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. A plethora of potential sources of non-linear transmission have been emphasised by the literature to date. Rather than focussing on individual sources of non-linearity, in this study we take a "big data" approach. We design and apply a framework that allows one to assess the role of many potential sources of non-linearity simultaneously, and rank the overall importance of their contribution. This represents an important step forward for the empirical literature, which typically focusses on one or two potential mechanisms, without systematically assessing their importance relative to other potential explanations. We apply our approach to the case of the Federal Reserve. Our estimates emphasise the role of labour markets and real variables at generating non-linear transmission, over certain financial variables that are often emphasised.

Keywords: Monetary policy, non-linear, event study, big data

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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 as far as Keynes (1936), who famously argued for the existence of a "liquidity trap" as interest rates fall to zero. As the subsequent macroeconomic literature developed, a host of additional potential sources of non-linear monetary policy transmission have been proposed and assessed. Researchers have documented evidence of state-dependence not only at the zero-lower bound, but also that monetary policy can be more powerful at different points of the business cycle (Tenreyro and Thwaites, 2016), or when uncertainty is high (De Pooter et al., 2021).

For a monetary policymaker, understanding whether transmission is subject to non-linearity is of crucial importance. Non-linear transmission increases the complexity of setting monetary policy to achieve one's policy goals. If the effects of monetary policy cannot be assumed to be the same at all points in the business cycle, for instance, then the policymaker must assess the state of the economy, and project how this will develop over their policy horizon, when making their policy choices.[1] The policymaking complexity arising from non-linearities would be greater still if the states of the world were determined jointly by a number of key variables rather than a single summary measure, such as the business cycle. The ultimate question for the policymaker is when are their tools at their most powerful.

With respect to assessing the state-dependence of transmission, studies have typically followed a *low dimensional* approach. Often a single potential source of state-dependence is proposed, usually motivated by theory, such as the state of the business cycle. A variable proxying the relevant state is then incorporated into a non-linear framework of varying forms. Provided the quantified state-dependent effects prove statistically and economically significant, one learns of an important additional dimension to deviations from linearity. Robustness checks may involve consideration of a small number alternative state-variables, and adopting specifications that allow for interaction effects between a small number of different states (for example, simultaneous consideration of the state of the business and financial cycle). However, such low dimensional approaches to state-dependence have a key drawback: the indicator variables used by the econometrician as the source of state-dependence could well be correlated with other omitted variables, each representing additional sources of state-dependence. This omitted variable bias can lead us to overestimate or underestimate the true level of state-dependence associated with given variables.

In this study we propose a *high dimensional* approach to the quantification of state-dependence, assessing the role of many sources of non-linearity simultaneously. We draw from the literature on "big data" to simultaneously evaluate a large number of non-linear channels in a unified framework. To do this we combine a standard non-linear event study regression with a Least Absolute Shrinkage and Selection Operator (LASSO) approach to estimation. We incorporate data from high-frequency asset price movements around meeting days of monetary policymakers, as has become common in recent years. Our asset price data focus on meetings of the Federal Open Market Committee. We are interested in monetary policy transmission to several distinct, key outcome variables. First, we examine transmission to the yield curve. This is a key metric of monetary policy's power to control financial conditions and to signal a policy path into the future. Second, we look at inflation-linked swap rates. These capture the ability of monetary policy to determine market-based expectations of future inflation. Finally, we look at transmission to equities. This is a key channel through which monetary policy affects financial intermediation and represents a link with the financial stability literature.

[1] For a description of the importance of assessment and projection of the state of the economy for the setting of monetary policy, see Byrne et al. (2023)

To examine the dimensionality of state-dependence of monetary policy transmission, we construct a high dimensional vector of variables through which monetary policy could be non-linear. We start with the factor dataset of McCracken and Ng (2016), which includes eight groups of variables representing different economic channels, including real variables, housing, labour, prices and financial variables. Leaning on the literatures that highlight the importance of uncertainty and of the balance sheets of financial intermediaries, we extend the dataset by adding key variables from the literature. The LASSO operator allows multiple potential interaction effects to be selected from a large pool in a sparse fashion, meaning the importance of one channel is evaluated against the importance of multiple other channels.

Our main contribution is empirical. Our results confirm that the transmission of monetary policy shocks to asset prices is a function not only of one or two variables, as typically modelled in the literature, but rather on multiple state variables. Based on a broad macro-financial dataset, we find that typically at least 10 interaction variables are selected by our LASSO algorithm as sources of non-linear transmission. Our results are strongly supportive of our high-dimensional approach to modelling non-linearity.

When examining exactly which variables are important drivers of non-linear transmission, we find that monetary policy shocks have stronger effects at the long-end of the yield curve according to developments in real variables, in particular those relating to the labour market. Variables relating to aggregate financial conditions seem to play a reduced role in our sample, when explaining yield curve responses. We find little evidence of an important role of policy rate uncertainty, as emphasised in recent work (De Pooter et al., 2021). When we examine the response of equities, we again find an important role for the state of the labour market, though we also find that the level of financial uncertainty as proxied by the VIX is an important explanatory variable.

We believe the high dimensional approach to non-linearity proposed in this study would be of use to researchers investigating transmission of other forms of macro-economic shocks. One natural setting would be to examine fiscal multipliers, and our approach could be profitably extended in this direction, to establish additional sources of non-linearity to those documented in Ramey and Zubairy (2018), Cloyne et al. (2020), and Bragoudakis and Panas (2021). Overall our approach is helpful because it provides researchers with an "acid test" to establish if proposed novel non-linear transmission mechanisms are truly different from many other relevant factors, in a systematic manner.

The paper is organized as follows. Section 2 is a literature review, and summarises existing approaches to non-linearity in macroeconomics in a general way. Section 3 explains our methodology. Section 4 discusses the data used in this study. Section 5 discusses empirical results, while Section 6 concludes.

2 Literature Review

When quantifying monetary policy, baseline approaches typically assume that monetary policy shocks are additively separable from lagged macroeconomic data, and specify a model that is linear in parameters (Christiano et al., 1996). However, the idea that monetary policy transmission could be non-linear has motivated a great deal of research, and has a long history. Keynes famously argued that monetary policy was weak in the liquidity trap (Keynes, 1936). Recent years have seen a plethora of important contributions establishing non-linear transmission at the effective lower bound, at different points of the business and financial cycle, and with respect to uncertainty. Before detailing existing evidence, this section will first summarise generally the way non-linear transmission has been handled in macroeconomics.

2.1 Non-Linearity and Research Design

When quantifying non-linear transmission, researchers make two important steps: (1) selection of interaction variables, and (2) specification of the non-linear model. 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 more 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 the macro-economic literature, there are broadly three approaches to specification. The first is to build and estimate a structural model, with an active non-linear channel according to the proposed mechanism. The second approach is to estimate a non-linear VAR model (Koop et al., 1996). The third, and increasingly popular approach, is to estimate state-dependent local projections (Tenreyro and Thwaites, 2016).

One key drawback with conventional approaches to non-linearity is that they are *low dimensional*. Non-linear mechanisms are proposed, and one or two variables are 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, it will remain unclear as to the true source of non-linearity. This problem is particularly acute in specifications in which there can only be a single source of non-linearity. To establish robustness, researchers frequently substitute the non-linear variable for alternatives, in order to show that their baseline results are less pronounced 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. Alternatively, researchers have examined whether state-dependence might be two or three-dimensional, for example by establishing if 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). In our study, the source of non-linear monetary policy is *high dimensional*. We adapt a parsimonious framework to quantify multiple sources of non-linearity simultaneously, in a systematic manner. We establish that this approach is a helpful one, since one can examine multiple potential non-linear transmission channels, while quantifying their relative importance.

2.2 Existing Evidence on Non-linear Transmission

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. Jordà et al. (2020) establish that monetary policy is stronger when the economy is above or below potential; (2) inflation is low; and (3) there is a credit boom in mortgage markets. Some researchers have established non-linearity in the sign of the surprise (Angrist et al., 2018), while others do not report evidence for these effects (Altavilla et al., 2019). More recently, Ascari and Haber (2022) show that the transmission of monetary policy shocks to the price level depends both on the size of the shock and the trend inflation regime.

In light of Keynes' arguments regarding the liquidity trap, the argument that monetary policy might be weaker at the ELB has a long tradition. Many studies have quantified such effects in the context of the experience of developed economies with the ELB after the 2008 financial crisis (Sims and Wu, 2021). We have a great deal of evidence that uncertainty could affect the transmission of monetary policy. See, for example, the studies of Pellegrino (2021), Bauer et al. (2022), De Pooter et al. (2021), Tillmann (2020) and Aastveit et al. (2017).

It is well established in the literature that the financial sector and financial variables can play an important role in transmitting and amplifying monetary impulses to the real economy (Bernanke et al., 1999). A more recent literature has focused on the structure and management of the balance sheets of financial intermediaries as the mechanisms through which this amplification can take place. Adrian and Shin (2014) showed that the leverage of broker-dealers, and their risk management, affects the availability of credit over the business cycle. Adrian et al. (2019) gave an intermediary-based causal mechanism for the stylized fact that the term spread can forecast recessions. Monetary tightening that flattens the yield curve reduces the profitability of the marginal loan a bank could extend, given the maturity transformation involved in shorter-term funding and longer-term lending. Bruno and Shin (2015) also showed that the leverage of intermediaries helps to determine the cross-border transmission of monetary policy in the form of capital flows, while Istiak and Serletis (2017) show that their leverage amplifies monetary policy shocks. Dou et al. (2020) provide a survey of the growing literature for the importance of the financial sector for determining macroeconomic outcomes.

While it is well established that the financial sector for monetary policy, it is less well studied how financial variables might cause differences in the effectiveness of monetary policy over time. A number of studies have examined evidence for this non-linearity. Kashyap and Stein (2000) and Kishan and Opiela (2000) looked at 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) showed 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. Eickmeier et al. (2016) find evidence for state-dependent uncertainty shocks through intermediary leverage. Looking at a panel of euro area countries, Rünstler and Bräuer (2020) find evidence for state-dependence in the effects of monetary policy shocks on GDP, depending on the leverage cycle. Saldías (2017) finds that the effects of monetary policy shocks on output are non-linear in financial stress.

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. Univariate representations of non-linearity are common, multivariate representations are rare, and it is very unusual for researchers to consider non-linearity in more than one or two interaction variables. An exception is the study of El-Shagi (2021), which is the closest paper to ours and also uses a LASSO approach. Our study differs from that of El-Shagi (2021) in terms of our identification, since we use high-frequency event studies, which allow us to consider the effects of monetary policy on financial variables while extracting exogenous variation in a model-free way. We also differ from El-Shagi (2021) in terms of the breadth of the variables we consider, and the number of potential channels we allow to operate. Bragoudakis and Panas (2021) use a "triple LASSO" approach to extend the work of Ramey and Zubairy (2018). They use these higher dimension to gain a fuller understanding of fiscal multipliers. Alpanda et al. (2021) examines the role of three broad sources of non-linearity, relating to business, financial, and monetary policy cycles. We allow for a "big data" approach to non-linearity, greatly increasing the number of potentially useful explanatory variables and channels we can model.

3 Methodology

A typical, univariate state-dependent event-study takes the following form:

$$y_{t(m)} = \beta_0 + \beta_1 MPS_{t(m)} + \gamma_1 MPS_{t(m)} \times w_{1,t(m)-1} + \sum_{i=1}^{N_x} \delta_i x_{i,t(m)-1} + \varepsilon_{t(m)}, \tag{1}$$

where $t(m)$ represents the day t of a meeting m, $y_{t(m)}$ is a dependent variable of interest, expressed as an intraday or daily difference around the meeting, and $MPS_{t(m)}$ is a high-frequency monetary surprise. Here $w_{1,t(m)-1}$ is a potential source of state-dependence, which is lagged relative to the event day. The parameters β_0 and β_1 capture the linear effect of the surprise on the dependent variable, while the parameter γ_1 captures non-linearity. Specifications may include control variables, which we denote by $\{x_{i,t}\}_{i=1}^{N_w}$ with associated coefficients $\{\delta_{i,t}\}_{i=1}^{i=N_w}$. The error term $\varepsilon_{t(m)}$ is assumed to be independently and identically distributed.

In the approach followed in this study, we take a multivariate approach to state-dependence, and we do so in a manner that includes a potentially large number of additional sources of state-dependence. Our baseline specification is therefore:

$$y_{t(m)} = \beta_0 + \beta_1 MPS_{t(m)} + \sum_{i=1}^{i=N_w} \gamma_i MPS_{t(m)} \times w_{i,t(m)-1} + \sum_{i=1}^{i=N_x} \delta_i x_{i,t(m)-1} + \varepsilon_{t(m)}, \tag{2}$$

where we allow for N_w potential sources of non-linearity, collected in variables $\{w_{i,t}\}_{i=1}^{i=N_w}$.

One feature of Equations 1 and 2 that deserves discussion is the decision as to whether to include or omit main effects. In a traditional micro-econometric assessment of state-dependence, non-linear terms are captured through the interaction of an explanatory variable of interest and a state-variable. One typically also includes the main effect of the state-variable, allowing for a direct effect of this variable on the dependent variable of interest. These main effects could easily be included in the control variable blocks of 1 and 2 respectively. However, in the high-frequency event study literature we have a theoretical reason to believe $MPS_{t(m)}$ to be uncorrelated with any variable in the $\{w_{i,t}\}_{i=1}^{i=N_w}$ block, regardless of what this variable may be. The reason is that $MPS_{t(m)}$ is a surprise movement in a high-frequency window, meaning information dated $t(m)-1$ should be orthogonal to an asset price movement at time $t(m)$. Much of the event study literature has operated on this basis, meaning the control block is ommitted. This also means that the inclusion of main effects is unnecessary.

Despite theoretical reasons to believe that $MPS_{t(m)}$ should not be predictable with respect to information at $t(m)-1$, several recent studies have in fact documented a level of predictability. Since the reasons behind this phenomenon are a subject of recent debate, we prefer to ommit the control block from our baseline specifications, which of course means main effects are excluded. However, we accompany our baseline analysis with studies that do include main effects, in order to assess robustness. Our flexible "big data" approach to state-dependence also allows for a systematic assessment of the role of main effects at influencing estimates of non-linear terms in local projections, which is an additional contribution of our study on a point of great interest to the event study literature.

Given that we allow for potentially large numbers of state-variables, i.e. N_w can be large, we are unable to estimate Equation 2 by OLS. We therefore adopt a LASSO specification, which is an algorithm designed to select a sparse specification. We adopt the Elastic Net generalisation of LASSO, using the approach of Zou and Hastie (2016). Expressing the non-linear terms as a vector, $W_t = [w_{1,t(m)-1}, \ldots, w_{N_w,t(m)-1}]'$, and gathering the associated parameters also as a vector, $\Gamma = [\gamma_1, \ldots, \gamma_{N_w}]'$, we solve the following minimisation problem:

$$\min_{\beta_0,\beta_1 \in \mathbb{R}, \Gamma \in \mathbb{R}^{N_w}} \left\{ \frac{1}{2} \sum_{i=1}^{N} (y_i - \beta_0 - \beta_1 MPS_i - MPS_i W' \Gamma)^2 + \lambda \left[\frac{1}{2}(1-\alpha)||\Gamma||_2^2 + \alpha ||\Gamma||_1 \right] \right\}, \tag{3}$$

for some $\lambda \geq 0$ and $\alpha \in [0,1]$, where $||u||_p \equiv \sum_{j=1}^{N} (|u_j|^p)^{1/p}$ is the l_1-norm. We set the parameter α to be equal to 0.99 and estimate λ by 10-fold cross-validation. We summarise the results from our LASSO estimation according to a non-parametric bootstrap, drawing with replacement from our dataset 5000 times, and re-estimating λ on each generated dataset. We do this to ensure our results are robust to well known problems of data "jitter" (Taddy, 2017), which can imply that LASSO routines can select between highly correlated variables in an arbitrary manner.

4 Data

In this paper, we use high-frequency identified monetary policy shocks and a large dimension of mixed-frequency covariates to investigate their impacts on changes in asset prices. To unveil how does the transmission of monetary policy shock changes depending on these macroeconomic and financial variables, the covariates multiplied with the monetary policy shock and "interaction" variables are obtained. The monetary policy shock is measured as the price change in two-year treasury futures around 30 minutes window of FOMC meetings. The intraday changes are retrieved from Bauer and Swanson (2022). As can be seen in Figure 1, the monetary policy shocks represent the surprise components of policy changes with a distribution centred nearly around zero and negative skewness. Although the variation of the series is not as high as the policy change itself, it captures purely unexpected elements and thus can be used as a good proxy for the policy shocks. The data cover 210 FOMC meetings from 01.02.1995 to 11.12.2019. As dependent variables, we use two-day changes in five-year and ten-year treasury yields, one-year inflation-linked swaps and the S&P500 index around the meetings.[2] The changes in medium and long-term yields are important to understand for policy-makers since they show how the short-term policy changes transmit into the various horizons in the yield curve. One-year inflation-linked swaps show the change in inflation expectations of market participants with regard to the policy surprise. The market expectations, in that sense, are directly related to the effectiveness of the monetary policy. On the other hand, the change in equities shows how different agents position themselves in financial markets associated with the policy surprises. Table 1 summarises the descriptive statistics for the policy shock and four dependent variables.

Table 1: Descriptive Statistics: Shock and Dependent Variables

	Shock	**T-Yield (5Y)**	**T-Yield (10Y)**	**ILS**	**SPX**
Mean	-0.010	-0.006	-0.007	-0.012	2.769
Standard Error	0.004	0.007	0.008	0.011	1.674
Median	-0.005	-0.008	-0.015	0.004	2.670
Kurtosis	25.655	1.131	3.002	3.844	2.340
Skewness	-3.130	0.187	-0.108	-0.524	-0.577
Minimum	-0.544	-0.403	-0.512	-0.537	-86.310
Maximum	0.205	0.365	0.425	0.452	88.490
N. of Obs.	209	210	210	130	209

In this paper, we include a great number of control variables as listed in Table 2 and their interactions with the policy shock. Groups 1-8 correspond to the FRED-MD dataset of McCracken and Ng (2016) but 23 of the financial variables are converted into higher frequencies based on the data availability.[3] Groups

[2]The sample period for one-year inflation-linked swaps is shorter and starts from 10.08.2004, unlike other dependent variables.

[3]Monthly variables except those in group 7 (prices) in the FRED-MD are transformed in line with the suggestions of McCracken and Ng (2016). Prices (monthly), weekly and daily covariates are transformed following Bauer and Swanson (2020)

1-4 are related to the real macroeconomic variables whereas 5-8 represent the financial variables.[4] In addition to the modified version of the FRED-MD dataset, we include a recently proposed measure of monetary policy uncertainty by Bauer et al. (2022), and macroeconomic and financial control variables (BS controls) of Bauer and Swanson (2022). BS controls include six variables that are pointed as useful to predict policy surprises: nonfarm payrolls surprise, employment growth, the S&P 500, yield curve slope, commodity prices, and treasury skewness.[5]

Table 2: Macroeconomic and Financial Variables (Control and Interaction)

No	Groups	Number of Variables	Frequency	HF_variable
1	Output and Income	16	Monthly	-
2	Labor Market	31	Monthly	-
3	Housing	10	Monthly	-
4	Consumption, Orders, and Inventories	10	Monthly	-
5	Money and Credit	13	Mixed	8 (weekly)
6	Interest and Exchange Rates	14	Mixed	12 (daily)
7	Prices	20	Monthly	-
8	Stock Market	5	Mixed	3 (daily)
9	Uncertainty (Bauer et al., 2022)	1	Daily	
10	Bauer and Swanson (2022) controls	6	Meetingly	

5 Results

5.1 Main Empirical Results

The event study regressions are estimated by LASSO and then, we applied a nonparametric bootstrap algorithm with 500 replications. Table 2 summarises the answers to our main empirical questions relying on probabilities obtained from the bootstrap samples. As demonstrated in Table 3, we do select interaction variables in more than 90 per cent of the samples for the yields and equities, and with a slightly lower probability in the inflation-linked swaps. The results clearly indicate that it is crucial to include interaction variables in the regressions as explanatory variables. With regards to the number of interaction variables that relates to the different states of the economy, the probability results show that the algorithm is in favour of selecting more than one variable contrasting the popular approach focusing on a low dimensional nonlinearity mechanisms. More specifically, the average or median number of selected interaction variables is ranging from 8 for the inflation-linked swaps to as high as 17 variables in the equities. Similarly, more than 10 interaction variables, on average, are selected for the yields. The probability values for including control variables in four of the regressions are considerably high.

Figure 2 and 3 show the frequency distribution of the number of interaction and control variables, respectively, in the bootstrap replications. As displayed by the top panel of Figure 2, the number of interaction variables selected for the yields exhibit approximately a bell-shaped distribution with a certain degree of positive skewness. The number of selected interactions tends to be higher with a peak of around

[4] We dropped the level of treasury and corporate yields from Group 6 as including them together with FEDFUNDs rate and spreads would pose a perfect multicollinearity problem.

[5] Please see Bauer and Swanson (2022) for a detailed explanation of variables. To illustrate, S&P 500 is "the log change in the S&P 500 stock price index from three months (65 trading days) before the FOMC announcement to the day before the FOMC announcement." Thus, it shows a longer-term change in the stock prices as opposed to our dependent variable S&P 500 showing the two-day change around the meeting.

16 variables for the ten-year yields than the five-year yields reaching the top of around 12 variables. On the other hand, the number of interactions for the one-year inflation-linked swap has an accumulation point around one variable indicating there might be fewer states affecting the transmission of monetary policy shocks. The results for the equities confirm that the number of interactions peaks around 24 variables way higher than the other dependent variables. Thus, the simple yet intuitive results from the histograms of the interaction variables confirm that while considering the transmission of monetary policy shocks to asset prices, more than one state variable is relevant. Figure 3 demonstrates the frequency distribution for the control variables in the event-study regressions. The results show that except for the inflation-linked swaps, the algorithm is in favour of selecting a great number of control variables to be included in the regressions. Overall, the evidence from the distribution of independent variables among the bootstrap replications implies that 1) the nonlinear transmission mechanism is multi-dimensional, and 2) the algorithm select the lagged control variables in the event-study regressions.

Table 3: Main Empirical Results

Do we select any interactions?	**5Y_Yield**	**10Y_Yield**	**ILS**	**SPX**
Yes	0.926	0.920	0.886	0.946
No	0.074	0.080	0.114	0.054
Do we select more than one interaction?	**5Y_Yield**	**10Y_Yield**	**ILS**	**SPX**
One	0.017	0.024	0.056	0.038
Two	0.032	0.030	0.077	0.025
Three	0.045	0.030	0.043	0.027
More	0.898	0.922	0.824	0.909
Descriptive - interactions	**5Y_Yield**	**10Y_Yield**	**ILS**	**SPX**
Mean	12.36	14.43	8.75	15.84
Median	12	14	8	17
Max	45	45	26	39
Do we select any controls?	**5Y_Yield**	**10Y_Yield**	**ILS**	**SPX**
Yes	0.936	0.924	0.860	0.924
No	0.064	0.076	0.140	0.076

5.2 Variable Selection

Having established that the relation between monetary policy surprises and asset prices is a function of a broad swathe of interaction variables, we now examine which variables are important for generating non-linear responses. To do this, we first examine the selection probabilities for our LASSO algorithm, by which we mean the fraction of times a given variable is selected across bootstrap draws. This statistic provides a summary measure of the usefulness of given interaction variables for explaining observed variation. Of course, however, the probability of selection does not indicate the overall quantitative role of a given variable at influencing asset prices, since this will be a function also of the variance of independent variables and coefficient size. However, if a given variable is important, a necessary condition is that it is selected by the LASSO algorithm.

In Figure 4 we display the probability that given variables are selected across bootstrap draws, when the dependent variable is the 5Y Treasury yield. We display the top 20 variables according to their selection probability. The selection probability for the intercept and the monetary policy surprise is one by construction, since we constrained these variables to be selected. As we have indicated in the previous section, our estimates are supportive of the presence of both lagged variables and interaction terms in the data generating process. The lag of one of the sub-indices of CPI (Apparel), and the consumer sentiment index are selected with high probability. This suggests an important role for the lag of these variables at accounting for the predictability of the response of the 5Y yield. This implies that the control set of Bauer and Swanson (2022) might be usefully extended by including the lag of price inflation and a measure of sentiment.

In Figure 4 can also detect that certain interaction effects are selected with high probability, as well as the lagged effects. Interestingly, the two variables with the highest probability of selection relate to real activity, namely a sub-index of industrial production (residential utilities), and a measure of average hourly earnings in manufacturing. We also select the interaction of our shock with the Treasury skewness measure of Bauer et al. This suggests that this variable could play an important role not only as a lagged control variable (as in Bauer and Swanson, 2022), but also as a source of non-linearity.

When examining Figure 5, which depicts selection probabilities when the dependent variable is the 10 year yield, we observe that the interaction between the shock and skewness is selected even more frequently than was the case for the 5Y yield case. Our findings are broadly robust across the two portions of the yield curve, however, with IP (residential utilities) and average hourly earnings featuring as interaction terms the model deems useful. We additionally chart the importance of non-linear interactions with securities in bank credit and the size of the monetary policy shock.

When we examine non-linear effects of monetary policy on equities, displayed in Figure 6 we observe a greater number of interaction terms are selected across bootstrap draws. This provides some initial evidence that the response of equities is potentially more non-linear, relative to the response of the yield curve to monetary policy surprises. The selected important interaction effects also differ relative to the selected effects for the yield curve. We observe the most important interaction is actually the lagged money supply, though the second most preferred variable is also a measure of price inflation. While we see a number of the same variables selected as preferred interaction effects as were evident for the yield curve case, we also see that the lagged VIX is an important interactor, suggesting that financial variables play a greater role at determining the non-linearity of the equities response, relative to the yield curve response. Nevertheless, it seems that real activity variables remain important as interaction effects when considering the response of equities.

We now examine the sources of non-linear transmission of monetary policy to inflation linked swaps, displayed in Figure 7. Interestingly, the most important interaction term is the interaction of the shock and the lagged level of the federal funds rate. We again see an important interaction between the shock and a price level variable (CPI services), average hourly earnings, and securities in bank credit. We also see a role for additional real variables, namely real manufacturing as well as unfilled orders for durable goods.

5.3 Group Selection

Figure 8 shows the group selection probabilities in the bootstrap samples, such that if at least one variable is selected from a group then it means this group is selected in that specific bootstrap sample. This measure enables us to track the relevance of different categories at a broader level than variables. In that respect, it is also useful to draw a general conclusion about whether the financial or macroeconomic variables matter most in the transmission of monetary policy shocks. For the yields, both five-year and ten-year seem to be affected mostly by the labour market, and output and income groups that represent real macro block in the dataset. These groups are then followed by interest and exchange rates, prices, money and credit groups more directly related to the financial side of the economy with more or less similar selection probabilities. Bauer and Swanson (2022) variables are also selected as important as the other financial categories in the FRED-MD. Although the total probabilities are not very high for both terms of the yields, the stock market group is more relevant for the transmission to the longer-term yields. The transmission to the one-year inflation-linked swaps is mainly affected by interest and exchange rates followed by the labour market, prices, money and credit groups. Different from yields, the changes in inflation-linked swaps depend more on the financial block. In real macroeconomic variables, the labour market arises as a prominent category also for the swaps. The changes in the S&P500 index are related to a balanced mix of macro and financial variables with money and credit, and the labour market leads each block. Different from other dependent variables, the transmission to the S&P500 index is also associated with the consumption, orders, and inventories which might represent the capacity utilization in the economy. Strikingly, housing that includes variables like house starts, housing permits etc., and monetary policy uncertainty do not play a role in the transmission of monetary policy shocks according to our results.

In addition to inspecting the selection probabilities of groups, another way to investigate the importance of groups in improving the model can be done via marginal adjusted $\bar{R}^2_{marginal}$. That is to say, $\bar{R}^2_{marginal}$ shows the portion of explained variance if we exclude that specific group of interactions from the set of variables. Table 4[6] shows $\bar{R^2}$ for all covariates and if we exclude control variables. As can be seen, the inclusion of control variables improves greatly compared to the other model with no controls.

The bottom panel of the table shows the differences between $\bar{R^2}$ of the full model (including all controls and interactions) and the other models in which a specific group of interactions are excluded in each version. The groups are ranked in descending order such that the group deteriorating the model fit most once excluded, i.e. the greatest contributor group, is on the top.[7] The change in the proportion of explained variance is not very high in any of the exclusion scenarios. That is to say, the results are not driven mainly by a peculiar group but rather the combination of multiple groups matters in explaining the state-dependent transmission mechanisms. Slightly different from the group selection probabilities in Figure 8,the exclusion of money and credit interactions worsens the model fit most for the yields followed by the labour market, output and income. On the other hand, for the inflation-linked swaps (equities) the most powerful group is prices (consumption, orders and inventories).

6 Conclusion

The extent to which monetary policy transmission is non-linear is a key question for monetary policymakers. Ultimately this question is tantamount to asking whether their tools are always as powerful, or whether they sometimes have less effectiveness. The relevance of this for the policymaker is immediate. They must use the tools at their disposal to achieve their objectives. If non-linearities exist, they cannot take for granted that the same action would give the same outcomes in all states of the world. To date, this question has been tackled through *low dimensional* approaches. Leaning on economic theory, or stylized facts about financial intermediaries, the previous literature has documented individual sources of state-dependence in transmission.

By contrast, this paper takes a *high dimensional* approach. Our key contribution is to empirically document that monetary policy transmission is typically related to several economic channels. We typically find that 10 or more variables contribute to determining the state-dependence. These are jointly selected in our empirical exercise, showing that each contributes to the nature of the state-dependence

[6] The statistics are obtained as averaging over the bootstrap samples.

[7] The difference between the $\bar{R^2}$ of the full model and $\bar{R}^2_{marginal}$ from the exclusion of the group is given in the parentheses.

conditional on the others. In this sense, a low dimensional representation of non-linearity suffers from omitted variable bias.

Using a high dimensional "big data" approach, we document non-linear transmission to a number of key outcome variables for the policymaker. These include the Treasury yields of medium and longer-term durations, market-based measures of inflation expectations and equities. Each of these represents a key channel through which monetary policy affects the financial system and real economy. We find evidence for non-linearity in each case, particularly with respect to real variables.

Key areas of future research include expanding the set of potential non-linear variables, including balance sheet variables of financial intermediaries such as primary-dealers, broker-dealers and commercial banks. We also intend to examine a broad range of measures of economic uncertainty to ascertain whether uncertainty can help to explain the state-dependence of monetary policy in a high dimensional setting.

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Figures and Tables

Figure 1 | Time-series of Baseline Monetary Policy Surprise

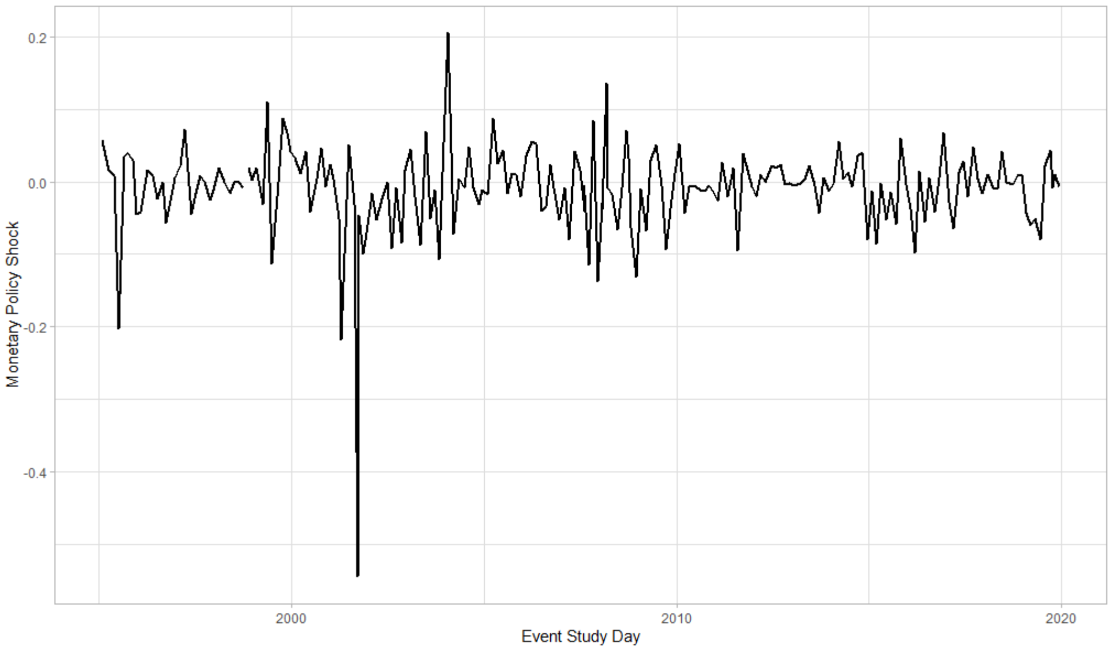

Figure 2 | Histogram for the interaction variables

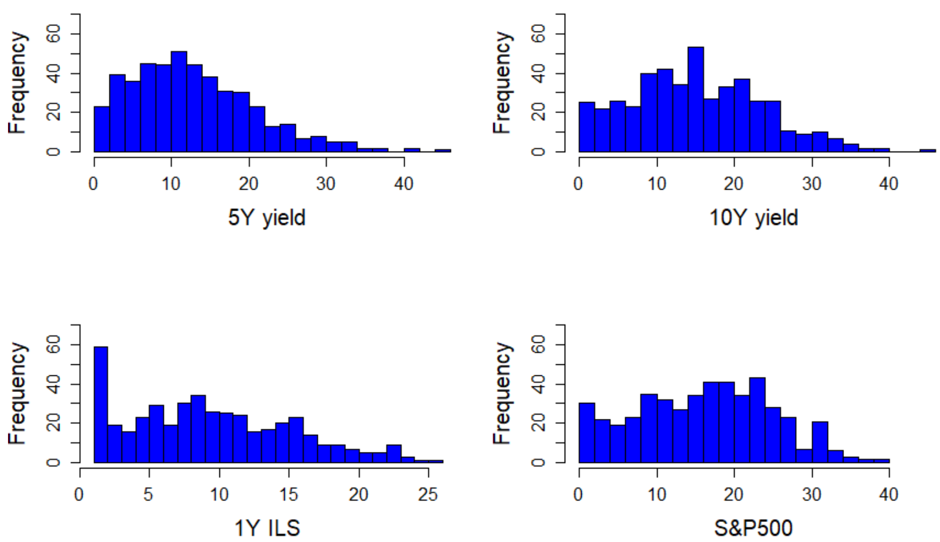

Figure 3 | Histogram for the control variables

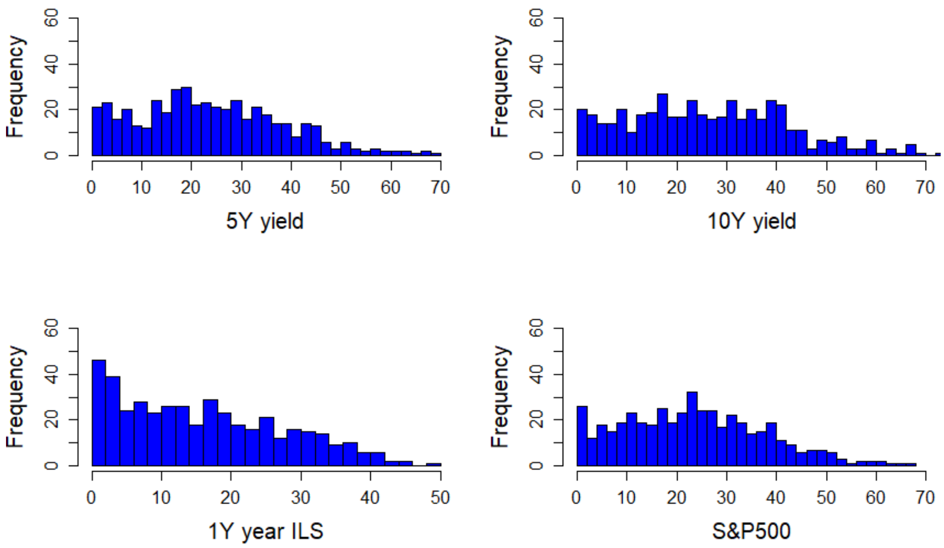

Figure 4 | Selection probabilities of the variables in the bootstrap samples, 5Y Yield (B=500)

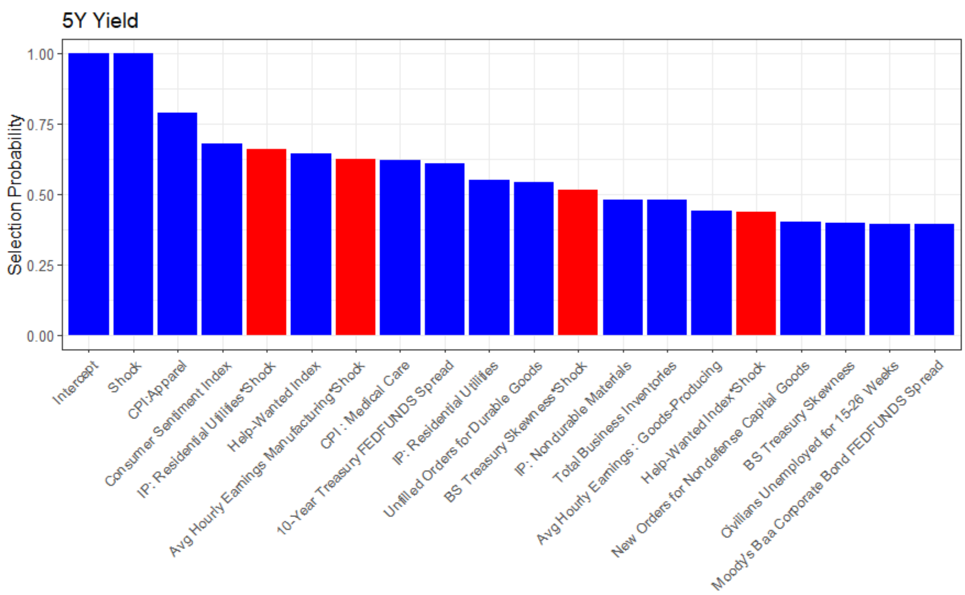

Figure 5 | **Selection probabilities of the variables in the bootstrap samples, 10Y Yield (B=500)**

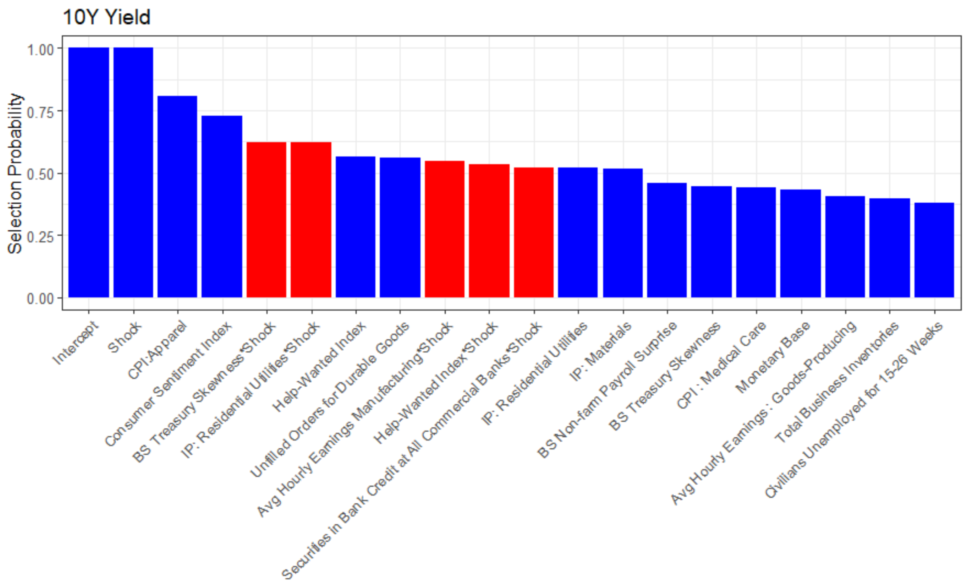

Figure 6 | **Selection probabilities of the variables in the bootstrap samples, S&P500 (B=500)**

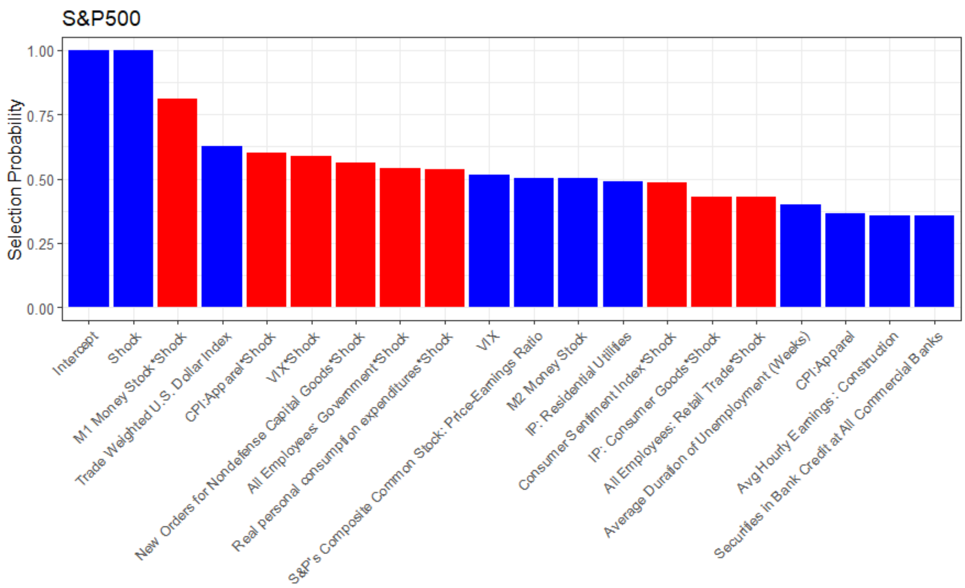

Figure 7 | **Selection probabilities of the variables in the bootstrap samples, 1Y ILS (B=500)**

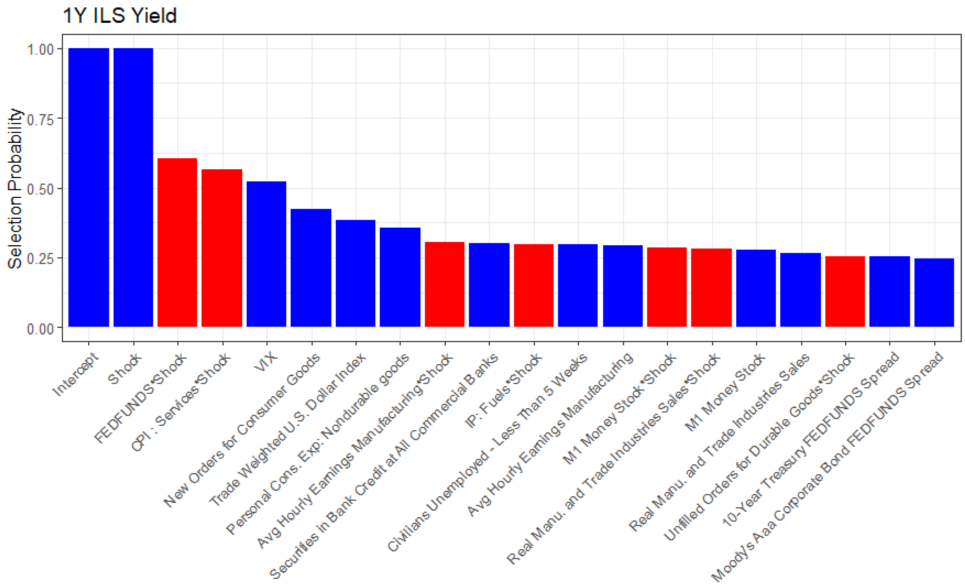

Figure 8 | **Selection probabilities of the groups in the bootstrap samples, all variables (B=500)**

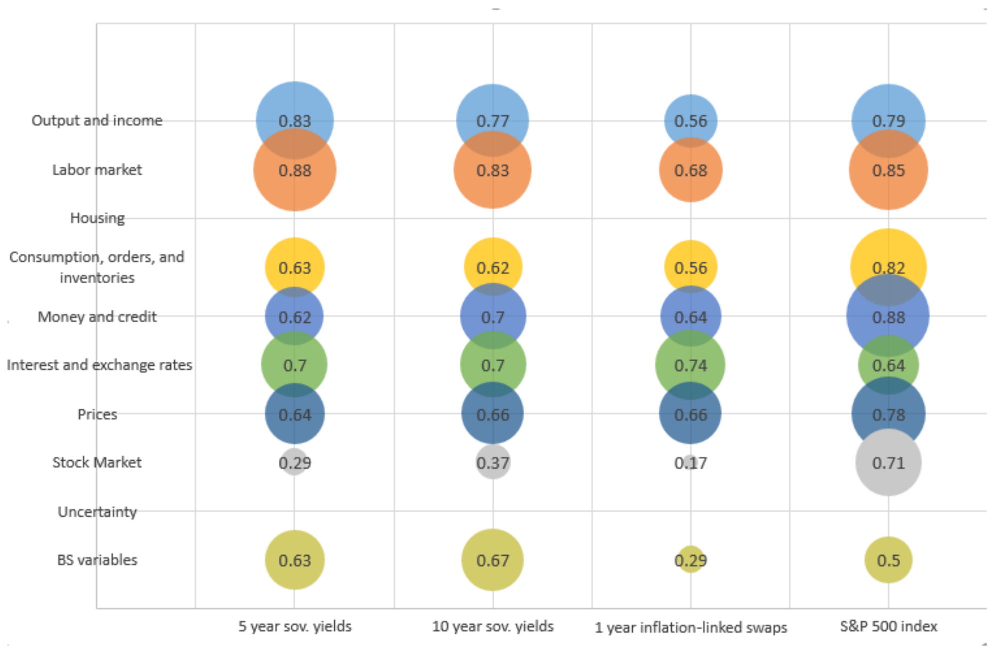

Table 4: Assessment of models based on the adjusted R^2

$\bar{R}^2$	**5Y_Yield**	**10Y_Yield**	**ILS**	**SPX**
All variables with controls	0.565	0.584	0.556	0.560
All variables exc. controls	0.295	0.295	0.389	0.372
$\bar{R}^2_{marginal}$				
	Money and credit (0.023)	Money and credit (0.053)	Prices (0.035)	Cons., orders, and inv. (0.055)
	Labour market (0.019)	Labour market (0.038)	Output and income (0.016)	Labour market (0.048)
	Output and income (0.014)	Output and income (0.017)	Int. and exc. Rate (0.006)	Prices (0.034)
	BS variables (0.010)	BS variables (0.012)	Cons., orders, and inv. (0.006)	Money and credit (0.007)
	Cons., orders, and inv. (0.003)	Cons., orders, and inv. (0.008)	BS variables (0.003)	Output and income (0.007)
	Stock Market (0.001)	Stock Market (0.002)	Labour market (0.001)	Stock Market (0.003)
	Housing (0.000)	Housing (0.000)	Stock Market (0.001)	Uncertainty (0.000)
	Uncertainty (0.000)	Uncertainty (0.000)	Housing (0.000)	Housing (0.000)
	Prices (-0.010)	Int. and exc. Rate (0.000)	Uncertainty (0.000)	BS variables (-0.005)
	Int. and exc. Rate (-0.010)	Prices (-0.003)	Money and credit (-0.016)	Int. and exc. Rate (-0.007)