which to evaluate its indirect effect. In Figure 4, we evaluated the interactions of the Labour and Spreads factors with the monetary policy surprise, for the 10 year yield. We do this for deviations of the factor of two standard deviations around its mean value, which is zero by construction. Looking first at the Labour factor, when this is one standard deviation above the mean, transmission is 46% stronger than the direct effect, at almost 11bp for a 10bp surprise, rather than 7.1bp. If this factor were two standard deviations above its mean, transmission would be almost double that of the state-independent result. In short, the non-linear effect arising through the Labour factor is economically large in magnitude.

Additionally, we find that transmission would be 42% stronger when the Spreads factor takes a value of two standard deviations above its mean, recalling that this occurs when the yield curve is steep. While a smaller effect than that of the Labour factor, this effect is also large and meaningful economically. In Figure 5, we examine transmission to equities, which we find to depend on factors representing equity valuations and the level of interest rates. Evaluating both of these factors at two standard deviations below the mean, the effect of a monetary policy surprise is two and a half to three times stronger. Not only is this state-dependence large, but the difference in operative factors for equities and yields emphasises that low dimensional approaches also suffer from comparability issues across different dependent variables in which the policymaker may be interested.

Figure 5: Magnitude of state-dependence – Equities

(a) Equity valuations (b) Interest rate



Notes: Factors are scaled to 1 S.D. increase. Error bands show 90 per cent confidence intervals.

5.2 When is monetary policy more powerful?

We can use our results to produce a form of historical decomposition of the strength of monetary policy transmission across our sample of FOMC meeting days. This allows us to examine when monetary policy transmission has been more or less powerful. Specifically, we compute the total effect of a 10bp positive surprise as a function of time

$$\widehat{TE}(t) = \left[\hat{\beta} + \hat{\delta} \times (\mathbf{Z}_{t-1} - \bar{\mathbf{Z}})\right] \times 10, \tag{4}$$

where the expression is evaluated as $\mathbf{Z}_t$ varies across the sample period. When computing $\widehat{TE}(t)$, we include only interactions with those factors that are statistically significant in our regressions. In Figure 6, we show this decomposition for yields and equities. The horizontal, dashed line represents the estimated state-independent, direct effect of transmission. Consistent with Figure 3, this is approximately a 7 basis point increase for yields. In this Figure, the bars represent the total effect of monetary policy transmission on that day.

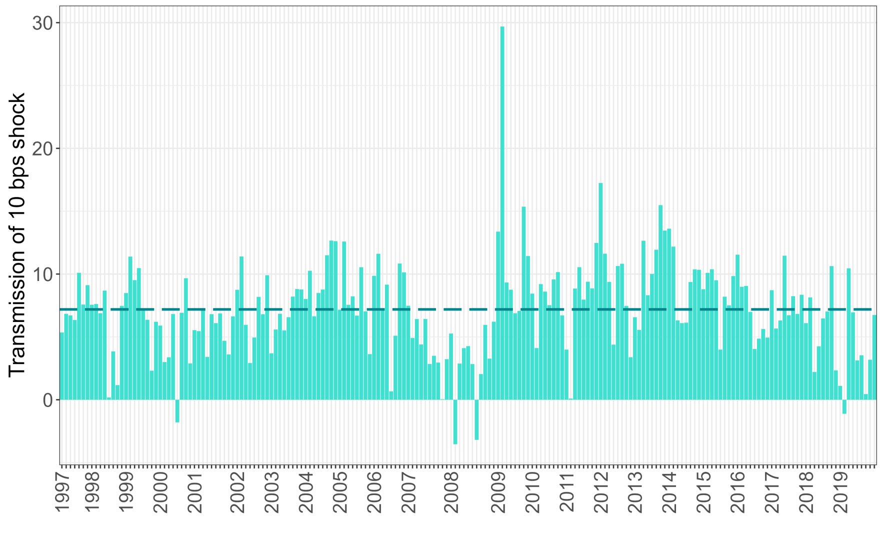
While we have shown strong evidence for state-dependence, this result is underscored here. If monetary policy transmission were not state-dependent, the total effect would always align with the dashed line. Instead, we find considerable variation in transmission to yields throughout our sample period. Monetary policy transmission to yields appears to be broadly pro-cyclical, in that there clearly are periods of weakness in transmission around 2000/2001, in the wake of the Dotcom bubble, and even more so around the Global Financial Crisis in 2007/2008. Transmission also weakens in the final portion of our sample. For transmission to equities, the degree of state-dependence appears to be stronger still. The response of equities to monetary policy surprises is highly variable over the sample and the relative size of the total effect to the direct effect can be large.

In Figure 7, we examine the drivers of this historical variation in transmission to yields in more detail. We include the contributions over time of two of the most economically significant factors: Labour and Spreads. Looking at the Labour factor, through which we represent the real economy, we can see that transmission is unambiguously pro-cyclical along this dimension, consistent with Keynes (1936) and Tenreyro and Thwaites (2016). This factor makes large, negative, contributions to transmission during the recessions in the wake of the Dotcom bubble and GFC. It is worth noting how this factor aligns with the periods of systematic weakness in transmission we have identified, particularly around 2007/2008. While the Labour factor begins to make a negative contribution in 2007, it makes its most negative contribution in 2009, lasting into 2010.

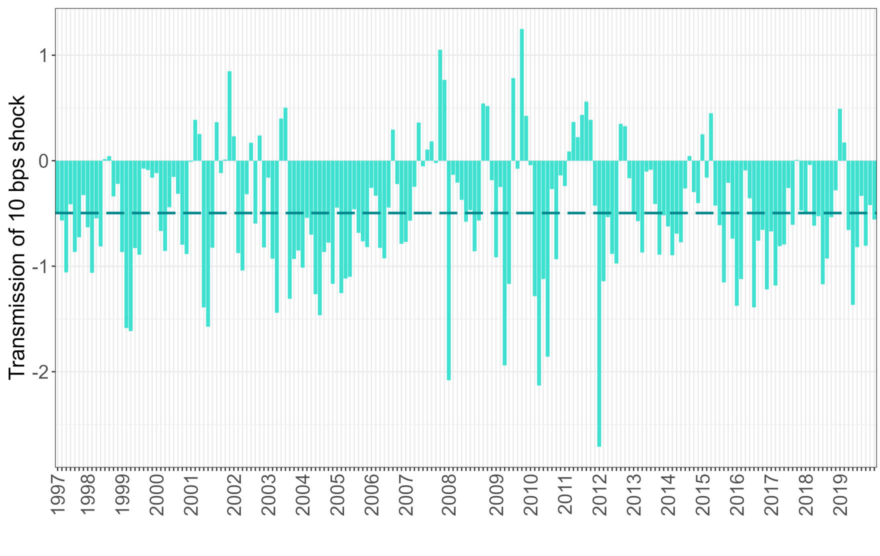
We can compare this finding to the contribution of the Spreads factor, which loads most strongly on the slope of the yield curve. The forward-looking information for output and inflation embedded in the slope of the yield is well known. This factor weakens transmission in

Figure 6: Historical decomposition of monetary policy transmission to yields and equities

(a) 10Y Yields



(b) Equities

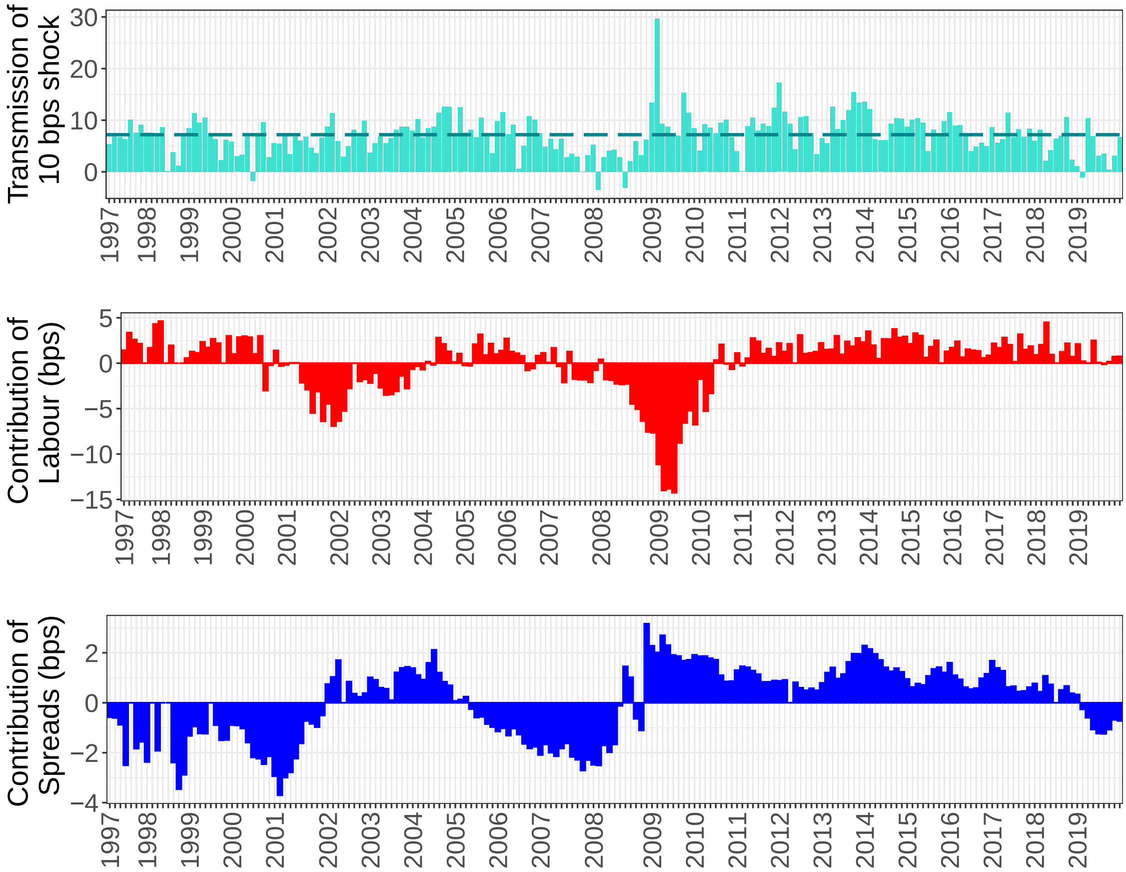


Notes: Figure shows the time-varying total effect, computed over the sample period, for yields and equities.

advance of the two recessions, reflecting the flat/inverted yield curves and the market expectations of weaker future economic conditions.

While the real economy (Labour) is important for understanding transmission, it is not the only factor that matters. The Spreads factor, among others, matters over time and these can swamp the contribution of the real economy. We observe that some of the FOMC days on which there was the strongest transmission came during 2009, which is during the latter portion

Figure 7: Historical decomposition of transmission to yields, with the contributions of Labour and Spreads factors



Notes: Figure shows the time-varying total effect, as well as time-varying interaction effects based on the Labour and Spreads factors, computed over the sample period, for yields and equities.

of the recession in the wake of the GFC. At this point, the real economy is still contributing strongly and negatively to transmission, but its contribution is outweighed. The Spreads factor makes a positive contribution at this point, anticipating the coming recovery period. From this, we can conclude that the common low dimensional stratification of one's data into expansion and recession periods misses a more complex story – there are important "within recession" dynamics at play. Our results show that transmission is not reducible to analyses applied to sub-periods.

5.3 The low dimensional approach

While we have shown that transmission has high dimensional state-dependence, it is also worth examining in more detail how our findings relate to those that can arise in low dimensional treatments. In Table 3 we present results from four models which look at how transmission down the yield curve might depend upon the state of the real economy. In column (1), we define a “weak growth” dummy, following Bauer et al. (2022b), which takes a value of one if the U.S. output gap is below its median. Interacting this dummy with the monetary policy surprise, along the lines of equation 2, we find that transmission is significantly stronger when the economy is weak. In a strong growth period, a 10bp tightening surprise would transmit to the 10 year as 5.7bp, but would transmit as 8.1bp if growth were weak. This finding is in line with the results in Bauer et al. (2022b), who employ a very similar specification, but contradicts the spirit of the contributions of Keynes (1936) and Tenreyro and Thwaites (2016).

In columns (2) and (3), we repeat the exercise but use the U.S. unemployment rate and real GDP growth rates to represent the state, respectively. A higher unemployment rate strengthens transmission, while a higher GDP growth rate weakens transmission. Finally, in column (4), we estimate a Smooth Transition regression with two regimes based on a moving average of U.S. real GDP growth. In the recessionary state, we find that transmission is almost twice as strong as in the expansionary state. Each of the models in Table 3 therefore supports the view that monetary policy transmission is counter-cyclical, i.e., stronger when the real economy is weaker.

Table 3 reduces state-dependence to a single dimension: the strength of the real economy. This naturally begs the question of how robust the findings are to other potential sources of non-linearity that one could include. To examine this, we take the specification in column (1), and add the factors we have extracted from our large mixed-frequency dataset. We omit factors that have a real economy interpretation, including our Labour factor, leaving the real economy to be represented by the weak growth dummy. We iteratively add the factors, starting with the specification in column (1) that includes none, finishing with all non-real economy factors included.

In Figure 8, we depict the path of the coefficient and t-statistic pair $\{\delta, t\}$ on the weak growth interaction with the monetary policy surprise, as we add the factors. The horizontal axis shows the t-statistic on the interaction variable, while the vertical axis shows the coefficient. The vertical, dashed lines demarcate the region $-1.645 < t < 1.645$, within which the coefficient would not be significant at the 90% confidence level. Starting from the upper right-most pair, which matches column (1) in Table 3, we find the statistically significant, counter-cyclical result in which monetary policy is stronger in recessions. After adding several factors, the coefficient

Table 3: Transmission to the 10 year: low-dimensional stratification approach

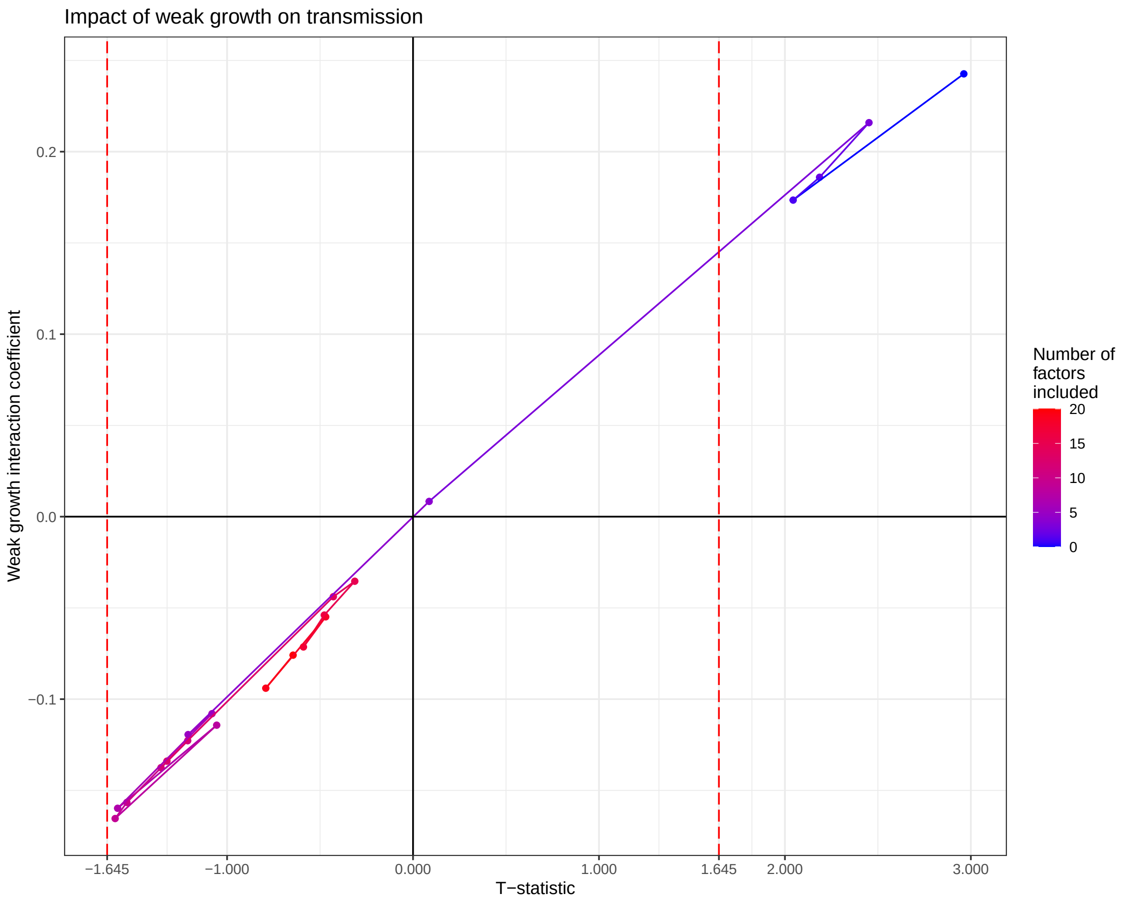
	Model			
	Weak growth (1)	Unemployment (2)	GDP growth (3)	Regimes (ST) (4)
MPS_t	0.568^{***}	0.690^{***}	0.648^{***}	
	(0.047)	(0.038)	(0.039)	
$Weak_t \times MPS_t$	0.243^{***}			
	(0.082)			
$Weak_t$	0.003			
	(0.391)			
$Unemp.Rate_t \times MPS_t$		0.131^{***}		
		(0.027)		
$Unemp.Rate_t$		-0.003		
		(0.108)		
$GDPgrowth_t \times MPS_t$			-0.056^{**}	
			(0.023)	
$GDPgrowth_t$			-0.001	
			(0.120)	
$Constant(expansion)$				0.282
				(0.266)
$MPS_t(expansion)$				0.478^{***}
				(0.052)
$Constant(recession)$				0.355
				(0.468)
$MPS_t(recession)$				1.100^{***}
				(0.105)
$Constant$	0.316	0.278	0.326	
	(0.268)	(0.187)	(0.199)	
Adjusted R^2	0.607	0.634	0.600	0.630
N	187	187	187	187

Notes: Models 1-3 are of the form in equation 2, with one state variable in each specification. Weak growth is a dummy taking the value 1 if the output gap is less than its median. Unemployment rate is the U.S. unemployment rate, demeaned. GDP growth is the 1 quarter lagged real U.S. GDP growth rate, demeaned. Model (4) is a Smooth Transmission regression with two regimes. The state variable is a 7 quarter moving average of real U.S. GDP growth, with the logistic function parameterised as in Tenreyro and Thwaites (2016). *p<0.1; **p<0.05; ***p<0.01

loses significance and becomes approximately zero. As we continue to add factors, the coefficient becomes negative, indicating the pro-cyclical result in which monetary policy is stronger in an period of strong economic growth.

It is of note that the factor that causes the weak growth dummy first to lose its significance is the Spreads factor mentioned in Section 4. This highlights the importance of considering the correlation of one's low dimensional state variable with other important drivers of non-linearity. In this case, the real economy state variable is correlated with a financial state variable. As such, the real economy variable does not cleanly represent the real economy state, and the estimated parameter suffers from omitted variable bias.

Figure 8: Effect of weak growth on transmission, with addition of non-macroeconomic factors



Notes: Figure displays the path of the coefficient and t-statistic pair $\{\delta, t\}$ on the weak growth interaction with the monetary policy surprise, as we sequentially add interaction effects with our factors. Only factors from groups that are not based on real economy variables are used in the exercise.

As we add more and more information, the effect of the real economy stabilises on a pro-cyclical conclusion, albeit without statistical significance. In Figure 3, we showed that our factor representing the real economy robustly shows the pro-cyclical result, controlling for the information in all other factors, and is in fact the most economically significant individual factor. From this we can conclude that a factor of real economy variables contains more information than a dummy variable does, emphasising the Cloyne et al. (2023) argument that stratification of data is a less robust method than using multiple, continuous interactions.

6 Robustness Checks

6.1 Estimator

As outlined in Section 4, our real and financial dataset is large. For tractability, it is necessary to apply some form of data reduction approach. While we favour PCA, one could also use alternative algorithms, for example, those that employ sparse approaches to estimation, such as LASSO. The Elastic Net generalisation of LASSO (Zou and Hastie, 2005) solves the following minimisation problem:

$$\min_{\alpha,\beta\in\mathbb{R};\delta,\phi\in\mathbb{R}^k} \left\{ \frac{1}{2}\sum_{t=1}^{N} \left(y_t - \alpha - \beta MPS_t - \delta MPS_t \times (\mathbf{X}_{t-1} - \bar{\mathbf{X}}) - \phi(\mathbf{X}_{t-1} - \bar{\mathbf{X}})\right)^2 \right. \\ \left. + \left[\frac{1}{2}(1-\psi)||\theta||_2^2 + \psi||\theta||_1\right] \right\} \quad (5)$$

for some $\lambda \geq 0$ and $\psi \in [0,1]$, where $||u||_p \equiv \sum_{j=1}^{N}(|u_j|^p)^{1/p}$ is the l_1-norm and $\theta = [\delta \quad \phi]$. We set the parameter ψ to equal 0.99 and estimate λ by 10-fold cross-validation. We summarise the results from our LASSO estimation using a non-parametric bootstrap, drawing with replacement from our dataset 500 times and re-estimating λ on each generated dataset. In each bootstrap draw, the data are partitioned into 10 groups, or folds, of equal size. Iteratively, one fold is held out of the sample and predicted using the set of variables selected for a given λ. The average mean squared error (MSE) out of sample is calculated over these folds for that λ, and the algorithm proceeds to search over different values of λ to find the minimum MSE. The λ that gives the minimum MSE is the optimal one. Although bootstrapping is not strictly necessary, it is employed for robustness, given some of our macro-financial variables may be correlated with each other. This way, we ensure our results are robust to well-known problems of data "jitter" (Taddy, 2017), by which LASSO routines can select across correlated variables in an arbitrary manner.

Note that equation 5 differs from equation 3 in taking as input data the vector of variables $\mathbf{X}$

in our data, rather than the vector of factors $\mathbf{Z}$ derived from the data. Figure 9 in the Appendix shows the histograms of numbers of variables selected by the LASSO algorithm for both 10 year yields and equities. From these histograms we can conclude that the multi-dimensional transmission is robust – the median number of variables selected is approximately 20 for both.

6.2 Factor extraction approach

We extracted the factors from our dataset group-by-group as these factors are the most economically interpretable. It is also possible to extract factors without reference to the groups. Figure 10 in the Appendix shows the estimated Direct and Indirect Effects of transmission to yields and equities using 20 non-group factors. From this we can observe that the magnitudes of the direct effects are similar for both dependent variables. For yields, we find 12 factors to be statistically significant, while for equities we find that three are. This shows that transmission is multi-dimensional, in both cases, using this alternative PCA approach.

Table 4 in the Appendix shows the out-of-sample performances of Elastic Net LASSO, Group factors and Non-Group factors. These MSEs are calculated with reference to the folds of the data in the cross-validation step of LASSO. We can run our PCA-based estimation within the same folds of data as LASSO generated, allowing comparison of performance. It is worth noting that LASSO optimises its selection of variables to minimise the MSE for each dependent variable. The PCA approaches do not do any optimisation and make no reference to any dependent variable during their extraction. It is unsurprising, therefore, that the lowest MSEs are those from the LASSO. However, it is very encouraging how similar the MSEs of the factor approaches are to the LASSO. We also note that the Group and Non-Group factors have broadly similar performance. In summary, our favoured Group factor approach has strong performance on this dimension compared with the alternatives.

6.3 Alternative monetary policy surprises

In the baseline analysis, and following a number of papers in the literature, we use the intraday changes in Two Year treasury yield as the measure of monetary policy surprise. Gürkaynak et al. (2005) showed that monetary policy surprises could be described in two dimensions; target and path. Extending upon this, Swanson (2021b) specify three structural monetary policy surprises: Federal Funds Rate (FFR), Large Scale Asset Purchases (LSAP) and Forward Guidance (FG) using the U.S. data. Hence, in Table 5 in the Appendix we show the significant factor interactions for the Two Year alongside those if the monetary policy surprise is one of the Swanson (2021b) surprises. This exercise is done both for the 10 year yield and equities, as before.

Our results on multi-dimensionality are robust across different monetary policy surprises. For most surprise-dependent variable combinations, more than one interaction is statistically significant with the numbers of similar order to our Two Year results. The one exception to this is transmission of the LSAP surprise to equities in which there is a single dimension of state-dependence.

6.4 Window size of the dependent variables

In the baseline analysis, we use intraday changes in asset prices as dependent variables. In the literature, daily changes or two-day changes in asset prices are also used. With reference to the yields, Swanson (2021a) explains that although changing the window size should not change the results in theory, in practice, this might not be the case due to some observations around 2008-2009. For equities, on the other hand, Lakdawala and Schaffer (2019) show that transmission may not be robust to the greater noise in a broad window. Similarly, Bauer et al. (2022a) reports smaller coefficients using daily changes rather than intraday.

In general, it is reasonable to expect that effects may become weaker the wider the window. Table 6 in the Appendix reports the correlation of the asset price changes in different window sizes. The correlation coefficient between intraday and daily changes is 0.66 for yields and 0.44 for the equities. The relations between daily and two-day changes are stronger than those with intraday changes.

In Table 7 in the Appendix, we provide results using daily and two-day changes in the dependent variables, in addition to the baseline. We find that our results on multi-dimensional state-dependence are robust to the window of the dependent variable, with three significant interaction effects for transmission to yields even with two-day changes in yields. The fit of the model reduces the the wider the window, indicating the greater difficulty in explaining variation in movements with wider changes.

6.5 Excluding unscheduled meetings

We investigate whether excluding unscheduled meetings FOMC changes our results. Lakdawala and Schaffer (2019) suggest that unscheduled meetings can affect equity prices differently than scheduled ones. Table 8 in the Appendix shows that our results are robust to excluding unscheduled meetings. The same interaction variables are found to be significant across two specifications for both yields and equities. The only notable change is the better performance of the model for equities once the unscheduled meetings are excluded from the sample.

6.6 Controlling for structurally identified surprises

Jarociński and Karadi (2020) provide two structurally identified surprises for the U.S. – one relating to monetary policy and one relating to central bank information. In Table 9 in the Appendix, we estimate the transmission of surprise to the Two Year yield to the 10 year yield controlling for the Jarociński and Karadi (2020) surprises each separately and then jointly. We find that the interaction effects of our factors to our monetary policy surprise are not sensitive to controlling for either or both of the Jarociński and Karadi (2020) surprises.

7 Conclusion

The extent to which monetary policy transmission is non-linear is a key question for monetary policymakers. Ultimately, the question is whether the policymakers' tools are always as powerful or whether they sometimes have more (or less) effectiveness. The relevance of this for the policymaker is immediate. They must use the tools at their disposal to achieve their objectives, but if non-linearities exist, they 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 state-dependence 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. We provide one example in which the estimated effect of the real economy on transmission can change, from being stronger in a recession to weaker in one, as more information about the state of the economy is added.

This paper contributes by taking a *high dimensional* approach. We design a large, mixed-frequency dataset of real and financial variables to incorporate many sources of non-linearity highlighted in the literature. From this, we extract "meeting frequency factors" aligned to meetings of the FOMC. To the best of our knowledge, this is the first paper to do so. Using these factors, we show that monetary policy transmission to the 10 year yield and to equities is multi-dimensional, with 10 and six significant states respectively. We show that these non-linear effects are economically large and meaningful. Transmission of a monetary policy surprise to yields can almost double if the labour market is very tight, while transmission to equities can be two-and-a-half to three times stronger if interest rates or equity levels are low.

Our approach allows us to examine times at which monetary policy transmission has been more, or less, powerful. We find that it is broadly "pro-cyclical", with some of the weakest periods of transmission coinciding with economic recessions. We also find an unambiguously pro-cyclical contribution of the real economy according to the most economically important individual factor that we extract. However, the real economy is not the only dimension that matters. We find important contributions from financial factors that can outweigh the real economy effects. Some of the days on which there is the strongest monetary policy transmission occur in the latter portion of the recession following the Global Financial Crisis. These dynamics in transmission within the same recession would be missed by stratifying the data into recessions vs. expansions. As such, our results are not reducible to low dimensional stratification of the data.

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 in high dimensional specifications.

Appendix

Figure 9: Histograms of numbers of LASSO-selected variables across bootstrap samples

(a) U.S. 10 Year yields

(b) U.S. Equities

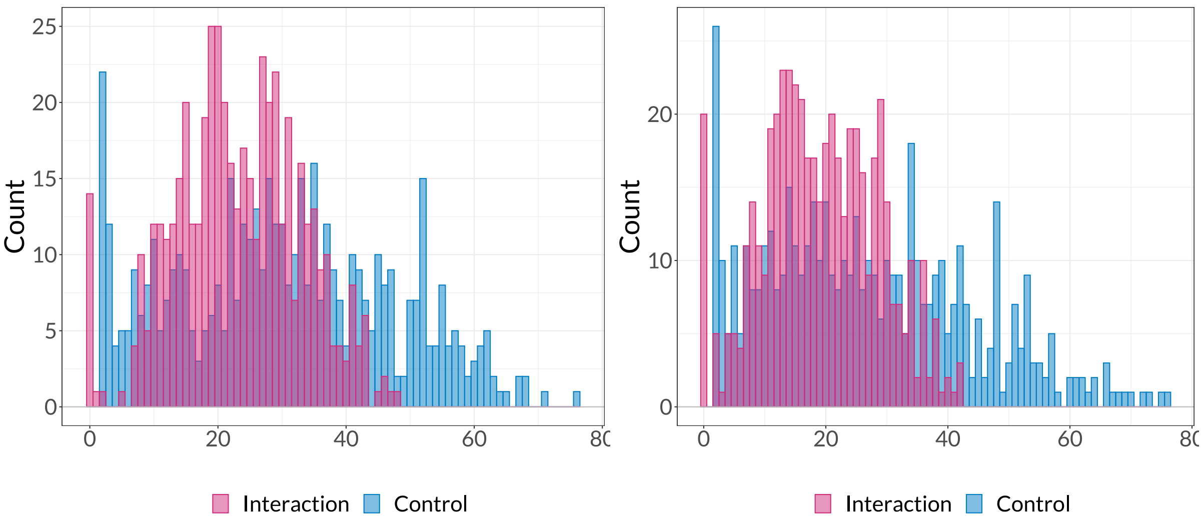
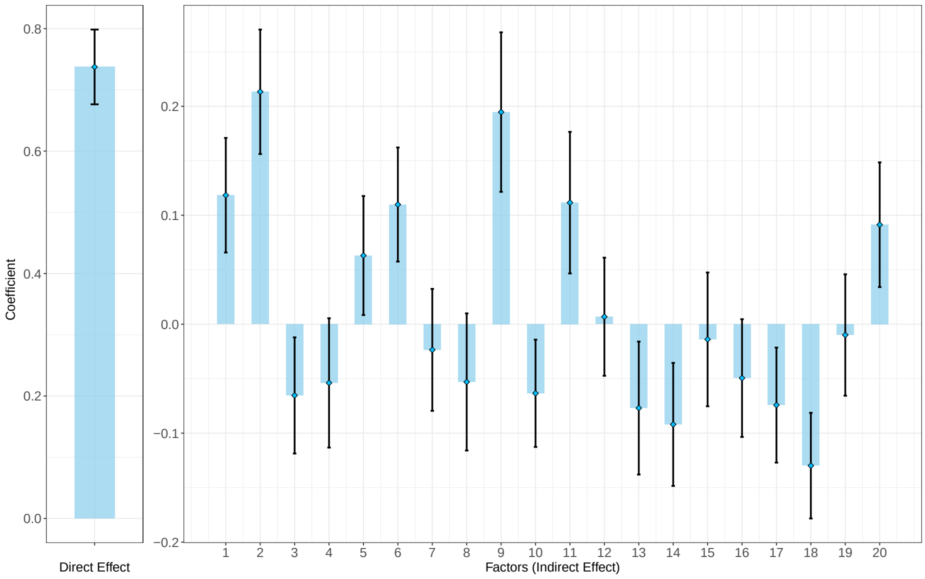


Table 4: Average Out-of-sample Mean Squared Error, sparsity method

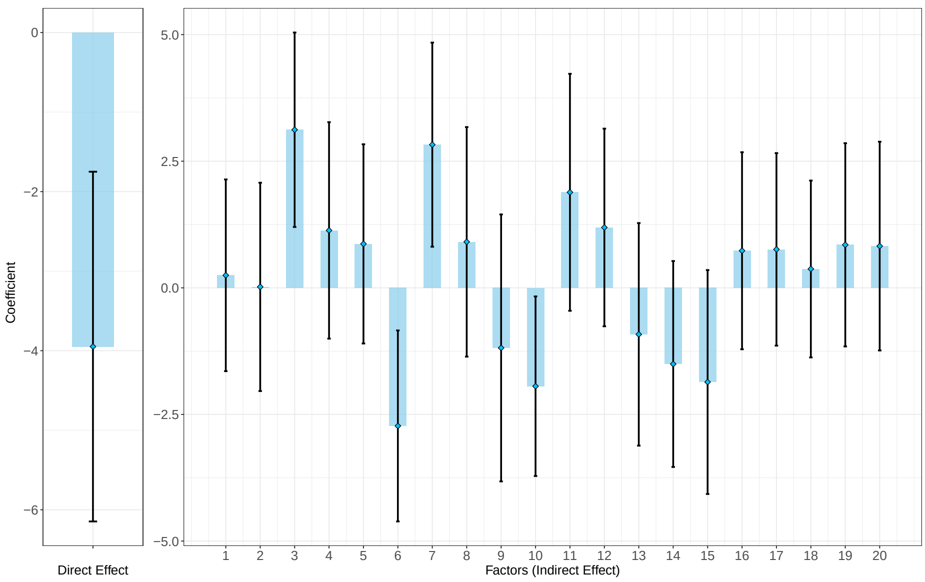
	LASSO	Non-Group Factors	Group Factors
10Y Yield	0.00068	0.00069	0.00082
Equities	0.48315	0.54340	0.51902

Figure 10: Transmission to yields and equities, based on Non-Group factors

(a) U.S. 10 Year yields



(b) U.S. Equities



Notes: Factors are scaled to 1 S.D. increase. Error bands show 90 per cent confidence intervals.

Table 5: Factor interactions, by dependent variable

		US10Y Yields				**U.S. Equities**			
		Baseline	**Swanson (2021)**			**Baseline**	**Swanson (2021)**		
PC	Factor names	Two Year	FFR	LSAP	FG	Two Year	FFR	LSAP	FG
1	Production		x	x					
2	Labour	x	x				x		x
3	Housing		x	x		x			
4	Consumption			x					
5	Loans credit			x					
6	Spreads	x			x	x	x		x
7	Oil prices	x	x		x				x
8	Equities								
9	Uncertainty								
10	Financial stress			x					x
11	Output	x					x		
12	Reserves	x			x				
13	Interest rates		x			x		x	
14	Food and comm. prices	x	x		x				
15	Equity valuations					x			x
16	Volatility	x		x		x			x
17	Financial conditions		x						
18	Income	x	x	x			x		
19	Money supply								x
20	Exchange rates								
21	Consumer prices					x			x
22	Equities change	x			x				
23	Policy uncertainty			x					
24	Financial cycle	x							

Table 6: Correlation between the changes in asset prices measured at different windows

10Y Yield	Two day change	Daily change	Intraday change
Two day change	1.00	0.75	0.46
Daily change	0.75	1.00	0.66
Intraday change	0.46	0.66	1.00
Equities	Two day change	Daily change	Intraday change
Two day change	1.00	0.66	0.33
Daily change	0.66	1.00	0.48
Intraday change	0.33	0.48	1.00

Table 7: Robustness to window of changes in asset prices

Dependent variable:	US 10Y Yields			US Equities		
	Intraday	Daily	Two-day	Intraday	Daily	Two-day
	(1)	(2)	(3)	(4)	(5)	(6)
MPS_t	0.719***	0.773***	0.811***	−0.050***	−0.011***	−0.013**
	(0.039)	(0.130)	(0.204)	(0.014)	(0.003)	(0.005)
ProductionxMPS_t	−0.019	−0.042	−0.045	−0.00003	−0.001	0.0003
	(0.023)	(0.078)	(0.123)	(0.008)	(0.002)	(0.003)
LabourxMPS_t	0.105***	0.156	0.146	0.015	0.007***	0.009**
	(0.030)	(0.101)	(0.159)	(0.011)	(0.003)	(0.004)
HousingxMPS_t	−0.085	−0.053	0.294	−0.040**	0.0003	0.003
	(0.052)	(0.176)	(0.276)	(0.019)	(0.004)	(0.007)
ConsumptionxMPS_t	0.024	0.008	0.037	−0.004	0.001	0.006*
	(0.026)	(0.086)	(0.135)	(0.009)	(0.002)	(0.003)
Loansxshock	0.013	0.029	0.002	−0.010	−0.003	−0.005*
	(0.020)	(0.068)	(0.106)	(0.007)	(0.002)	(0.003)
SpreadxMPS_t	0.068***	0.114*	0.343***	−0.014**	−0.002	0.001
	(0.018)	(0.061)	(0.096)	(0.007)	(0.002)	(0.002)
Oil pricesxMPS_t	−0.072***	0.035	0.025	0.010	−0.002	0.0001
	(0.024)	(0.081)	(0.127)	(0.009)	(0.002)	(0.003)
EquitiesxMPS_t	−0.012	0.067	−0.008	−0.005	−0.0001	−0.0001
	(0.035)	(0.117)	(0.184)	(0.013)	(0.003)	(0.005)
UncertaintyxMPS_t	0.003	−0.010	0.014	−0.004	0.002	0.005
	(0.027)	(0.090)	(0.141)	(0.010)	(0.002)	(0.003)
Financial stressxMPS_t	0.037	0.096	0.094	0.016	0.009**	0.007
	(0.046)	(0.156)	(0.245)	(0.017)	(0.004)	(0.006)
OutputxMPS_t	0.084***	0.213**	0.203	0.016	0.005**	0.009**
	(0.030)	(0.101)	(0.159)	(0.011)	(0.003)	(0.004)
ReservesxMPS_t	0.089***	0.265**	0.222	−0.009	−0.001	0.005
	(0.034)	(0.113)	(0.178)	(0.012)	(0.003)	(0.004)
Interest ratexMPS_t	−0.030	−0.122	−0.087	0.021*	0.0003	0.0003
	(0.029)	(0.099)	(0.156)	(0.011)	(0.002)	(0.004)
Food commodity pricesxMPS_t	−0.142***	−0.305**	−0.369*	0.022	0.011***	0.016***
	(0.042)	(0.140)	(0.220)	(0.015)	(0.004)	(0.005)
Equity valuationxMPS_t	−0.014	0.163	0.483**	0.049***	0.003	0.005
	(0.045)	(0.152)	(0.239)	(0.016)	(0.004)	(0.006)
VolatilityMPS_t	0.081**	0.112	−0.005	−0.030**	−0.003	0.005
	(0.039)	(0.132)	(0.208)	(0.014)	(0.003)	(0.005)
Financial conditionsxMPS_t	0.023	0.024	0.027	−0.004	−0.003	−0.005
	(0.035)	(0.119)	(0.187)	(0.013)	(0.003)	(0.005)
IncomexMPS_t	−0.066**	−0.176*	−0.278*	−0.001	0.001	−0.002
	(0.028)	(0.094)	(0.148)	(0.010)	(0.002)	(0.004)
MoneyxMPS_t	−0.050	0.005	−0.129	−0.024	−0.003	0.011*
	(0.045)	(0.152)	(0.238)	(0.016)	(0.004)	(0.006)
Exchange ratexMPS_t	0.042	0.106	−0.006	−0.017	−0.0003	0.001
	(0.037)	(0.126)	(0.198)	(0.014)	(0.003)	(0.005)
Consumer pricesxMPS_t	−0.070	−0.159	0.094	−0.034*	−0.002	0.002
	(0.048)	(0.163)	(0.256)	(0.018)	(0.004)	(0.006)
Equities changexMPS_t	−0.187***	−0.234	−0.718***	−0.013	−0.007*	−0.016**
	(0.049)	(0.167)	(0.262)	(0.018)	(0.004)	(0.006)
Policy uncertaintyxMPS_t	0.048	0.105	0.133	0.016	0.001	−0.001
	(0.034)	(0.116)	(0.183)	(0.013)	(0.003)	(0.004)
Financial cyclexMPS_t	0.128***	0.108	−0.062	0.022	0.007*	0.006
	(0.045)	(0.152)	(0.239)	(0.016)	(0.004)	(0.006)
Constant	0.446***	0.635	0.031	0.023	0.043***	0.022
	(0.138)	(0.467)	(0.733)	(0.050)	(0.012)	(0.018)
Factor main effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.821	0.349	0.257	0.177	0.192	0.150
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 8: Robustness to exclusion of unscheduled meetings

Dependent variable:	US 10Y Yields		US Equities	
	All meetings	Scheduled meetings	All meetings	Scheduled meetings
	(1)	(2)	(3)	(4)
MPS_t	0.719^{***}	0.719^{***}	-0.050^{***}	-0.056^{***}
	(0.039)	(0.041)	(0.014)	(0.011)
ProductionxMPS_t	-0.019	-0.015	-0.00003	0.0001
	(0.023)	(0.024)	(0.008)	(0.007)
LabourxMPS_t	0.105^{***}	0.094^{***}	0.015	0.002
	(0.030)	(0.035)	(0.011)	(0.010)
HousingxMPS_t	-0.085	-0.081	-0.040^{**}	-0.034^{**}
	(0.052)	(0.053)	(0.019)	(0.015)
ConsumptionxMPS_t	0.024	0.026	-0.004	0.0003
	(0.026)	(0.028)	(0.009)	(0.008)
LoansxMPS_t	0.013	0.013	-0.010	-0.012^{**}
	(0.020)	(0.020)	(0.007)	(0.006)
SpreadxMPS_t	0.068^{***}	0.072^{***}	-0.014^{**}	-0.013^{**}
	(0.018)	(0.020)	(0.007)	(0.006)
Oil pricesxMPS_t	-0.072^{***}	-0.087^{***}	0.010	0.005
	(0.024)	(0.027)	(0.009)	(0.008)
EquitiesxMPS_t	-0.012	-0.007	-0.005	-0.006
	(0.035)	(0.035)	(0.013)	(0.010)
UncertaintyxMPS_t	0.003	-0.004	-0.004	-0.008
	(0.027)	(0.027)	(0.010)	(0.008)
Financial stressxMPS_t	0.037	0.049	0.016	0.015
	(0.046)	(0.049)	(0.017)	(0.014)
OutputxMPS_t	0.084^{***}	0.074^{**}	0.016	0.003
	(0.030)	(0.031)	(0.011)	(0.009)
ReservesxMPS_t	0.089^{***}	0.087^{**}	-0.009	-0.015
	(0.034)	(0.034)	(0.012)	(0.009)
Interest ratexMPS_t	-0.030	-0.008	0.021^{*}	0.032^{***}
	(0.029)	(0.035)	(0.011)	(0.010)
Food commodity pricesxMPS_t	-0.142^{***}	-0.170^{***}	0.022	0.019
	(0.042)	(0.047)	(0.015)	(0.013)
Equity valuationxMPS_t	-0.014	-0.038	0.049^{***}	0.025^{*}
	(0.045)	(0.049)	(0.016)	(0.014)
VolatilityxMPS_t	0.081^{**}	0.063	-0.030^{**}	-0.030^{**}
	(0.039)	(0.045)	(0.014)	(0.012)
Financial conditionsxMPS_t	0.023	0.025	-0.004	-0.004
	(0.035)	(0.041)	(0.013)	(0.011)
IncomexMPS_t	-0.066^{**}	-0.070^{**}	-0.001	-0.001
	(0.028)	(0.028)	(0.010)	(0.008)
MoneyxMPS_t	-0.050	-0.049	-0.024	-0.008
	(0.045)	(0.048)	(0.016)	(0.013)
Exchange ratexMPS_t	0.042	0.056	-0.017	-0.007
	(0.037)	(0.040)	(0.014)	(0.011)
Consumer pricesxMPS_t	-0.070	-0.065	-0.034^{*}	-0.023^{*}
	(0.048)	(0.049)	(0.018)	(0.013)
Equities changexMPS_t	-0.187^{***}	-0.182^{***}	-0.013	0.002
	(0.049)	(0.053)	(0.018)	(0.015)
Policy uncertaintyxMPS_t	0.048	0.044	0.016	0.013
	(0.034)	(0.036)	(0.013)	(0.010)
Financial cyclexMPS_t	0.128^{***}	0.113^{**}	0.022	0.009
	(0.045)	(0.048)	(0.016)	(0.013)
Constant	0.446^{***}	0.396^{***}	0.023	-0.061
	(0.138)	(0.145)	(0.050)	(0.040)
Factor main effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.821	0.819	0.177	0.287
Note:				$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 9: Robustness to Jarociński and Karadi (2020) surprises

	Model			
	Baseline	INFO surprise	MPOL surprise	Both surprises
	(1)	(2)	(3)	(4)
MPS_t	0.719***	0.754***	0.799***	0.912***
	(0.039)	(0.049)	(0.065)	(0.079)
ProductionxMPS_t	−0.019	−0.011	−0.011	−0.015
	(0.023)	(0.026)	(0.026)	(0.025)
EmploymentxMPS_t	0.105***	0.078**	0.074**	0.061*
	(0.030)	(0.034)	(0.034)	(0.033)
HousingxMPS_t	−0.085	−0.107	−0.098	−0.066
	(0.052)	(0.066)	(0.067)	(0.067)
ConsumptionxMPS_t	0.024	0.005	0.010	0.007
	(0.026)	(0.031)	(0.031)	(0.031)
LoansxMPS_t	0.013	0.011	0.020	0.024
	(0.020)	(0.024)	(0.024)	(0.023)
SpreadxMPS_t	0.068***	0.049**	0.056**	0.049**
	(0.018)	(0.021)	(0.021)	(0.021)
OilpricesxMPS_t	−0.072***	−0.065**	−0.069**	−0.065**
	(0.024)	(0.029)	(0.029)	(0.028)
EquitiesxMPS_t	−0.012	0.004	−0.003	−0.006
	(0.035)	(0.042)	(0.042)	(0.041)
UncertaintyxMPS_t	0.003	−0.023	−0.017	−0.019
	(0.027)	(0.036)	(0.036)	(0.035)
FinancialstressxMPS_t	0.037	0.061	0.039	0.046
	(0.046)	(0.058)	(0.058)	(0.057)
OutputxMPS_t	0.084***	0.086**	0.079**	0.068*
	(0.030)	(0.037)	(0.037)	(0.036)
ReservesxMPS_t	0.089***	0.115***	0.132***	0.115***
	(0.034)	(0.040)	(0.039)	(0.039)
InterestratexMPS_t	−0.030	−0.010	−0.020	−0.018
	(0.029)	(0.037)	(0.037)	(0.036)
FoodcommmoditypricesxMPS_t	−0.142***	−0.135***	−0.154***	−0.146***
	(0.042)	(0.049)	(0.049)	(0.048)
EquityvaluationxMPS_t	−0.014	−0.021	−0.027	−0.020
	(0.045)	(0.055)	(0.055)	(0.053)
VolatilityxMPS_t	0.081**	0.040	0.054	0.058
	(0.039)	(0.048)	(0.048)	(0.047)
FinancialconditionsxMPS_t	0.023	0.041	0.036	0.033
	(0.035)	(0.045)	(0.045)	(0.044)
IncomexMPS_t	−0.066**	−0.067*	−0.067*	−0.054
	(0.028)	(0.035)	(0.035)	(0.034)
MoneyxMPS_t	−0.050	−0.050	−0.041	−0.045
	(0.045)	(0.051)	(0.050)	(0.049)
ExchangeratexMPS_t	0.042	0.021	0.021	0.019
	(0.037)	(0.043)	(0.042)	(0.041)
ConsumerpricesxMPS_t	−0.070	−0.076	−0.064	−0.049
	(0.048)	(0.057)	(0.057)	(0.056)
Equities changexMPS_t	−0.187***	−0.129**	−0.133**	−0.118*
	(0.049)	(0.064)	(0.063)	(0.062)
PolicyuncertaintyxMPS_t	0.048	0.072	0.047	0.047
	(0.034)	(0.046)	(0.047)	(0.045)
FinancialcyclexMPS_t	0.128***	0.083	0.082	0.064
	(0.045)	(0.055)	(0.055)	(0.054)
Information surprise		−6.219		−22.693**
		(6.909)		(9.368)
MPOL surprise			−6.470	−19.465**
			(5.669)	(7.706)
Constant	0.446***	0.243	0.267	0.226
	(0.138)	(0.170)	(0.169)	(0.165)
Observations	191	148	148	148
Factor main effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.821	0.839	0.840	0.847

Note: *p<0.1; **p<0.05; ***p<0.01

Table 10: Name of group factors and top loading variables

PC1: Production	**PC2: Labour**	**PC3: Housing**	**PC4: Cons. Inventories**	**PC5: Loans credit**
US_FREDMD_INDPRO	US_FREDMD_PAYEMS	US_FREDMD_HOUST	US_FREDMD_CMRMTSPLx	US_FREDMD_DTCTHFNM
US_FREDMD_IPMANSICS	US_FREDMD_USGOOD	US_FREDMD_PERMIT	US_FREDMD_ISRATIOx	US_FREDMD_NONREVSL
US_FREDMD_CUMFNS	US_FREDMD_USTPU	US_FREDMD_HOUSTNE	US_FREDMD_RETAILx	US_FREDMD_CONSPI
US_FREDMD_IPFINAL	US_FREDMD_MANEMP		US_FREDMD_ACOGNO	US_FREDMD_DTCOLNVHFNM
US_FREDMD_IPMAT	US_FREDMD_SRVPRD		US_FREDMD_DPCERA3M086SBEA	US_FREDMD_NONBORRES
PC6: Spreads	**PC7: Oil prices**	**PC8: Equities**	**PC9: Uncertainty**	**PC10: Financial stress**
US_FREDMD_T10YFFM	US_FREDMD_OILPRICEx	US_FREDMD_SP_500	US_EMVOLTK	US_NFCI_Credit
US_FREDMD_FEDFUNDS	US_FREDMD_WPSID62	US_FREDMD_SP_indust	US_EMVOLTK_COMDTY	US_CISS
US_FREDMD_AAAFFM	US_FREDMD_WPSID61	US_FREDMD_SP_div_yield	US_EMVOLTK_MPOL	US_FINSTRESS_KCF
US_FREDMD_BAAFFM	US_FREDMD_CPIAUCSL	US_SP500_3M_BS	US_EMVOLTK_MACROBDQUANT	US_FINSTRESS_STLF
US_FREDMD_TB3SMFFM	US_FREDMD_PPICMM	US_FREDMD_SP_PE_ratio	US_EMVOLTK_MACROLAB	US_CREDTTIGHT_LRG2SML
PC11: Output (utilities)	**PC12: Reserves**	**PC13: Interest rate**	**PC14: Food and comm. Prices**	**PC15: Equities valuation**
US_FREDMD_IPB51222S	US_FREDMD_NONBORRES	US_FREDMD_GS1	WW_GLOBPRC_FOOD	US_FREDMD_SP_PE_ratio
US_FREDMD_IPNCONGD	US_FREDMD_TOTRESNS	US_FREDMD_TB3MS	US_BCOM_3M_BS	US_FREDMD_SP_div_yield
US_FREDMD_IPCONGD	US_FREDMD_REALLN	US_FREDMD_GS10	US_CONF_INFL_OECD	US_FREDMD_SP_indust
US_FREDMD_IPFINAL	US_FREDMD_BUSLOANS	US_TR_SKEW_BS	US_FREDMD_WPSID61	US_SP500_3M_BS
US_FREDMD_IPNMAT	US_FREDMD_INVEST	US_FREDMD_EXCAUSx	US_FREDMD_CPIAUCSL	US_FREDMD_SP_500
PC16: Volatility	**PC17: Financial conditions**	**PC18: Income**	**PC19: Money**	**PC20: Exchange rate**
US_MOVE3M_IX	US_ANFCI	US_FREDMD_RPI	US_FREDMD_M2SL	US_FREDMD_EXUSUKx
WW_JPM_FX_VOL	US_NFCI_Risk	US_FREDMD_W875RX1	US_FREDMD_M2REAL	US_EBP_FG
US_RA_BHD	US_RES_PRICE_GAP	US_FREDMD_IPFUELS	US_FREDMD_BUSLOANS	US_FREDMD_TWEXAFEGSMTHx
US_EMVOLTK_MACROINFL	US_LEVERAGE_BSS	US_FREDMD_IPNMAT	US_FREDMD_REALLN	US_FREDMD_EXCAUSx
US_EMVOLTK_MACROINTRST	US_NFCI_Leverage	WW_GLOB_ACTIVITY	US_FREDMD_M1SL	US_FREDMD_GS10
PC21: Consumer prices	**PC22: Equities change**	**PC23: Policy uncertainty**	**PC24: Financial cycle**	
US_FREDMD_CPIAPPSL	US_SP500_3M_BS	WW_EPU_ADJPPPGDP	US_RES_PRICE_GAP	
US_FREDMD_CUSR0000SAD	US_FREDMD_SP_indust	US_EPU_CAT	US_LEVERAGE_BSS	
US_CONF_INFL_OECD	US_FREDMD_SP_500	US_MMU_JLN12	US_CREDIT_GAP_BIS	
US_FREDMD_PPICMM	US_FREDMD_SP_div_yield	US_EMVOLTK_MACROBUS	US_ANFCI	
WW_GLOBPRC_FOOD	US_FREDMD_SP_PE_ratio	US_MPU_BLM	US_NFCI_Risk	

Figure 11: The estimated group factors from the dataset

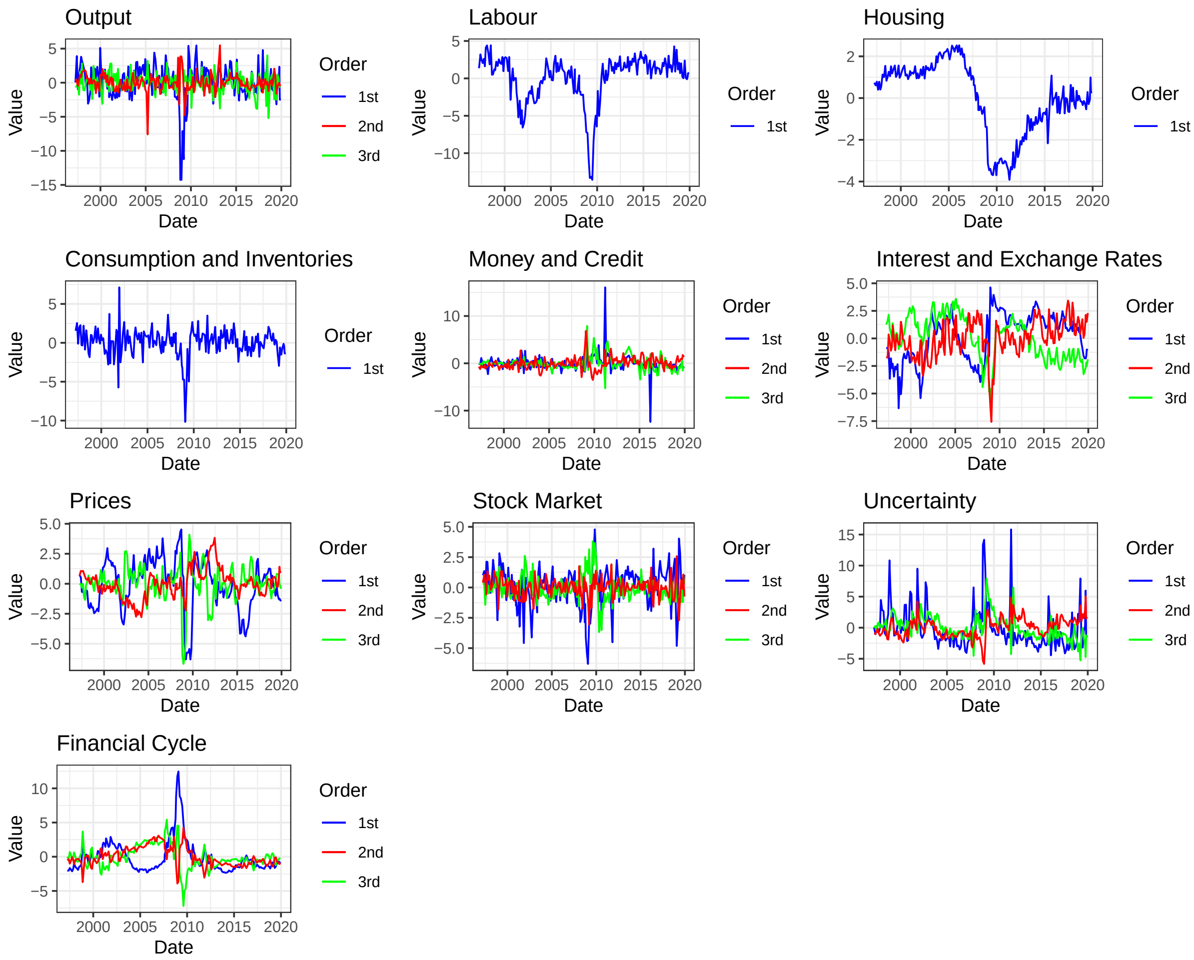


Table 11: Group and transformation keys

Transformation		Groups	
tcode	Operation	gcode	Name
1	No transformation	1	Output
2	First difference	2	Labour
3	Second difference	3	Housing
4	Log	4	Consumption, inventories
5	Log difference	5	Money and credit
6	Log second difference	6	Interest and 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
11	Second difference of six-month change		
12	YoY change for monthly data		
13	YoY change for quarterly data		

Table 12: Variable definitions

gcode	tcode	Freq.	Variable Name	Definition
1	2	M	US_FREDMD_CUMFNS[a]	Capacity Utilization: Manufacturing
1	5	M	US_FREDMD_INDPRO[a]	IP Index
1	5	M	US_FREDMD_IPB51222S[a]	IP: Residential Utilities
1	5	M	US_FREDMD_IPBUSEQ[a]	IP: Business Equipment
1	5	M	US_FREDMD_IPCONGD[a]	IP: Consumer Goods
1	5	M	US_FREDMD_IPDCONGD[a]	IP: Durable Consumer Goods
1	5	M	US_FREDMD_IPDMAT[a]	IP: Durable Materials
1	5	M	US_FREDMD_IPFINAL[a]	IP: Final Products (Market Group)
1	5	M	US_FREDMD_IPFUELS[a]	IP: Fuels
1	5	M	US_FREDMD_IPMANSICS[a]	IP: Manufacturing (SIC)
1	5	M	US_FREDMD_IPMAT[a]	IP: Materials
1	5	M	US_FREDMD_IPNCONGD[a]	IP: Nondurable Consumer Goods
1	5	M	US_FREDMD_IPNMAT[a]	IP: Nondurable Materials
1	5	M	US_FREDMD_RPI[a]	Real Personal Income
1	5	M	US_FREDMD_W875RX1[a]	Real personal income ex transfer receipts
1	5	M	WW_GLOB_ACTIVITY[b]	Index of Global Real Economic Activity
2	1	M	US_FREDMD_AWHMAN[a]	Avg Weekly Hours : Manufacturing
2	1	M	US_FREDMD_AWOTMAN[a]	Avg Weekly Overtime Hours : Manufacturing
2	5	M	US_FREDMD_CE16OV[a]	Civilian Employment
2	12	M	US_FREDMD_CES0600000008[a]	Avg Hourly Earnings : Goods-Producing
2	5	M	US_FREDMD_CES1021000001[a]	All Employees: Mining and Logging: Mining
2	12	M	US_FREDMD_CES2000000008[a]	Avg Hourly Earnings : Construction
2	12	M	US_FREDMD_CES3000000008[a]	Avg Hourly Earnings : Manufacturing
2	5	M	US_FREDMD_CLAIMSx[a]	Initial Claims
2	12	M	US_FREDMD_CLF16OV[a]	Civilian Labor Force
2	2	M	US_FREDMD_HWI[a]	Help-Wanted Index for United States
2	2	M	US_FREDMD_HWIURATIO[a]	Ratio of Help Wanted/No. Unemployed
2	5	M	US_FREDMD_MANEMP[a]	All Employees: Manufacturing
2	5	M	US_FREDMD_NDMANEMP[a]	All Employees: Nondurable goods
2	5	M	US_FREDMD_PAYEMS[a]	All Employees: Total nonfarm
2	5	M	US_FREDMD_SRVPRD[a]	All Employees: Service-Providing Industries
2	5	M	US_FREDMD_UEMP15OV[a]	Civilians Unemployed - 15 Weeks & Over
2	5	M	US_FREDMD_UEMP15T26[a]	Civilians Unemployed for 15-26 Weeks
2	5	M	US_FREDMD_UEMP27OV[a]	Civilians Unemployed for 27 Weeks and Over

2	5	M	US_FREDMD_UEMP5TO14[a]	Civilians Unemployed for 5-14 Weeks
2	5	M	US_FREDMD_UEMPLT5[a]	Civilians Unemployed - Less Than 5 Weeks
2	2	M	US_FREDMD_UEMPMEAN[a]	Average Duration of Unemployment (Weeks)
2	2	M	US_FREDMD_UNRATE[a]	Civilian Unemployment Rate
2	5	M	US_FREDMD_USCONS[a]	All Employees: Construction
2	5	M	US_FREDMD_USFIRE[a]	All Employees: Financial Activities
2	5	M	US_FREDMD_USGOOD[a]	All Employees: Goods-Producing Industries
2	5	M	US_FREDMD_USGOVT[a]	All Employees: Government
2	5	M	US_FREDMD_USTPU[a]	All Employees: Trade, Transportation & Utilities
2	5	M	US_FREDMD_USTRADE[a]	All Employees: Retail Trade
2	5	M	US_FREDMD_USWTRADE[a]	All Employees: Wholesale Trade
2	1	D	US_NFP_12M_BS[c]	Employment growth
2	1	D	US_NFP_SURP_BS[c]	Non-farm payroll surprise
3	12	M	US_FREDMD_HOUST[a]	Housing Starts: Total New Privately Owned
3	12	M	US_FREDMD_HOUSTNE[a]	Housing Starts, Northeast
3	4	M	US_FREDMD_PERMIT[a]	New Private Housing Permits (SAAR)
4	1	M	US_CONF_OECD[b]	Consumer Opinion Surveys, OECD Indicator for the United States
4	5	M	US_FREDMD_ACOGNO[a]	New Orders for Consumer Goods
4	5	M	US_FREDMD_AMDMNOx[a]	New Orders for Durable Goods
4	5	M	US_FREDMD_AMDMUOx[a]	Unfilled Orders for Durable Goods
4	5	M	US_FREDMD_ANDENOx[a]	New Orders for Nondefense Capital Goods
4	5	M	US_FREDMD_BUSINVx[a]	Total Business Inventories
4	5	M	US_FREDMD_CMRMTSPLx[a]	Real Manu. and Trade Industries Sales
4	5	M	US_FREDMD_DPCERA3M086SBEA[a]	Real personal consumption expenditures
4	2	M	US_FREDMD_ISRATIOx[a]	Total Business: Inventories to Sales Ratio
4	5	M	US_FREDMD_RETAILx[a]	Retail and Food Services Sales
4	2	M	US_FREDMD_UMCSENTx[a]	Consumer Sentiment Index
5	2	M	US_FREDMD_CONSPI[a]	Nonrevolving consumer credit to Personal Income
5	6	M	US_FREDMD_DTCOLNVHFNM[a]	Consumer Motor Vehicle Loans Outstanding
5	6	M	US_FREDMD_DTCTHFNM[a]	Total Consumer Loans and Leases Outstanding
5	5	M	US_FREDMD_M2REAL[a]	Real M2 Money Stock
5	6	M	US_FREDMD_NONREVSL[a]	Total Nonrevolving Credit
5	8	W	US_FREDMD_M1SL[a]	M1 Money Stock
5	8	W	US_FREDMD_M2SL[a]	M2 Money Stock
5	8	W	US_FREDMD_TOTRESNS[a]	Total Reserves of Depository Institutions
5	8	W	US_FREDMD_NONBORRES[a]	Reserves of Depository Institutions
5	8	W	US_FREDMD_BUSLOANS[a]	Commercial and Industrial Loans

5	8	W	US_FREDMD_REALLN[a]	Real Estate Loans at All Commercial Banks
5	8	W	US_FREDMD_INVEST[a]	Securities in Bank Credit at All Commercial Banks
6	1	M	US_EBP_FG[d]	Excess bond premium
6	1	M	US_FREDMD_COMPAPFFx[a]	3-Month Commercial Paper Minus FEDFUNDS
6	5	M	US_FREDMD_TWEXAFEGSMTHx[a]	Trade Weighted U.S. Dollar Index
6	1	M	US_IRDECOMP_IRP[b]	Inflation risk premium
6	1	M	US_IRDECOMP_RRP[b]	Real risk premium†
6	1	D	US_FREDMD_FEDFUNDS[a]	Effective Federal Funds Rate
6	1	D	US_FREDMD_TB3SMFFM[a]	3-Month Treasury C Minus FEDFUNDS
6	1	D	US_FREDMD_T1YFFM[a]	1-Year Treasury C Minus FEDFUNDS
6	1	D	US_FREDMD_T10YFFM[a]	10-Year Treasury C Minus FEDFUNDS
6	1	D	US_FREDMD_AAAFFM[a]	Moody's Aaa Corporate Bond Minus FEDFUNDS
6	1	D	US_FREDMD_BAAFFM[a]	Moody's Baa Corporate Bond Minus FEDFUNDS
6	10	D	US_FREDMD_EXSZUSx[a]	Switzerland / U.S. Foreign Exchange Rate
6	10	D	US_FREDMD_EXJPUSx[a]	Japan / U.S. Foreign Exchange Rate
6	10	D	US_FREDMD_EXUSUKx[a]	U.S. / U.K. Foreign Exchange Rate
6	10	D	US_FREDMD_EXCAUSx[a]	Canada / U.S. Foreign Exchange Rate
6	1	D	US_TR_SKEW_BS[c]	Treasury skewness†† :
6	1	D	US_SLOPE_3M_BS[c]	Yield curve slope‡
6	1	D	US_FREDMD_CP3Mx[a]	3-Month Commercial Paper
6	1	D	US_FREDMD_TB3MS[a]	3-Month Treasury
6	1	D	US_FREDMD_GS1[a]	1-Year Treasury
6	1	D	US_FREDMD_GS10[a]	10-Year Treasury
6	1	D	US_FREDMD_BAA_AAA[a]	Moody's Baa Corporate Bond Minus Aaa
7	1	M	US_CONF_INFL_OECD[b]	Consumer Opinion Surveys§
7	12	M	US_FREDMD_CPIAPPSL[a]	CPI : Apparel
7	12	M	US_FREDMD_CPIAUCSL[a]	CPI : All Items
7	12	M	US_FREDMD_CUSR0000SAD[a]	CPI : Durables
7	12	M	US_FREDMD_OILPRICEx[a]	Crude Oil, spliced WTI and Cushing
7	12	M	US_FREDMD_PPICMM[a]	PPI: Metals and metal products:
7	12	M	US_FREDMD_WPSID61[a]	PPI: Intermediate Materials
7	12	M	US_FREDMD_WPSID62[a]	PPI: Crude Materials
7	5	M	WW_GLOBPRC_FOOD[b]	Global price of Food index
7	1	D	US_BCOM_3M_BS[c]	Commodity prices§§
8	2	M	US_FREDMD_SP_div_yield[a]	S&P's Composite Common Stock: Dividend Yield
8	5	M	US_FREDMD_SP_PE_ratio[a]	S&P's Composite Common Stock: Price-Earnings Ratio

8	10	D	US_FREDMD_SP_500[a]	S&P's Common Stock Price Index: Composite
8	10	D	US_FREDMD_SP_indust[a]	S&P's Common Stock Price Index: Industrials
8	1	D	US_SP500_3M_BS[c]	
9	1	M	US_EMVOLTK[b]	Baker et al. (2019) Equity Market Volatility Tracker (EMVT) - Overall
9	1	M	US_EMVOLTK_COMDTY[b]	Baker et al. (2019) EMVT - Commodity markets
9	1	M	US_EMVOLTK_EXR[b]	Baker et al. (2019) EMVT - Exchange rates
9	1	M	US_EMVOLTK_FINCRIS[b]	Baker et al. (2019) EMVT - Financial crises
9	1	M	US_EMVOLTK_FISCAL[b]	Baker et al. (2019) EMVT - Fiscal Policy
9	1	M	US_EMVOLTK_MACROBDQUANT[b]	Baker et al. (2019) EMVT - Macroeconomic outlook - Broad quantity indicators
9	1	M	US_EMVOLTK_MACROBUS[b]	Baker et al. (2019) EMVT - Macroeconomic outlook - Business sentiment
9	1	M	US_EMVOLTK_MACROCONS[b]	Baker et al. (2019) EMVT - Macroeconomic outlook - Consumer spending and sentiment
9	1	M	US_EMVOLTK_MACROINFL[b]	Baker et al. (2019) EMVT - Macroeconomic outlook - Inflation
9	1	M	US_EMVOLTK_MACROINTRST[b]	Baker et al. (2019) EMVT - Macroeconomic outlook - Interest rates
9	1	M	US_EMVOLTK_MACROLAB[b]	Baker et al. (2019) EMVT - Macroeconomic outlook - Labour markets
9	1	M	US_EMVOLTK_MACROREALEST[b]	Baker et al. (2019) EMVT - Real estate markets
9	1	M	US_EMVOLTK_MACROTRADE[b]	Baker et al. (2019) EMVT - Macroeconomic outlook - Trade
9	1	M	US_EMVOLTK_MPOL[b]	Baker et al. (2019) EMVT - Monetary policy
9	1	M	US_EMVOLTK_OTHERFIN[b]	Baker et al. (2019) EMVT - Macroeconomic outlook - Other financial indicators
9	1	M	US_EPU_CAT[e]	Overall Economic Policy Uncertainty
9	1	M	US_EPU_CAT_MPOL[e]	Monetary Policy Uncertainty
9	1	M	US_MBOS_SURVEY_GAC[f]	Aastveit et al. (2017)
9	1	M	US_MBOS_SURVEY_GAF[f]	Aastveit et al. (2017)
9	1	M	US_MFU_JLN12[g]	Jurado et al. (2015)
9	1	M	US_MMU_JLN12[g]	Jurado et al. (2015)
9	1	M	US_MPU_HRS[h]	Husted et al. (2017) MPU
9	1	M	US_MRU_JLN12[g]	Jurado et al. (2015)
9	1	M	US_RA_BHD[i]	Bekaert et al. (2013) - Risk Aversion
9	1	M	US_UC_BHD[i]	Bekaert et al. (2013) - Uncertainty
9	1	M	WW_EPU_ADJPPPGDP[e]	Davis (2016) Global economic policy uncertainty index
9	1	D	US_FREDMD_VIXCLSx[a]	VIX
9	1	D	US_MPU_BLM[j]	MPOL uncertainty
9	1	D	US_EPU[e]	Economic Policy Uncertainty
9	1	D	US_MOVE3M_IX[k]	BofA ML MOVE Index 3M Treasury Volatility
9	1	D	WW_JPM_FX_VOL[k]	JP Morgan Global FX Volatility Index
10	1	M	US_CAP_RATIO_HKM[l]	He et al. (2017)

10	1	M	US_FINSTRESS_KCF[b]	Kansas City Financial Stress Index
10	1	D	US_CISS[m]	Composite Indicator of Systemic Risk
10	8	W	US_ANFCI[b]	Adjusted NFCI
10	8	W	US_NFCI_Risk[b]	NFCI Risk
10	1	W	US_NFCI_Credit[b]	NFCI Credit
10	8	W	US_NFCI_Leverage[b]	NFCI Leverage
10	8	W	US_NFCI_Nonfinancial_Leverage[b]	NFCI Non financial Leverage
10	1	W	US_FINSTRESS_STLF[b]	St. Louis Fed Financial Stress Index
10	1	Q	US_LEVERAGE_BSS[b]	Bruno and Shin (2015) - computed from Fred data acc to formula in the paper
10	1	Q	US_CREDIT_GAP_BIS[n]	Rünstler and Bräuer (2020) BIS data
10	1	Q	US_RES_PRICE_GAP[b]	Rünstler and Bräuer (2020) - FRED Data - Hodrick-Prescott
10	1	Q	US_CRDTTIGHT_LRG2LRG[b]	Net Percentage of Large Domestic Banks Tightening Standards for Commercial and Industrial Loans to Large and Middle-Market Firms
10	1	Q	US_CREDTTIGHT_LRG2SML[b]	Net Percentage of Large Domestic Banks Tightening Standards for Commercial and Industrial Loans to Small Firms

Notes: a: FRED_MD; b: FRED ; c: Bauer and Swanson (2022); d: Gilchrist et al. (2016); e: Davis (2016); f: Federal Reserve Bank of Philadelphia; g: Ludvigson; h: Sun; i: Bekaert and Hoerova (2014); j: Bauer et al. (2022a); k: Bloomberg; l: Husted et al.; m: ECB; n: BIS;

† : The Federal Reserve Bank of Cleveland estimates the expected rate of inflation over the next 30 years, along with the inflation risk premium, the real risk premium, and the real interest rate.

†† : The implied skewness of the ten-year Treasury yield, measured using options on 10-year Treasury note futures with expirations in 1–3 months, averaged over the preceding month, from Bauer and Chernov (2023).

‡ : The change in the slope of the yield curve from three months before the FOMC announcement to the day before the FOMC announcement, measured as the second principal component of one- to ten-year zero-coupon Treasury yields from Gürkaynak et al. (2007).

§: Consumer Prices: Future Tendency of Inflation: European Commission and National Indicators for the US.

§§: The log change in the Bloomberg Commodity Spot Price Index (BCOMSP) from three months before the FOMC announcement to the day before the FOMC announcement.

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