What explains the stock market's response to QE policy?

Evidence from a decomposition of the S&P500 index*

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Abstract

This paper analyses the effects of Quantitative easing (QE) on the US stock market by decomposing the S&P500 index into two components, its risk-neutral fundamental value, and the equity premium. The causal effects of QE are identified by using a state-of-the-art instrumental variable (IV) that is based on high-frequency price revisions of the medium-long end of the yield curve, triggered by Federal Open Market Committee (FOMC) policy announcements. The IV is constructed by controlling for both information and risk premia shocks to identify QE policy shocks. Findings from a Structural Vector Autoregression (SVAR) model suggest that a QE policy shock results in a positive response of the stock index, due to upward adjustment of both the fundamental and the equity premium components. However, the adjustment of the latter is roughly three times as big as the fundamental value. Both components display persistence, with the equity premium response declining gradually over a period of two years.

JEL classification: E52, G12

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1 Introduction

Quantitative easing (QE) emerged as a key policy tool for central banks when the short-term interest rate was stuck at the Zero lower bound following the global financial crisis. Its main purpose was to transmit monetary policy to the economy through purchases of medium-long term maturity bond purchases. With short-term yields at near zero, a reduction in yields at the medium-long term maturity would provide stimulus and spur economic growth. Over time, QE policy has become a standard part of the central bank toolbox, yet relatively little is known about the quantitative significance of mechanisms through which it moves stock prices. There is ample empirical evidence for the effect of conventional monetary policy on the stock market (Rigobon and Sack, 2003; Bernanke and Kuttner, 2005; Pflueger and Rinaldi, 2022). This evidence can be rationalized through two mechanisms of monetary transmission - first, it impacts the path of future cash flow and risk-free rate, both of which determine the fundamental value of the stock in a risk-neutral environment. Second, it affects the risk premium through a change in risk-taking behaviour (Borio and Zhu, 2012; Kashyap and Stein, 2023). This impacts stock valuation through an increase in the discount rate. Are both of these mechanisms relevant for the transmission of QE policy? If yes, then which mechanism is more important?

This paper examines the impact of QE policy shocks on the decomposition of the S&P500 index to shed light on the mechanisms through which QE drives the response of stock prices. The first step in my analysis is to obtain the fundamental value of the stock index using the asset pricing equation of the present value model and decompose it into two components: the risk-neutral fundamental component and the equity premium component. The former is the sum of discounted dividends at the risk-free rate and captures the effect of QE shocks via its effect on expected profitability of firms. The second component captures the effect of QE shocks through changes in risk premia and reflects the additional return required to invest in riskier assets. The difference between stock price and the fundamental value is the residual which is a catch-all term that is consistent with a range of explanations.[1,2] Early evidence points to the role played by QE in compressing term premia and boosting investment in riskier asset classes (Gagnon et al., 2011; Krishnamurthy and Vissing-Jorgensen, 2011; Hanson and Stein, 2015; Rogers et al., 2018). This paper analyses whether this is also the case for equity markets, by assessing the share of the stock market response that is due to each of the two components.

The empirical evaluation relies on a Structural Vector Autoregression (SVAR) model that includes standard macroeconomic aggregates along with components of stock prices to gauge their response to a QE policy shock. The identification utilizes an external instrument for the unobserved monetary policy shock. External instruments are an increasingly popular choice for the identification of shocks in a VAR model.[3] In the monetary literature, these are typically constructed using high frequency changes in yield of a risk-free futures contract around monetary policy announcements (Cook and Hahn, 1989; Gürkaynak et al., 2004; Swanson, 2021). One of the assumptions required to identify the impulse responses to a monetary policy shock is that the instrument is correlated *only* with the shock of interest (Stock and Watson, 2018; Miranda-Agrippino and Ricco, 2023). This is because presence of non-monetary shocks in the instrument may result in theoretically implausible impact and dynamic responses of macroeconomic variables to a monetary shock. Typically, the focus is on unexpected news about future economic prospects or endogenous responses to past shocks by the central bank (Romer and Romer, 2000; Melosi, 2017; Miranda-Agrippino and Ricco, 2021; Nakamura and Steinsson, 2018; Jarociński and Karadi, 2020) and more recently, on risk premium shocks (Cieslak and Schrimpf, 2019; Cieslak and Pang, 2021). For instance, along with an announcement of additional asset purchases to meet its inflation target, the central bank may reveal private information that deteriorates the risk sentiment of market participants or their beliefs about expected economic conditions. Hence, I use a two step procedure to construct the instrument prior to using it for identification. First, I test for the

[1]For example, it could be mis-pricing between agents in a model when they have heterogeneous beliefs. It could also be a result of differences in valuations due to different information sets.

[2]I assume the No-Ponzi game condition in which no bubbles survive in the infinite time horizon.

[3]This approach was popularized by Stock and Watson (2012); Mertens and Ravn (2013); Gertler and Karadi (2015).

presence of information effects, as is standard in the literature. In particular, I regress the yield surprise on greenbook forecasts and obtain its residual. The residual series contains variation in yield surprises unrelated to information effects. Second, I perform a correction for risk premium shocks that zeroes out residual yield surprise of any event where the co-movement between financial market surprise and and risk premium surprise is negative. This is in the spirit of the correction used by Jarociński and Karadi (2020) for cleansing information effects from yield surprises. I call the instrument derived from these two steps as the information and risk corrected instrument.

The SVAR model estimates identified using the information and risk corrected instrument show that the two steps taken to eliminate non-monetary shocks from the instrument are crucial for resolving empirical puzzles in the impulse responses (IRFs) of various variables. The first step of information correction in the instrument resolves the puzzling responses in output and the stock index while the second step of risk correction resolves the puzzling response of equity premium. Based on this identification strategy and median IRFs, I find that a QE policy shock increases dividends persistently and decreases equity premium up to 6 months. The risk-neutral fundamental component declines by 5% on impact and is persistent while the equity premium *component* response is about 16%. Hence, the response of the equity premium component is approximately three times larger than the response of the risk-neutral fundamental component. In terms of the dynamics, both components display persistence and therefore, the share of equity premium response within stock price response declines gradually roughly two years out into the future.

In addition to the main results, I also present evidence for the effect of a QE policy shock on risk-neutral fundamental of industry specific Fama-French portfolios. First, I find that QE shocks have a larger impact on stock prices of high tech and health sector with little or no effect on utilities and energy. In addition, the impact on durables is significant while there is no effect on the non-durables sector, which is in line with the fact that monetary policy should have a greater effect on rate sensitive industries of the economy. Second, the risk-neutral fundamental component response is large only for durables and others category. This indicates that technology dominated sectors such as high-tech, telecommunications, and health are potentially impacted more by risk premium than risk-neutral fundamental value of the asset. Hence, the two components are likely to have heterogeneous effects on various industries.

This paper contributes to the literature on three counts. First, it improves our understanding of the relative importance of the two mechanisms of transmission for QE policy by quantifying the effect of each component. This relates to the literature that examines the effectiveness of monetary policy shocks on the decomposition of stock prices via the asset pricing equation (Galí and Gambetti, 2015; Beckers and Bernoth, 2016; Paul, 2020). The major departure from this literature is that I use the decomposition to analyse the effect of QE policy shocks. Similar to Beckers and Bernoth (2016), I explicitly incorporate the role of equity premium in the decomposition. The theoretical link between monetary policy and risk attitudes has been well documented in the literature (Borio and Zhu, 2012; Bauer et al., 2023; Kekre and Lenel, 2022; Kashyap and Stein, 2023). This ranges from search for yields, consumption volatility, change in future uncertainty about the economy, heterogeneity in households' marginal propensity to risk, etc. Specific to stocks, equity premium has been shown to be an important channel through which monetary policy shocks impacts stock prices (Patelis, 1997; Thorbecke, 1997; Bernanke and Kuttner, 2005; Jordà et al., 2019; Ozdagli and Velikov, 2020; Pflueger and Rinaldi, 2022). I add to this strand of the literature by quantifying the importance of equity premium in stock market response to a QE policy shock. In addition, I use an equity premium measure constructed from options data (Martin, 2017). This provides a lower bound on expected excess returns that are likely to hold tightly in the data and has the advantage that it correctly captures the timing of jumps in equity premium prior to, and during every crisis episode, in particular a higher premium during the dot-com bubble.

Second, this paper shows the relevance of risk correction in construction of the instrument for identifying the effect of a QE policy shock. Many studies use high frequency surprises in yields for constructing an external instrument (Altavilla et al., 2019; Cesa-Bianchi et al., 2020; Bauer and Swanson, 2023b). Ideally, if a high frequency yield surprise were to result from a monetary policy shock, it should lead to a negative co-movement in stock-yield surprises and a positive co-movement in risk premium-yield surprises. Using daily change in a risk premium measure around FOMC announcements, I document the existence of events where the co-movement in risk premium-yield surprise is negative even when the co-movement in stock-yield surprises is negative. This surprising finding is the motivation behind a further correction for risk in the yield to construct the external instrument, which is in addition to correction for information shocks. I show that this risk and informationally robust instrument resolves empirical puzzles in output, equity premium and stock index. The risk correction is crucial to identify the equity premium response. Hence, I contribute to the literature by showcasing the presence of risk premium shocks on FOMC event days that are usually classified as an event consistent with monetary policy shocks. I also propose a simple risk correction in the form of a risk-corrected poor man proxy.

Third, a growing literature has examined heterogeneity in the effects of monetary policy on different dimensions such as riskiness, and debt structure (Bernanke and Kuttner, 2005; Ippolito et al., 2018; Anderson and Cesa-Bianchi, 2020; Gürkaynak et al., 2022). I contribute to this literature by providing empirical evidence of heterogeneity in QE policy effects on industry level risk-neutral fundamental stock value.

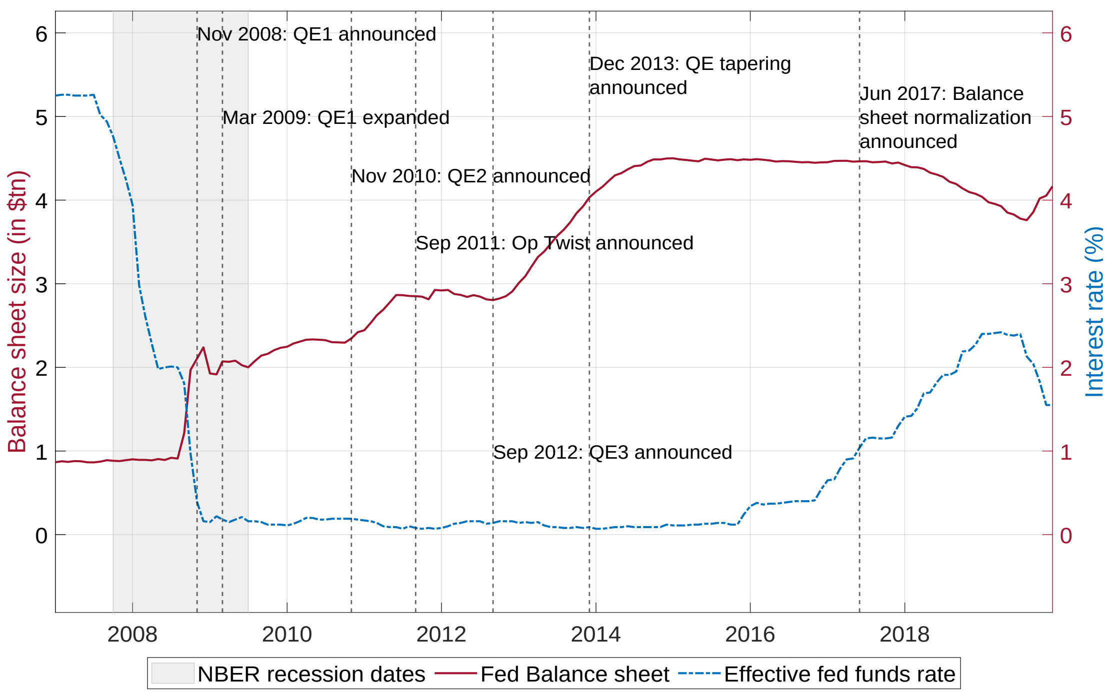
The papers closest to this study are Cieslak and Schrimpf (2019), Beckers and Bernoth (2016) and Jordà et al. (2019). Cieslak and Schrimpf (2019) use sign restrictions for identification to decompose asset returns into monetary and non-monetary shocks. In contrast, I demonstrate an alternative identification strategy for examining the impact of monetary policy shocks in the presence of risk premium shock. Beckers and Bernoth (2016) examine the importance of equity premium in the response of the stock index to a monetary policy shock. I diverge from their analysis in two aspects. First, I examine the impact of QE policy shocks in contrast to conventional policy shocks. Second, I construct the measure of equity premium using options data rather than forecasts from a VAR. This has the advantage that one abstracts from the worry of capturing the entire information set of market participants in the VAR model. Finally, Jordà et al. (2019) also study the impact of conventional policy on the decomposition. They use responses of ex-post excess returns to derive the responses of equity premium under the assumption that the impact response of equity premium to monetary policy shocks is zero. By explicitly incorporating an indicator for equity premium, my results do not require this assumption.

The paper proceeds as follows. Section 2 provides a brief description of quantitative easing programs effected by the Federal Open Market Committee (FOMC). Section 3 defines the components derived from the asset pricing equation and describes computation of their dynamic response to a monetary policy shock. Section 4 provides description of the data and details on the external instrument being used in the SVAR-IV methodology. Section 5 provides details about the estimation method. Section 6 presents the results and its discussion. Section 7 concludes the paper with a summary.

2 Quantitative easing in the US

Quantitative easing is an umbrella term used for large scale asset purchases of government sponsored enterprise (GSE) bonds, mortgage backed securities and treasury notes by the US Federal Reserve. It introduced quantitative easing in late 2008 as a response to the spike in financial stress precipitated by the collapse of big lending institutions. Prior to the onset of the financial crisis, the US economy was already experiencing a slowdown since Q3:2007. During such phases of the business cycle, the Federal Reserve typically reduces the Federal Funds rate (FFR) with the aim of lowering the cost of borrowing, thereby supporting consumption and investment. Since 1990, the FOMC cut rates by an average of 580 basis points (bps) during an economic slowdown (Bernanke, 2016). Since its meeting in September 2007 and up to October 2, 2008, the Federal reserve had already cut FFR by 375 bps. At the onset of the financial crisis in October 2008, the FOMC further slashed the policy rate by 175 basis points (bps) to bring the total reduction to 550 bps, bringing the target rate to 0-25 bps. Although this brought the total decline in FFR very close to the average reduction during recessions, there were two issues particular to this crisis. First, the target range was now at the zero lower bound; any further reduction would take the economy to a negative interest rates environment. Burke et al. (2010) discuss the practical and legal constraints of conducting Fed policy using conventional tools in this environment. Second, Joyce et al. (2012) argues that the transmission of this decline in rates immediately after the financial crisis did not happen because of the broken link between the policy rate and market interest rates. These considerations underscore the advantages of adopting QE policy that specifically targeted longer maturities of the yield curve, ultimately becoming a crucial policy tool for the Federal Reserve post 2008. Figure 1 plots the time series of assets held by the Federal reserve at monthly frequency from January, 2007 - December, 2019. Over a span of 7 years, these policies quintupled the size of the Fed's balance sheet from roughly \$0.9 tn to about \$4.5 tn in 2014. Interest rates normalization began in late 2015, while QE policy rewind began only in October, 2017. Table 7 in the appendix provides a breakup of the purchases for various asset classes.

Figure 1: Timeline of Fed policy tools since the Global Financial Crisis



Note: This figure documents the expansion of Federal Reserve Board's balance sheet as the Federal Funds rate hit the zero lower bound. The sample length is from Jan, 2007-Dec, 2019. Shaded area represents recession periods identified by the NBER's Business cycle dating committee.

The asset purchases were conducted under four distinct rounds beginning with

QE1 in November, 2008 and ending with QE3 in October, 2014. The primary goal under each phase ranged from maintaining financial stability in the first phase to explicitly targeting the twin goals of achieving 2% inflation and full employment in the later phases. I briefly summarize the four phases. The first round, QE1, was a \$1.725tn program that also saw the fastest pace of asset purchases at about \$120bn a month. The aim was to provide a cushion to the economy against the huge shock faced by the financial sector after the collapse of big banks and lenders. It restored functioning in the mortgage market as well as reduced credit spreads in other segments of bond markets. The second round began in November, 2010 with a focus on giving a boost to economic growth and ensuring that inflation increases to the target of 2%. The Maturity Extension Program or Operation Twist was the only sterilized round of QE. The aim was to flatten the treasury yield curve by selling treasury securities with maturity of less than 3 years and purchase an equivalent amount of treasuries with maturities of 6 years to 30 years. The final round of QE, QE3, was initiated because the FOMC was concerned about the slow pace of economic recovery and its consequences for the labour market. In December, 2013, the FOMC provided a glide path to the conclusion of QE in the coming months. It formally concluded bond buying in October, 2014, only after it was satisfied with the pace of economic recovery. Policy rates were lifted for the first time in December, 2015 but the size of the balance sheet remained above \$4 tn for a long time as proceeds from purchases were reinvested in specific asset segments. Balance sheet normalization was announced only in June 2017, after which assets held by the Federal Reserve declined gradually.

3 Stock price decomposition

In this section, I describe the decomposition of stock prices and define the formula used for constructing their response to a monetary policy shock. I begin by fixing notation. Let the stock price and its fundamental component be denoted by Q_t and Q_t^F. Let the *risk-neutral* part of the components be $Q_t^{F,RN}$, R_t denote gross returns, R_t^f as the risk-free rate, equity premium by ep_t and dividends by D_t. Stock prices are directly observable in the market but the fundamental component is unobservable. It is possible to define the fundamental value of the stock in terms of future dividends and future gross returns. This can be seen via the accounting identity of stock returns along with applying the expectations operator in the next step:

$$
\begin{aligned}
& Q_t = R_{t+1}^{-1}(Q_{t+1} + D_{t+1}) \\
\implies & Q_t = \sum_{k=1}^{\infty} \mathbb{E}\Big(\prod_{j=1}^{k} (\frac{1}{R_{t+j}}) D_{t+k} + \lim_{k\to\infty} \frac{Q_{t+k}}{\Pi_{k=1}^{\infty} R_{t+k}} \Big) \\
\implies & Q_t = Q_t^F = \sum_{k=1}^{\infty} \mathbb{E}\Big(\prod_{j=1}^{k} (\frac{1}{R_{t+j}}) D_{t+k} \Big) \qquad (1)
\end{aligned}
$$

where the second step follows from a forward iteration of the first equation and the last step follows from the assumption that growth of prices cannot rise faster than growth of returns. This is the standard transversality condition required for Q_t to be well-defined. The final equation shows that any fluctuation in the stock index can be mapped to movements in its expected future dividends and/or the expected return. Here, I define the *fundamental component* as the present discounted value of expected cash flows,i.e., the sum of discounted expected cash flows accrued for holding the stock.

Note that the above equation is an accounting identity, have no economic content and hold both ex-ante and ex-post. Note also that they are non-linear and have a long history of being linearised to allow use of linear time series methods following Campbell and Shiller (1988). Letting the lower-case letters denote a variable in log terms, one can derive the linearised version using Taylor expansion around a constant $\frac{Q}{D} = e^{q-d}$ and write the fundamental component in log terms as:

$$
\begin{aligned}
q_t &= q_t^F && (2)\\
&= c + \sum_{k=1}^{\infty} \rho^{k-1}[(1-\rho)\mathbb{E}_t d_{t+k} - \mathbb{E}_t r_{t+k}]\\
\implies q_t &= c + \sum_{k=1}^{\infty} \rho^{k-1}[(1-\rho)\mathbb{E}_t d_{t+k} - r_{t+k}^f + ep_{t+k}]\\
\implies q_t &= q_t^{F,RN} - \sum_{k=1}^{\infty} \rho^{k-1}[\mathbb{E}_t ep_{t+k}]\\
\implies q_t &= q_t^{F,RN} + q_t^{EP} && (3)
\end{aligned}
$$

where $c = ln\left(1 + \frac{Q}{D}\right) - \rho(q - d)$, $\lim_{k\to\infty} \rho^k(q_{t+k}) = 0$ is the log-equivalent of the transversality condition mentioned above and $\rho = \frac{Q}{Q+D}$.[4] Here, the second step uses the fact that $E(r_t) = r_t^f + ep_t$. The equity premium (ep_t) is the additional expected return required to incentivize the agent to hold the stock. In standard asset pricing models, it can be shown to be the product of the quantity of risk and price of risk. The price of risk is common across asset classes. In the third step, I begin defining the components that I use to present results. I define the *risk-neutral fundamental component* as the present discounted value of expected (log) cash flows discounted at the risk-free rate. The *equity premium component* is the present discounted value of future equity premium. Equation (3) states that any increase in q_t reflects either an increase in the risk-neutral fundamental component through change in d_{t+k} or a lower r_{t+k}^f, and/or lower equity premium component through changes in ep_{t+k}.

3.1 Construction of dynamic response of asset prices

To examine the dynamic response of asset prices and its components to a monetary shock ε_t^m, I take the derivative of the log-linearised version of equation (2) at time $(t + j)$:

[4] According to Cochrane (2005), $\frac{Q}{D} \sim 25$ in historical US data. In the sample I use, this ratio is much higher at $\frac{Q}{D} \sim 50$ Hence, I set $\rho = 0.98$ in empirical analysis of this paper.

$$\begin{aligned}
&\frac{\partial q_{t+j}}{\partial \varepsilon_t^m} = \frac{\partial q_{t+j}^F}{\partial \varepsilon_t^m} \\
\implies &\frac{\partial q_{t+j}}{\partial \varepsilon_t^m} = \frac{\partial q_{t+j}^{F,RN}}{\partial \varepsilon_t^m} - \sum_{k=1}^{\infty} \rho^{k-1} \frac{\partial ep_{t+k+j}}{\partial \varepsilon_t^m} \\
\implies &\frac{\partial q_{t+j}}{\partial \varepsilon_t^m} = \frac{\partial q_{t+j}^{F,RN}}{\partial \varepsilon_t^m} + \frac{\partial q_{t+j}^{EP}}{\partial \varepsilon_t^m} \qquad (4)
\end{aligned}$$

where ε_t^m is the monetary policy shock. This equation shows that a monetary policy shock impacts stock prices through three mechanisms. First, through its impact on expected dividends by altering the future profitability of the asset. Second, it directly impacts the discount rate via the risk-free rate. Third, monetary policy shocks also have an impact on future equity premium. In contrast with conventional policy shocks, the effect of quantitative easing policy shocks on the risk-neutral fundamental component is likely to reflect more of the first mechanism.[5]

Technically, the effect of monetary policy shocks on equity premium is ambiguous because it leads to a change in both the expected returns as well as the risk-free rate in the same direction. However, a burgeoning literature shows that there is a positive link between monetary policy shocks and riskiness, theoretically (Borio and Zhu, 2012; Cieslak and Schrimpf, 2019; Caballero and Simsek, 2022; Kekre and Lenel, 2022) as well as empirically (Bernanke and Kuttner, 2005; Hanson and Stein, 2015; Jordà et al., 2019; Cieslak and Pang, 2021; Bauer and Swanson, 2023b; Pflueger and Rinaldi, 2022; Bauer et al., 2023). Moreover, QE policy is less likely to encounter a countervailing force in the form of changing risk-free rates since the latter was stuck at the zero lower bound and remained low even after lift-off in 2015. Therefore, I expect a positive effect of QE policy shock on equity premium and the equity premium component.

[5] In particular, for a ceteris paribus effect of any type of monetary policy shocks on future cash flows, the effect through risk-neutral fundamental component is likely to be greater for conventional shocks relative to QE shocks because of the additional effect through change in the risk-free rate.

4 Empirical strategy

In keeping with the objectives of the study, the VAR includes variables that allow construction of structural impulse response functions of each component in equation (4). I utilize the S&P500 index as an indicator for the stock market (Q_t). To proxy for the cash-flow of stock, I use dividends (D_t) sourced from Shiller's website. I convert dividends and stock index into real terms by dividing the series by the Personal Consumption Expenditure (PCE) price index, as is standard in the literature. For the risk-free rate (r_t^f), I use the Federal funds rate. The measure of equity premium (ep_t) is constructed using options data for the S&P500 index, as described in Martin (2017). Appendix D contains a description of the steps used to construct this measure. Relative to other alternatives, it has the advantage that it correctly captures every episode of a spike in premium in the market, especially during the dot-com bubble. Other alternatives do not capture the spike during the dot-com bubble as well and are relatively slower in capturing shifts in risk sentiment. Apart from these variables, a mix of macro-aggregates and financial indicators are included to control for the economic environment. This includes standard variables such as industrial production (Y_t) and aggregate price (P_t). I use the excess bond premium (ebp_t) as a measure of financial conditions. In particular, it captures market sentiment about US corporate credit risk (Gilchrist and Zakrajšek, 2012). Finally, the ten year rate is the long-term rate (i_t^l) included to be a monetary indicator for QE policy. A long-term rate is a better indicator for QE policy relative to a medium-term rate (for instance, one or two year rate) because it shifted the weighted average maturity duration of Federal Reserve holdings from about 1.5 years in October, 2008 to roughly 8 years in December, 2019.[6] Data for industries is sourced from Kenneth French's website. The dataset contains returns on 10 industry portfolios with and without dividends. The broad 10 industry classification includes non-durables, durables, manufacturing, energy, hi-tech, telecom, retail, health, utilities and others.[7]. Since returns are available both with and without dividends, it can be used to obtain series

[6] Source: Federal Reserve Board

[7] The classification uses Standard Industry Classification (SIC) codes to construct the portfolios. Details of the groups are available here The others category includes diverse industries, so it is difficult to identify some characteristics specific to this grouping.

on real prices and real dividends for each industry as described in Hodrick (1992). Other details on the variables and their data source is given in Table 6.

The dynamic response of a monetary shock is computed using a vector autoregression (VAR) model at monthly frequency. The estimation of the VAR model is done using Bayesian methodology and I impose a standard Normal Inverse Wishart (NIW) prior Litterman (1986); Kadiyala and Karlsson (1997) with optimal hyperparameter selection approach of Giannone et al. (2015). The idea implements the belief that each variable in the system is well approximated by a random walk model with drift. The prior help in incorporating a greater number of variables and lags relative to the frequentist approach. This is especially useful since a small number of variables in the VAR or an inappropriate number of lags may pose an issue for correctly capturing dynamics of the system. Define the vector $x_t = [y_t, p_t, i_t^l, ebp_t, q_t, r_t^f, d_t, ep_t]'$ and let the structural model be of the following form:

$$Ax_t = B_0 + \sum_{i=1}^{k} B_i x_{t-i} + \varepsilon_t, \;\; \varepsilon_t \sim N(0, \Sigma_\varepsilon) \tag{5}$$

where B_i is a (8×8) matrix of coefficients and ε is the (8×1) vector of uncorrelated structural shocks. The reduced form can be derived under the assumptions of invertibility:

$$x_t = C_0 + \sum_{i=1}^{k} C_i x_{t-i} + u_t, \;\; u_t \sim N(0, \Sigma_u) \tag{6}$$

where $C_i = A^{-1}B_i$ and $u_t = A^{-1}\varepsilon_t$. The posterior median IRFs and confidence bands are generated based on the Gibbs sampling procedure with 2000 draws and 20% burn-in period. The impulse responses to structural shocks are computed as per the Vector Moving Average (VMA) representation:

$$x_t = \mathbf{D(L)}\varepsilon$$
$$= \sum_{i=0}^{k} D_i \varepsilon_{t-i} \tag{7}$$

where $\mathbf{D(L)} = [\mathbf{I} - \mathbf{C(L)}]^{-\mathbf{1}} A^{-1}$.

The variables included in the VAR model ensure that I observe the stock index and both components. The theoretical dynamic responses of components in equation (4) are infinite sums and require an approximation. I therefore use an approximation of the infinite sum with 10 years of responses.[8]

4.1 External instrument

The residuals from a VAR model are a linear combination of structural shocks. Hence, it is vital to identify the structural shock for examining the dynamic response. I utilize the external instrument approach for identifying the monetary policy shock, popularized by Gertler and Karadi (2015) in the monetary literature. The QE policy shock is the structural shock associated with the long-term interest rate. Any external instrument, z_t, must satisfy two assumptions in order to identify a shock of interest ε_t^m:

$$\mathbb{E}(\varepsilon_t^m . z_t') \neq 0 \tag{8}$$
$$\mathbb{E}(\varepsilon_t^{\not m} . z_t') = 0 \tag{9}$$

The first assumption is instrument relevance - the instrument must be contemporaneously correlated with the structural shock. The second assumption relates to instrument exogeneity - the instrument must be contemporaneously uncorrelated with other structural shocks. Using a valid instrument allows identification of the

[8]The results are robust to using a higher number of months for approximating the infinite sum.

monetary policy shock. Details of the operational steps of the methodology are provided in appendix E. The above assumptions assume invertibility of the structural moving average [9] (Stock and Watson, 2018). Since I am only interested in examining the response of a single shock, an assumption milder than full invertibility can be used to obtain the shock of interest. Miranda-Agrippino and Ricco (2023) formalize a condition that combines with equations (8-9) for recovering structural shocks in an SVAR-IV framework under partial invertibility:

$$\mathbb{E}(\varepsilon_{t-j}^{m,NI}.z_t^{'}) = 0 \text{ for} j \neq 0 \text{ for which } \mathbb{E}(\varepsilon_{t-j}^{m,I}.z_t^{'}) \neq 0 \tag{10}$$

where $\varepsilon_{t-j}^{m,I}$ and $\varepsilon_{t-j}^{m,NI}$ are invertible and non-invertible shocks respectively. This 'limited lead-lag exogeneity condition' states that any valid instrument must be uncorrelated with past and future non-invertible shocks while allowing for the possibility of the instrument to be correlated with the leads and lags of the invertible shocks.

The instrument used in this paper is sourced from Swanson (2021). The paper estimates 3 factors from surprises in contracts of Fed Funds Futures, Eurodollar futures and Treasury yields at different maturities [10] around monetary announcements of the Federal Reserve. These contracts contain expectations about the policy rate and are a popular source of obtaining exogenous variation in monetary policy. I utilize the Large Scale Asset Purchases (LSAP) factor that loads heavily on the five year and ten year treasury yields.

A potential issue is that during the event window, these contracts may also be impacted by non-monetary shocks that originate from the policy decision and the accompanying press release. Disentangling monetary and non-monetary policy shocks is important for identification since the assumption requires that the instrument be correlated only with the shock of interest. Two important non-monetary shocks

[9] This is equivalent to stating that all structural shocks can be written as a linear combination of VAR residuals.

[10] In particular, the contracts include 1-month and 3-months federal funds futures, 2-, 3- and 4-months Eurodollar futures, and as 2-,5- and 10-year Treasury yields.

have been previously discussed in the literature. First, a comparison of market participants' beliefs about economic fundamentals with the perceived wisdom of the FOMC about the expected path of the economy, popularly known as information effects.[11] Second, risk premium shocks that may be an important factor in movement of yields at the medium-long end of the yield curve. Note that one of the mechanisms through which unconventional policies operate is the risk premium channel. Hence, mere presence of non-zero premium changes is not a problem. It is the presence of risk premium shocks that can confound the causal effect of monetary policy shocks.

To think more about the effect of non-monetary shocks on the instrument, let's begin by summarizing the expected signs of shocks on surprises in yields, stock price and risk premium. Table 1 contains all the expected signs. The table provides two key messages: first, monetary policy shocks lead to a negative link between stock and yield surprises, and a positive link between risk premium and yield surprises. Second, positive information shocks and negative risk premium shocks both induce a positive co-movement between stocks and yields, and a negative link between risk premium and yields. Hence, the three surprise series provide two sets of co-movements to examine whether the market reaction is consistent with a monetary policy shock or a non-monetary shock. This is a natural extension of the idea of detecting presence of information effects by looking at stock-yield co-movements (Jarociński and Karadi, 2020).

Table 1: Expected effect of shocks on market surprises

	ΔYield	ΔStock	ΔRisk premium
Quantitative easing shock ($\varepsilon_t^m \downarrow$)	$\downarrow$	$\uparrow$	$\downarrow$
Negative growth shock ($\varepsilon_t^g \downarrow$)	$\downarrow$	$\downarrow$	$\uparrow$
Positive risk premium shock ($\varepsilon_t^{rp} \uparrow$)	$\downarrow$	$\downarrow$	$\uparrow$

Note: This table shows the expected signs on surprises in yields, stocks and risk premium in an event window around monetary policy decisions to a monetary policy shock ε_t^m, growth shock ε_t^g and risk premium shock ε_t^{rp}.

If only a single shock were to emanate from the FOMC announcement, char-

[11] Bauer and Swanson (2023a) have shown this effect to be consistent with revelation of the Federal Reserve's response to publicly available news with a stronger response to incoming macro news during some periods in the business cycle. Controlling for publicly available information can account for this "response to news effect" (Bauer and Swanson, 2023b).

acterizing the yield surprise of any particular event as either a monetary policy shock or a non-monetary shock requires an examination of only two of the three available market surprises. In conjunction with yield surprises, either stock surprises or risk premium surprises may be used. The idea of inspecting three market surprise series becomes useful in situations where a combination of shocks materialize on the same FOMC announcement day. On such event days, two market surprises may not provide enough information to correctly associate the event with a monetary policy or non-monetary shock; they may reveal only a partial picture of the combination of shocks. I illustrate below the extent to which this happened since the beginning of the QE period.

Table 2 reports data for FOMC events associated with the ten biggest surprises in the LSAP factor. Column (1) contains data on the LSAP factor as a measure of yield surprises while columns (2-3) contain measures of market surprises in stock market and risk premium. These measures are the S&P 500 index sourced from Bauer et al. (2023) and a measure of daily changes in risk premium respectively. The latter is a variant of the risk appetite index in Bauer et al. (2023) and I use the first principal component of nine indicators on volatility and credit spreads. A positive value reflects an increase in risk premium on any given day as the indicators load positively on indicators of credit spread and volatility. The index is standardized, so its units are in standard deviations. Details of loadings of various indicators are in appendix G. Column (4) specifies the type of shock that one would associate with the FOMC event based *only* on the stock-yield co-movement - a distinction between monetary shock and non-monetary shock. A negative co-movement points towards a monetary policy shock while a positive co-movement implies either an info shock or a risk premium shock. Column (5) uses surprises in risk premium to verify this classification by using two co-movements among the three market surprises. The idea is that if it is indeed an event associated with a particular policy shock, it should result in a co-movement consistent with expected signs in Table 1. Instead, I find that many of the events that are initially associated with a particular shock based on the stock-yield co-movement, are inconsistent with the risk-yield co-movement. This points towards presence of a combination of shocks. In fact, there were 29 FOMC event days (out of 85) during 2009-19 where the stock-yield co-movement is negative along with a negative risk-yield co-movement.

Table 2: Classification of 10 largest LSAP events into a monetary or a non-monetary shock

date	LSAP factor	SP500	Risk premium	stock-yield	risk-stock-yield
18/03/2009	-5.63	1.75	3.77	MPS	N
24/06/2009	0.80	-0.58	-1.11	MPS	N
03/11/2010	0.81	-0.39	-0.96	MPS	N
21/09/2011	-1.29	-0.19	-0.23	Info/RP	N
13/09/2012	1.01	0.60	-0.72	Info/RP	Y
20/03/2013	0.77	0.10	-0.35	Info/RP	Y
19/06/2013	1.96	-0.04	-0.39	MPS	N
18/09/2013	-2.55	1.16	0.17	MPS	N
18/03/2015	-0.77	1.51	0.81	MPS	N
29/04/2015	0.87	0.15	0.34	Info/RP	N

Note: This table determines the classification of biggest surprises in the LSAP factor into a monetary policy surprise or a non-monetary policy surprise. Column (4) uses the stock-yield co-movement for this purpose. Column (5) uses additional information from changes in risk premium to verify this classification. In some cases, the classification in column (4) is incorrect.
Y: yes; N: no
MPS: Monetary policy shock; Info: Information shock; RP: Risk premium shock

Table 3 presents details from a few FOMC statements listed above where additional narrative evidence on a shift in risk sentiment is presented from FOMC statements. For instance, in March 2009, the FOMC expanded the QE-I program by $1.15 tn, which is an expansionary surprise. However, it also stressed on a bleak economic environment for the current and next year which may have led to a risk-off sentiment in the market. The expansionary unexpected policy announcement along with a positive risk premium shock is a plausible explanation for these market movements. In June 2009, the FOMC noted the slowing pace of economic contraction and stabilization of financial conditions. The risk premium index shows improvement in risk sentiment and the risk-stock-yield co-movement is consistent with combination of monetary and non-monetary shocks. Note that these shifts in risk sentiment are unrelated to a shift in monetary policy regime because the monetary policy stance was accommodative since September 2008.

To summarize, market surprises in yields contain monetary, information, and risk premium shocks. Combining yield surprises with surprises in stocks and risk premium helps associate events with monetary or non-monetary shocks. Either stock or risk premium surprises should be enough to disentangle the two types of shocks. However, during some events, stocks and risk premium surprises move in directions that cannot be explained by a single shock. In fact, risk premium surprises show presence of events which are initially associated with monetary shocks based on stock-yield co-movement but are consistent with presence of a combination of monetary policy and non-monetary shocks based on stock-risk-yield co-movement.

Table 3: Events with presence of non-monetary shocks

Dates	Combination of shocks MPS	Non-MPS	FOMC statement
March 2009	↓	↓	Discusses deteriorating economic situation during the global financial crisis. QE-I expanded.
June 2009	↑	↑	Discusses signs of stabilization in HH spending and inventories.
Nov 2010	↑	↑	Discusses slow pace of economic recovery. QE-II announced.

Note: ↓ Non-MPS could be either a negative information shock or a positive risk premium shock

The presence of non-monetary shocks in yield surprises has implications for using the LSAP factor as an instrument for a monetary policy shock. It violates the assumption of instrument exogeneity (equation 9) due to non-zero correlation between the instrument and non-monetary shock. This implies that the dynamic responses to the monetary policy shock estimated using the external instruments approach is a combination of the response to the monetary policy and non-monetary shock. This poses a challenge for obtaining the causal effect of monetary policy shocks on macroeconomic aggregates included in the VAR because their response to non-monetary shocks are likely to be in the opposite direction to that for the monetary policy shock. For instance, the stock index response is negative to a negative information shock, or a positive risk premium shock, while it is positive in response to an expansionary monetary policy shock. Hence, the estimated effect may be incorrect not only in magnitude but also the direction. This could lead to empirical puzzles in the estimated dynamic responses from the SVAR model. To conclude, it matters for identification whether market surprise in yields was driven by a monetary policy shock or a non-monetary shock. If it is driven by a combination of the two types of shocks, then it is possible that we will not be able to recover the causal effect of monetary policy shocks by simply accounting for one type of non-monetary shock.

I follow a two step procedure and construct an information and risk-corrected instrument to control for information and risk premium shocks. In the first step, I account for information effects. The literature uses either market based (Jarociński and Karadi, 2020) or survey based approaches (Romer and Romer, 2000; Miranda-Agrippino and Ricco, 2018). The survey based approach creates an informationally robust instrument by controlling for information content in a series of monetary surprises using a regression. I use the survey based approach because it is common for central bank announcements to contain a mix of monetary shocks with information about future economic fundamentals. This allows retention of more information relative to the market based approach. This is because in the latter, the instrument uses only those monetary surprises where the stock market surprise and factor surprise co-move in the opposite direction. For the regression, I utilize data from Greenbook[12] of the Federal Reserve Board of Governers. It includes fixed event quarter on quarter projections (in annualized percentage points) for 15 macroeconomic macro aggregates. The major aggregates include measures of output, inflation and unemployment. The projections trace the expected path of these measures up to 9 quarters ahead. While the data is available to the members of FOMC one week prior to their meeting, it is released to the public only after a lag of 5 years. This has an implication for the surprises measured in the event window; it is possible that financial markets move in response to an update in beliefs about future economic aggregates rather than the policy rate decision itself. I begin by aligning the forecasts data with every FOMC meeting. For every meeting, the market surprises are regressed on the latest greenbook data available to the FOMC according to the following equation:

$$y_m = \alpha_0 + \sum_{j=-1}^{k} \alpha_j F_m x_{q+j} + \sum_{j=-1}^{k} \beta_j \left[F_m x_{q+j} - F_{m-1} x_{q+j} \right] + \nu_m \tag{11}$$

where $k = 3$ is the maximum horizon, y_m is the LSAP factor, $\mathrm{x} \in$ {Real GDP, Real

[12]The Greenbook is part of the Tealbook since January, 2010. The data is sourced from the Philadelphia Fed's Tealbook Data Set.

deflator,unemployment rate} is a vector of forecast data from the Fed's Greenbook. The backcast of variables is also included in the regression in order to control for the real-time prevailing conditions that is likely to impact the decision making of the FOMC (Romer and Romer, 2004). The residual, ν_m, contains variation in y_m that is exogenous to the central bank's private information on forecasts. Hence, the residual is the information corrected version of y_m.

In order to disentangle monetary policy shocks and risk premium shocks in the instrument z_t, the second step zeros-out data points on those dates where the co-movement between informationally robust instrument and informationally robust risk premium surprises is negative. Note that an informationally robust version of risk premium measure is used, instead of the raw series, in order to isolate variation in risk premium that is independent of information shocks. This is done for two reasons (Reichlin et al., 2022). First, this ensures that in the second step, the focus is only on removing risk premium shocks. Second, it is not desirable to control for risk premium shocks using risk premium surprises and including it in the same regression as used to control for information effects. This requires that surprises in risk premium are not impacted by monetary policy shocks. However, this assumption on risk premium surprise is highly likely to fail in the data. A detailed discussion about these assumptions is provided in appendix F.

5 Results

5.1 Instrument with information and risk-correction

I begin with discussing the presence of information content in the LSAP factor. The regressors include quarter on quarter forecasts and revisions of real GDP, GDP deflator and unemployment rate. Since all forecasts and revisions are highly correlated and it is difficult to pinpoint the source of explanatory power from the regression, I estimate additional regressions that contain a subset of variables and vary based on the variable group, whether they are forecasts or revisions and their horizon. This improves understanding of sources of the explanatory power of the LSAP factor. Table 4 displays results of regression of the factor on to the Greenbook forecasts and revisions. The sample period is from November, 2008-December, 2017 since this is the last data vintage available from the Philadelphia Federal Reserve. The parentheses below coefficients contain the Newey-West heteroskedasticity and autocorrelation corrected standard errors with a possible autocorrelation structure of up to one lag.

Starting with column (1) that includes forecasts and revisions only related to GDP growth as regressors, the GDP block's null of no significance is rejected at 1% level. Column (2) contains results from the inflation block and it is significant at 5% level. Column (3) suggests that news about unemployment rate does not have any significant impact on the factor. Columns (4) shows that projections of GDP and unemployment are significant predictors of the LSAP factor but they are not jointly significant even at 10% level. The specification on revisions in column (5) displays joint significance at 1% level and largely driven by GDP revisions in the 3 quarters ahead forecast. Turning to specifications at different horizons, variables at longer horizons from $h = 2$ and $h = 3$ are jointly significant at 5% level and 1% level respectively. Finally, the last column contains all variables in the regression and the F-test is rejected at 1% level of significance. These results confirm the presence of information effects around FOMC announcements in the medium and long term maturity of the yield curve.

Based on these regressions, I conclude that the market's reaction to Fed announcements contains inference about future economic fundamentals, in particular on the central bank's assessment of future economic growth and to a lesser extent, the inflation rate. In contrast, forecasts and revisions in price level seem to have little significance in the above tables. A potential reason behind this might be that inflation was benign during most of this period and was not of much concern to the market. Instead, it focussed more on receiving a signal about the state of economic growth in the coming quarters. To control for these effects, I utilize the residual estimated from the regression specification of column (11). This is the first step in constructing the external instrument. Although the regression is at meeting frequency, converting it to monthly frequency has no consequence since each month

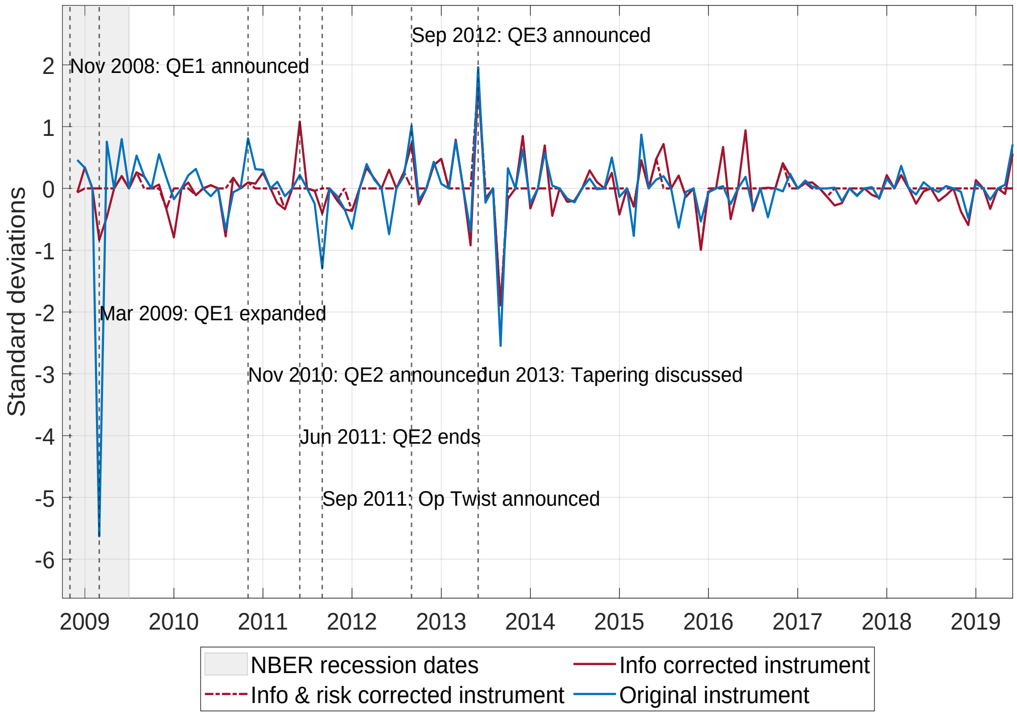
Table 4: Information effects in the LSAP factor

Column Specs	1 GDP growth	2 Deflator	3 Unemp	4 Forecasts	5 Revisions	6 h=-1	7 h=0	8 h=1	9 h=2	10 h=3	11 All
GDP growth$_{t-1}$	-0.01			-0.01		0.07					0.05
	(-0.19)			(-0.15)		(0.71)					(0.45)
GDP growth$_{t}$	0.17			0.23*			0.21*				0.16
	(1.22)			(1.70)			(1.94)				(0.79)
GDP growth$_{t+1}$	-0.02			-0.35				0.14			0.21
	(-0.06)			(-1.63)				(0.76)			(0.51)
GDP growth$_{t+2}$	-0.25			0.08					0.31		-0.09
	(-0.70)			(0.22)					(1.52)		(-0.21)
GDP growth$_{t+3}$	0.38**			1.04**						0.48***	-0.06
	(2.14)			(2.56)						(2.73)	(-0.19)
ΔGDP growth$_{t-1}$	-0.03				-0.00	0.05					-0.04
	(-0.18)				(-0.01)	(0.30)					(-0.20)
ΔGDP growth$_{t}$	-0.31				-0.11		-0.04				-0.12
	(-1.53)				(-0.69)		(-0.27)				(-0.40)
ΔGDP growth$_{t+1}$	0.03				0.18			0.19			0.09
	(0.06)				(0.89)			(0.73)			(0.19)
ΔGDP growth$_{t+2}$	0.52				0.24				1.13***		0.42
	(1.22)				(0.81)				(3.25)		(0.84)
ΔGDP growth$_{t+3}$	0.90**				1.12**					1.33***	1.16**
	(2.40)				(2.49)					(4.72)	(2.56)
Deflator$_{t-1}$		0.07		0.14		0.16					0.11
		(0.72)		(1.02)		(1.04)					(1.12)
Deflator$_{t}$		-0.12		-0.14			-0.00				0.13
		(-0.81)		(-0.97)			(-0.01)				(0.85)
Deflator$_{t+1}$		-0.06		0.25				0.02			0.09
		(-0.17)		(1.35)				(0.08)			(0.31)
Deflator$_{t+2}$		-0.21		0.34					0.43		-0.18
		(-0.92)		(1.14)					(1.57)		(-0.53)
Deflator$_{t+3}$		0.22		0.14						0.21	-0.52
		(0.48)		(0.55)						(0.71)	(-1.32)
Δ Deflator$_{t-1}$		0.54			0.21	0.41					-0.10
		(1.25)			(0.71)	(0.96)					(-0.34)
Δ Deflator$_{t}$		-0.43			-0.22		-0.66*				-0.41
		(-1.54)			(-1.35)		(-1.82)				(-1.61)
Δ Deflator$_{t+1}$		0.00			-0.00			0.39			-0.17
		(0.00)			(-0.02)			(0.51)			(-0.53)
Δ Deflator$_{t+2}$		0.67			0.03				-0.37		-0.19
		(1.26)			(0.08)				(-1.00)		(-0.44)
Δ Deflator$_{t+3}$		0.73*			0.42					-0.01	0.09
		(1.81)			(0.98)					(-0.04)	(0.17)
Unemp$_{t-1}$			0.62	-0.66		0.05					
			(0.68)	(-1.45)		(1.35)					
Unemp$_{t}$			1.45	1.77			0.02				-0.02
			(0.75)	(1.37)			(0.56)				(-0.26)
Unemp$_{t+1}$			-3.77	-3.49**				-0.02			
			(-1.58)	(-2.01)				(-0.24)			
Unemp$_{t+2}$			2.73	0.79					0.03		
			(0.98)	(0.33)					(0.89)		
Unemp$_{t+3}$			-0.94	1.52						-0.02	
			(-0.67)	(0.84)						(-0.38)	
Δ Unemp$_{t-1}$			1.20		0.68	2.44					1.70
			(0.90)		(0.54)	(1.28)					(1.33)
Δ Unemp$_{t}$			-1.49		0.14		0.62				-0.47
			(-0.75)		(0.15)		(1.19)				(-0.50)
Δ Unemp$_{t+1}$			6.80		-0.85			0.48			0.85
			(1.57)		(-0.56)			(0.93)			(0.50)
Δ Unemp$_{t+2}$			-1.37		-1.46				0.96**		-0.73
			(-0.52)		(-0.67)				(2.10)		(-0.37)
Δ Unemp$_{t+3}$			-3.24		2.00					0.58*	1.23
			(-1.63)		(1.10)					(1.93)	(0.75)
Constant	-0.68**	0.16	-0.70	-3.00**	0.00	-0.68	-0.52	-0.25	-1.66*	-1.51	0.25
	(-2.22)	(0.38)	(-1.56)	(-2.13)	(0.03)	(-1.34)	(-1.29)	(-0.54)	(-1.74)	(-1.57)	(0.19)
Observations	73	73	73	73	73	73	73	73	73	73	73
F-test	4.69	2.11	0.99	0.96	3.50	0.51	1.00	0.96	3.03	6.67	3.99
Prob>F	0	0.04	0.46	0.51	0	0.80	0.43	0.46	0.01	0	0

Note: This table reports results for regression of LSAP factor in (Swanson, 2021) on Greenbook forecasts and revisions. Each column represents a different specification of regressors. Sample length is Nov, 2008-Dec, 2017. *p<0.1, **p<0.05,***p<0.01. Standard errors in parentheses.

only has a single meeting. Any months for which no meeting took place, I replace the missing values with a zero.

Figure 2: Time series plot of informationally robust LSAP factor



Note: This figure plots the time series of the LSAP factor (in orange) along with it's informationally robust variant (in yellow), obtained as the residual from estimating regression equation (11).

Figure 2 shows the impact of this step by comparing the time series plots of the LSAP factor along with the residual. Some of the dates coincide with announcements about QE. For example, March, 2009 had the biggest impact on long term bond yields. It is plausible that the FOMC announcement of a $1.15tn expansion of the QE1 program led to this decline. It committed to additional purchases of GSE and MBS and added treasury securities to the purchase program. However, it also painted a grim picture of the economic outlook in its statement. The lower value of the residual relative to the LSAP factor suggests that this may have also played a role in the big decline in the factor and this is corrected by the regression. A similar story may have played out in September 2011, when the Federal reserve announced details of Operation Twist alongside concerns about "elevated" unemployment rate and slow pace of economic recovery. Another interesting episode is from November 2010, when the FOMC announced expansion of securities holdings and the LSAP factor registered a positive value. Since the average duration of additional purchases was about 5-6 years and only 6% of new purchases were in treasuries with maturities equal or greater than 10 years, treasuries at the longer end of the yield curve witnessed a sell-off. But the value of the residual declines to near zero since Greenbook data shows an improvement in real GDP growth in the coming year. The regression removes this positive information effect from the LSAP factor. Finally, in June 2011, the FOMC announced the end of QE2. Despite noting a slower than anticipated pace of economic recovery, the FOMC did not commit to any further stimulus. This may have led to a rise in yields at the long end of the yield curve. The negative sentiment about pace of growth in the statement was matched with downward revisions of growth projections in the greenbook forecasts. The regression removes this effect and leads to an even higher positive magnitude for the residual than the LSAP factor.

In the second step, I zero out values in the residual where there is negative co-movement between the residual and informationally robust risk premium surprise series. This disentangles monetary policy shocks from any risk premium shocks that emanate from the Federal reserve announcements. The resultant series is the information and risk-corrected instrument that is used as an external instrument in the VAR exercise.

Following Forni and Gambetti (2014), I also test for information sufficiency of the instrument using 7 factors estimated from the FRED-MD database. These factors represent state variables in the economy and are interpreted on the basis of the incremental explanatory power of the factors for various time series in the database (McCracken and Ng, 2016). The results are presented in Table 5 and show that none of the factors granger cause the information and risk corrected instrument.[13]

[13] In contrast, some factors do granger cause the original LSAP factor. Results available on request.

Table 5: Granger causality test of information and risk corrected instrument

Excluded	χ^2 statistic	DF	p-value
Factor 1	0.08	2	0.95
Factor 2	0.44	2	0.80
Factor 3	2.89	2	0.24
Factor 4	0.84	2	0.65
Factor 5	3.78	2	0.15
Factor 6	1.64	2	0.44
Factor 7	0.69	2	0.71
All	6.78	14	0.94

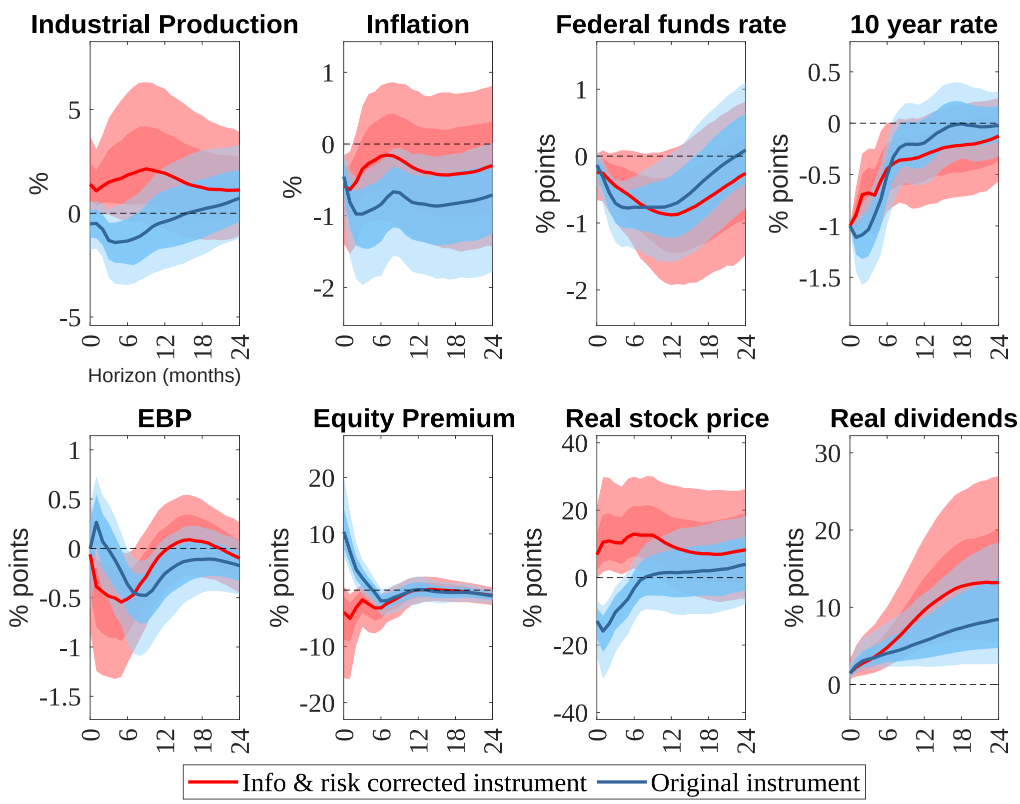
Note: Each row reports the χ^2 statistic, degrees of freedom and p=value of a hypothesis test that the variable in the first column does not granger cause the information and risk corrected instrument.

5.2 VAR results with information and risk-corrected instrument

The estimation sample length is from Jan. 1996 to Dec, 2019, ending just prior to the start of the pandemic. The median responses are plotted along with 68% and 90% confidence bands where dark shaded bands reflect 68% bands while light shaded bands reflect 90% bands. I begin with results for variables included in the VAR and show the importance of disentangling monetary policy shocks from non-monetary policy shocks in the instrument series. I then discuss results for responses of the decomposed stock price components.

The responses to a 100 bps expansionary QE shock are in Figure 3. Each chart includes responses of information and risk corrected instrument (in red) along with the original instrument (in blue). In contrast, results with the information and risk-corrected instrument are largely in the expected direction. In particular, responses of industrial production, stock index and equity premium are free from any puzzles *after the information and risk correction.* Focussing only on responses with the information and risk corrected instrument, output response increases by 1% on impact and is weakly significant for roughly six months. The risk-free rate response is near-zero on impact and the hump shaped dynamic response probably reflects dynamics from the period prior to the global financial crisis. The excess bond premium decreases in the

Figure 3: IRFs for Quantitative Easing policy shock

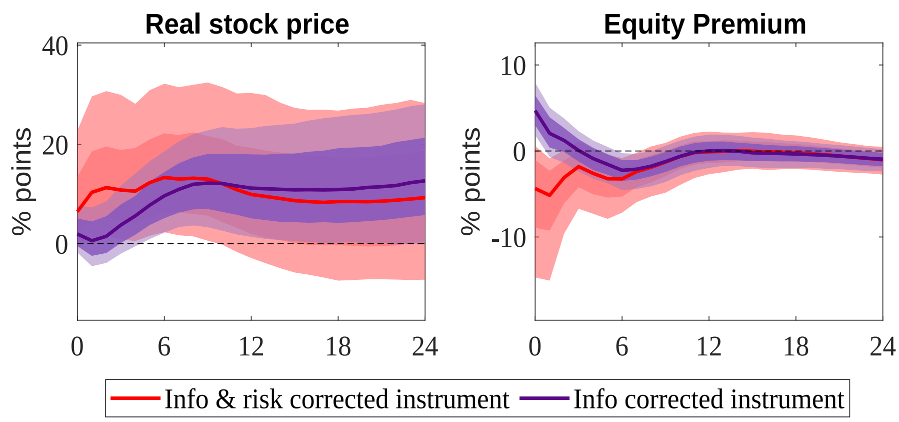


Note: Impulse responses to a Quantitative easing policy shock using information and risk-corrected instrument (solid red), and LSAP factor (solid blue). The shock is normalised to induce a 1% decrease in the 10 year rate. Sample: 1996:1-2019:12. Dark and light shaded areas represent 68% and 90% posterior coverage bands respectively.

short run suggesting some easing of financial conditions in the bond market. The equity premium decreases by about 4% points on impact. Real stock index increases by about 7% points with a peak effect of about 12% in the first six months. Real dividends also register a persistent increase with a peak of roughly 13% points at the end of two years.

My findings on the importance of information and risk correction in the IV for obtaining causal effects of QE policy shocks complements recent work on using the LSAP factor as an external instrument. Miranda-Agrippino and Ricco (2023) suggest that the correlation of the instrument with contemporaneous shocks may have lead to confounding estimates for impact responses of macro variables. Swanson (2023) finds that a correction in the factor for publicly available economic and financial news improves identification for financial variables but there are still puzzles in output and prices. I show the importance of controlling for risk premium shocks in eliminating empirical puzzles in estimated effects of QE policy shocks. Figure 4 highlights this by plotting the IRFs for the stock index and equity premium using two different instruments: the information and risk corrected instrument (in red), i.e., the instrument that uses both steps and an instrument that *only* corrects for information shocks (in purple). The impact response and subsequent dynamics for equity premium are positive in response to an expansionary shock when the instrument is corrected for only information effects. In addition, the response of stock price is stronger after risk correction. Hence, the use of both steps is crucial to correctly quantify the impact of QE policy shock of stock index and equity premium. This becomes relevant while quantifying the decomposition of the stock index.

Figure 4: Importance of risk correction in constructing the instrument



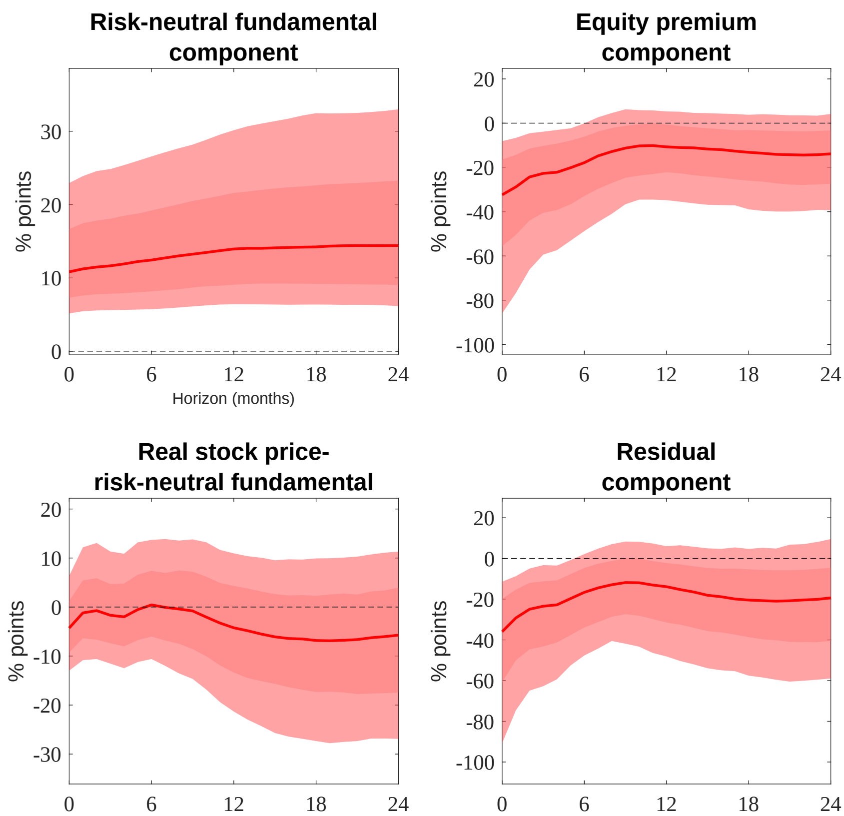
Note: Impulse responses to a Quantitative easing policy shock using information and risk-corrected instrument (solid red), and information corrected instrument (solid purple). Horizontal axis indicates horizon (months). The shock is normalised to induce a 1% decrease in the 10 year rate. Sample: 1996:1-2019:12. Dark and light shaded areas represent 68% and 90% posterior coverage bands respectively.

I now turn to the dynamic responses of the two components based on equation 4. The first row of Figure 5 shows the IRFs. The risk-neutral fundamental value declines by about 10% points and is persistent for more than 2 years. The equity premium component increases by about 30% points on impact. Hence, the equity premium component is the dominant channel through which QE policy impacted the S&P500 index. These results are consistent with some of the findings in the literature on conventional policy shocks. Pflueger and Rinaldi (2022) finds a similar ratio between risk premium and risk-neutral fundamental value of the stock index in their simulated model. Jordà et al. (2015) find a similar response of risk-neutral fundamental component of stock prices to a conventional monetary policy shock.

The second row shows the response of the difference between stock price and its fundamental value as well as the difference between stock index and the risk-neutral fundamental component (bottom right panel). The former shows that the impact response of the median residual component is negative and significant in the short run. One explanation for the residual is that it captures mis-pricing of the stock index, potentially due to presence of heterogeneous agents in financial markets. The figure in the bottom right panel is constructed to think about the case of a risk-neutral world which implies there is no role for equity premium. Then, under risk-neutrality, the residual component response is positive and weakly significant in the short run. This shows the importance of building an information and risk corrected instrument. If the instrument without any correction was used, then the difference between responses of the stock index and the risk-neutral fundamental component would have been negative as the response of stock index with an IV without information and risk correction was negative. This result complements Paul (2020) who also documents that improving identification of the shock reverses the sign of the response of the bubble component, though it demonstrates this for the case of conventional monetary policy.

The above results provide three important takeaways: first, the importance of information and risk correction in the original instrument to correctly identify the effect of QE policy shocks on components of the stock index. Without these corrections, there is a negative response in the stock price and a positive response of equity premium to an expansionary shock. Further, the additional risk correction in the instrument is crucial to achieve correct identification of QE policy shocks. Second, the response of equity premium is an important component of the stock price response. It moves the stock market 3 times more relative to the risk-neutral fundamental component. Third, both components have persistent effects over a period of two years with the relative importance of equity premium remaining largely unchanged.

Figure 5: Results from decomposition of stock index



Note: Row one: Decomposition of impulse response of stock index to a Quantitative easing policy shock using information and risk-corrected instrument into the response of risk-neutral fundamental component and the EP component. Row two: The residual component response is the difference between the response of stock index and the sum of responses of risk-neutral fundamental and EP component. The bottom right panel presents the the difference between the response of stock index and the response of risk-neutral fundamental component. The shock is normalised to induce a 1% decrease in the 10 year rate. Sample: 1996:1-2019:12. Dark and light shaded areas represent 68% and 90% posterior coverage bands respectively.

5.3 Heterogeneous effects of monetary policy shocks

This subsection presents evidence for the effect of QE policy shock on risk-neutral fundamental of industry specific Fama-French portfolios. Indusrty specific data on stock price and dividends replace the aggregate stock index and corresponding dividends in the VAR model to obtain industry specific impulse responses to the QE policy shock.

Results for response of the industry level stock index and the risk-neutral fundamental value are in Figure 6. It contains responses from impact to two years for a select number of horizons. Greater fading intensity reflects more distant horizons.

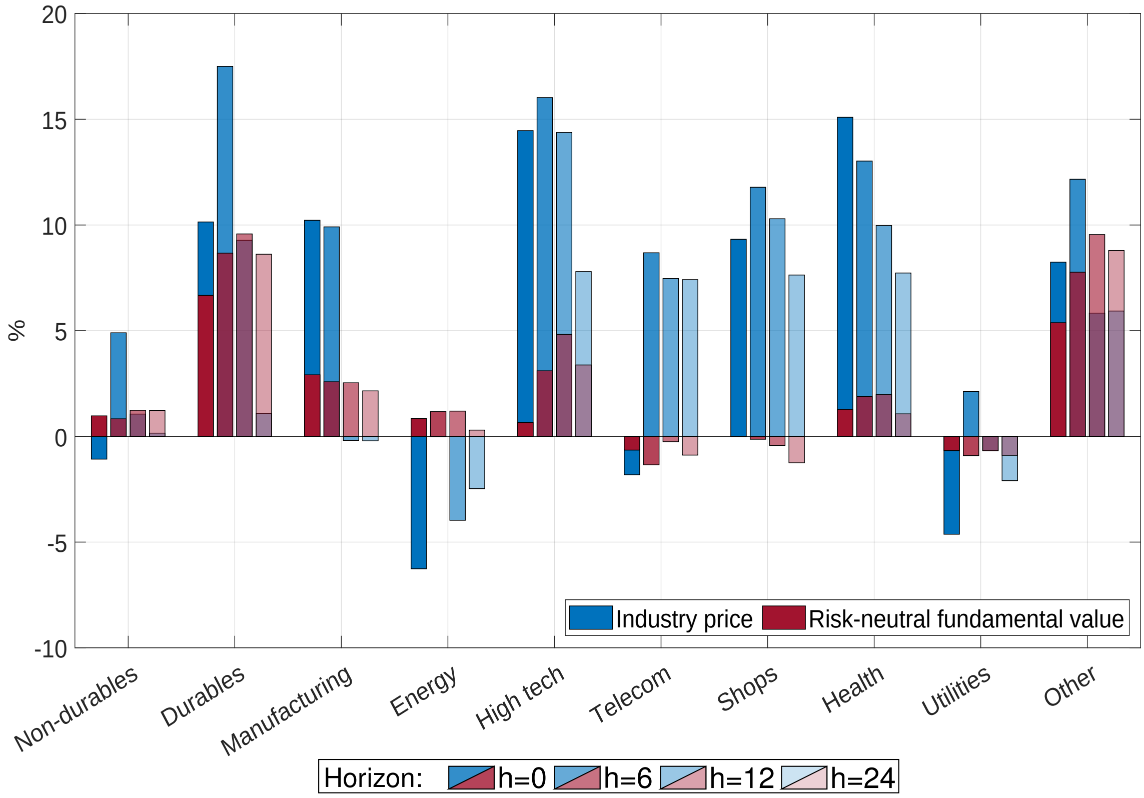
I begin with responses of the industry level stock index, given in blue. QE policy shocks exerted a large effect on stock prices in seven out of ten industry groups. The high tech and health sector have the largest effect followed by manufacturing, durables and retail. Non-durables, energy and utilities either have a small effect or they are insignificant. On impact, the increase among industries is in a wide range of 0-15%. In addition, industries also differ in persistence of the effect, although the responses are within a narrower range as horizons increase. Next, I discuss the risk-neutral fundamental component response in red. The response of this component is large only for durables and others. Note that the others grouping includes finance, so this result might be due to the interest sensitive nature of durables and finance industries. In terms of persistence, the effects on all industries are relatively more persistent than the effect on the aggregate. The smaller effect of QE policy shocks on risk-neutral fundamental component of other industries indicates that, perhaps, tech dominated sectors such as high tech, health and telecom are impacted more by the risk premium mechanism than cash flows.

These results point towards two key takeaways from these results. First, there is high degree of heterogeneity in the response of industry groups to monetary policy shocks. Second, heterogeneity exists not only at the aggregate level but also at the component level. In particular, only durables and others' industries report a big increase in risk-neutral fundamental value. This opens the possibility that equity premium plays a key role in movement of majority of industries. In addition, all industries differ in persistence of the effects of QE policy shocks.

5.4 Robustness checks

I verify the robustness of results on several fronts. The results are in appendix H. First, I verify that IRFs are qualitatively similar to an alternate construction of the external instrument. In the first step, I zero out all those dates where the surprises in stocks and yields co-move negatively (Jarociński and Karadi, 2020). In addition, I do an additional step in which I zero out dates where the co-movement between LSAP factor and risk premium is negative. I find that results are similar to the main result

Figure 6: Industry level IRFs for Quantitative Easing policy shocks



Note: Industry level impulse responses of industry level stock index (in blue) and its corresponding risk-neutral fundamental value (in red) to a Quantitative easing policy shock using information and risk-corrected instrument at select horizons ($h = 0, 6, 12, 24$ months). Increased fading intensity reflects more distant horizons. The shock is normalised to induce a 1% decrease in the 10 year rate. Sample: 1996:1-2019:12.

in Figure 3. Second, I check if results are sensitive to alternative monetary policy indicators. This is because it might be possible that monetary policy may not be an important factor at a maturity as long as 10 years. The alternative is to use the 5 year treasury yield. Again, the VAR results from using the 5 year rate are similar to those from the 10 year rate. Third, I verify that the results are qualitatively similar for a sample starting after the dot-com bubble, i.e., November, 2001-December, 2019. Fourth, I verify my results using an alternate methodology as the F-statistic of the instrument is low. This was also reported in the literature by Miranda-Agrippino and Ricco (2023); Swanson (2023). Hence, I re-estimate my results by using sign restrictions approach for identification. The two restrictions are first, a QE policy shock should lead to negative co-movement in stock index surprises and LSAP factor, and second, a non-monetary shock should lead to positive co-movement in stock index surprises and LSAP factor. The results in Figure 11 of the appendix shows that sieving out non-monetary shocks from the LSAP factor is important for correctly estimating the causal effect of monetary policy shock on equity premium.

6 Conclusion

Quantitative easing (QE) played a pivotal role for central banks during the global financial crisis, serving as a means to transmit monetary policy when the economy was stuck at the zero lower bound. Empirical evidence supports its effectiveness on the stock market, but it is unclear which mechanism is more relevant for the transmission of monetary policy. This paper fills this gap in the literature by examining the relevance of both mechanisms within the same framework.

I utilize the standard asset pricing equation to break down the fundamental value of the S&P500 index into two components: the risk-neutral fundamental component and the equity premium component. The former represents discounted dividends at the risk-free rate, while the latter signifies the extra return required for riskier assets. This decomposition allows for an evaluation of the share of the stock market response attributed to these two components.

Empirical analysis employs a VAR model encompassing macroeconomic aggregates and stock price components. For the identification of a QE policy shock, I use a two step procedure to construct an information and risk-corrected external instrument. This ensures separation of monetary policy shocks from non-monetary shocks, which is an important assumption for the use of external instruments.

The results indicate that QE policy shocks increase the risk-neutral fundamental component although this impact is heterogeneous across industries. The equity premium's response is negative and its share of the stock price response is substantial, about 16%, and three times larger than the fundamental component's response. Both components exhibit persistence, with the share of equity premium response gradually declining over two years. This highlights the role of risk premium in transmitting monetary policy shocks to the equity market.

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A Appendix

B Tables

Table 6: Data Sources of variables included in the VAR model

Variable	Series	Symbol	Logs	Random Walk	Source
Output	Index of industrial production	ip_t	•	•	FRED
Prices	PCE price index	p_t	•	•	FRED
Risk-free rate	Fed Funds Rate	r_t^f			FRED
Long-term rate	End-of-month GS10	r_t^L		•	FRED
Credit risk	Excess bond premium	ebp_t			Favara et al. (2016)
Stock index [1]	S&P 500 stock index	q_t	•	•	Robert Shiller
Dividends [1]	S&P 500 index dividends	d_t	•	•	Robert Shiller
Equity premium	Equity premium lower bound [2]	ep_t			OptionMetrics, FRED
Industry portfolios					
Stock index	Author [3]	q_t^i	•	•	Kenneth French
Dividends	Author [3]	d_t^i	•	•	Kenneth French

[1] Stock price and dividends are deflated by the price index
[2] Construction follows Martin (2017)
[3] Construction follows Hodrick (1992)

Table 7: Details of asset purchases under different QE phases

Name	Duration	Asset class	Purchases (in \$bn)
QE1	11:2008-03:2010	Agency	175
		MBS	1250
		Long-term treasury	300
QE2	11:2010-06:2011	Long-term treasury	600
Operation Twist[1]	09:2011-12:2012	Long-term treasury	667
		Short-term treasury	-667
QE3	09:2012-10:2014	Long-term treasury	770
		Agency	823

Source: FRB of New York
[1] The aim of this programme was to change the composition of the Fed balance sheet towards long-term assets, hence the name operation twist.

C Asset pricing equation in the Present Value Model

This section provides detailed steps for various equations described in section 3.

Let R_t denote gross returns (equivalent to gross returns on the risk-free bond (R_t^f) under the assumption of risk neutrality) and D_t be dividends at time t. Start with the identity:

$$
\begin{aligned}
1 &= R_{t+1}^{-1} R_{t+1} \\
\implies 1 &= R_{t+1}^{-1}\left[\frac{Q_{t+1} + D_{t+1}}{Q_t}\right] \\
\implies Q_t &= R_{t+1}^{-1}[Q_{t+1} + D_{t+1}] \\
\implies Q_t &= \sum_{k=1}^{\infty}\left(\prod_{j=1}^{k}\left(\frac{1}{R_{t+j}}\right)\right)D_{t+k} + \lim_{k\to\infty}\frac{Q_{t+k}}{\prod_{j=1}^{k}\left(\frac{1}{R_{t+j}}\right)} \\
\implies Q_t^F &= \sum_{k=1}^{\infty}\left(\prod_{j=1}^{k}\left(\frac{1}{R_{t+j}}\right)\right)D_{t+k} \qquad (12)
\end{aligned}
$$

The above equation is non-linear and has a long history of it being linearised to allow use of linear time series methods. Starting again from the identity, Campbell and Shiller (1988) shows how to derive this:

$$
\begin{aligned}
\frac{Q_t}{D_t} &= R_{t+1}^{-1}\left[1 + \frac{Q_{t+1}}{D_{t+1}}\right]\frac{D_{t+1}}{D_t} \\
\implies q_t - d_t &= -r_{t+1} + \Delta d_{t+1} + ln(1 + e^{q_{t+1} - d_{t+1}})
\end{aligned}
$$

where the lower-case letters denote the variable in log terms. Using Taylor expansion around a constant $\frac{Q}{D} = e^{q-d}$,

$$
\begin{aligned}
& q_t - d_t = -r_{t+1} + \Delta d_{t+1} + k + \rho(q_{t+1} - d_{t+1}) \\
\implies & q_t = (1-\rho)d_{t+1} - r_{t+1} + k + \rho(q_{t+1}) \\
\implies & q_t = c + \lim_{n\to\infty} \rho^n q_{t+n} + \sum_{k=1}^{\infty} \rho^{k-1}\big[(1-\rho)d_{t+k} - r_{t+k}\big] \qquad (13)
\end{aligned}
$$

where $c = ln\left(1 + \frac{Q}{D}\right) - \rho(q-d)$ and $\rho = \frac{Q}{Q+D}$

Note that ρ can also be written in terms of the price-dividend ratio of the asset. According to Cochrane (2005), this ratio averages about 25. Hence, ρ should be close to 1. Under the standard assumption of no bubbles ($\lim_{n\to\infty} \rho^n(q_{t+n}) = 0$), the above can be written as:

$$
\begin{aligned}
& q_t = const + \sum_{k=1}^{\infty} \rho^{k-1}[(1-\rho)E_t d_{t+k} - E_t r_{t+k}] \\
\implies & q_t = const + \sum_{k=1}^{\infty} \rho^{k-1}[(1-\rho)E_t d_{t+k} - E_t(r^f_{t+k} + ep_{t+k})] \\
\implies & q_t = const + q_t^{F,RN} - \sum_{k=1}^{\infty} \rho^{k-1} ep_{t+k} \\
\implies & q_t = const + q_t^{F,RN} - q_t^{EP}
\end{aligned}
$$

The above equation shows that any fluctuation in the asset price is driven by its risk-neutral fundamental value and equity premium.

D Construction of equity premium lower bound using options data

The lower bound on equity premium is constructed using options contracts on the S&P500 index. Options contracts are akin to futures contracts but with the difference that it gives a right to the holder whether to proceed with the transaction at the agreed date. There are two types of contracts - a call option and a put option. The call option gives the right to the holder to buy the underlying asset at an agreed date and at an agreed price, also commonly known as strike price (K). The put option has the same features but gives the holder the right to sell the asset. In exchange for this right, the holder pays a premium (P) to the seller.

The equity premium for the stock index can be described by the following relation:

$$E_t R_T - R_{f,t} = \frac{var_t^* R_T}{R_{f,t}} - cov_t(M_T R_T, R_T) \tag{14}$$

where
R_T= stock returns
$R_{f,t}$ = risk-free rate
M_T = SDF

where $*$ denotes the risk-neutral measure. Martin (2017) provides a couple of insights about equity premium using this equation. The first term on the right hand side is directly observable using options data and the risk-free rate. The second term on the right side is likely to be negative and hence, we can derive a lower bound for the equity premium measure.

The first term can be expanded to see how to obtain the measure using options data:

$$\frac{1}{R_{f,t}} var^* R_T = \frac{1}{S_t^2}\left[\frac{1}{R_{f,t}}(E_t^* S_T^2) - \frac{1}{R_{f,t}}(E^* S_T)^2\right] \tag{15}$$

where S is the stock price. Note that the second term can be found by using the forward price at time t ($F_{t,T} = E_t^* S_T$). This uses the condition that $F_{t,T}$ can be found as the x^* that solves $call_{t,T}(x) = put_{t,T}(x)$. Evaluating the first term requires obtaining the price of the squared contract. This can be achieved using prices of call options:

$$\frac{1}{R_{f,t}} E_t^* S_T^2 = 2 \int_0^\infty \frac{1}{R_{f,t}} E_t^* max\{0, S_T - K\} dK \tag{16}$$

$$= 2 \int_0^\infty call_{t,T}(K) dK \tag{17}$$

Since In the money (ITM) call options are generally illiquid [14], Martin (2017) uses the put call parity formula [15] to replace a range of call options with Out the Money (OTM) put options,

$$\frac{1}{R_{f,t}} var^* R_T = \frac{2}{S_t^2} \left[\int_0^{F_{t,T}} put_{t,T}(K) dK + \int_{F_{t,T}}^\infty call_{t,T}(K) dK \right] \tag{18}$$

Now, the expression uses only OTM options to estimate the risk-neutral variance of returns at time T. Since a continuum of strike prices is not available in the data, a discrete version of this expression is used. Finally, it can be shown that:

$$\frac{1}{R_{f,t}} var^* R_T = (T - t) \times SVIX_{t \to T}^2 \tag{19}$$

$$\text{where } SVIX_{t \to T}^2 = \frac{2}{(T-t) R_{f,t} S_T^2} \left[\int_0^{F_{t,T}} put_{t,T}(K) dK + \int_{F_{t,T}}^\infty call_{t,T}(K) dK \right] \tag{20}$$

$$= \frac{1}{T-t} var^* \left(\frac{R_T}{R_{f,t}} \right) \tag{21}$$

[14] If the market price is greater than the strike price, the investor is more likely to hold the option than sell it in the secondary market

[15] This formula suggests that the return from buying a call option is equal to return from a put option and buying the actual asset

where $SVIX$ is a measure of the annualized risk-neutral variance of the realized excess return from t to T. Note that this formula requires fixing of a duration. Dividing LHS by $(T-t)$ gives the *per period* expected equity premium. In terms of the inequality, we therefore have the following lower bound:

$$\frac{1}{T-t}(E_t R_T - R_{f,t}) \geq R_{f,t}.SVIX^2_{t\to T} \tag{22}$$

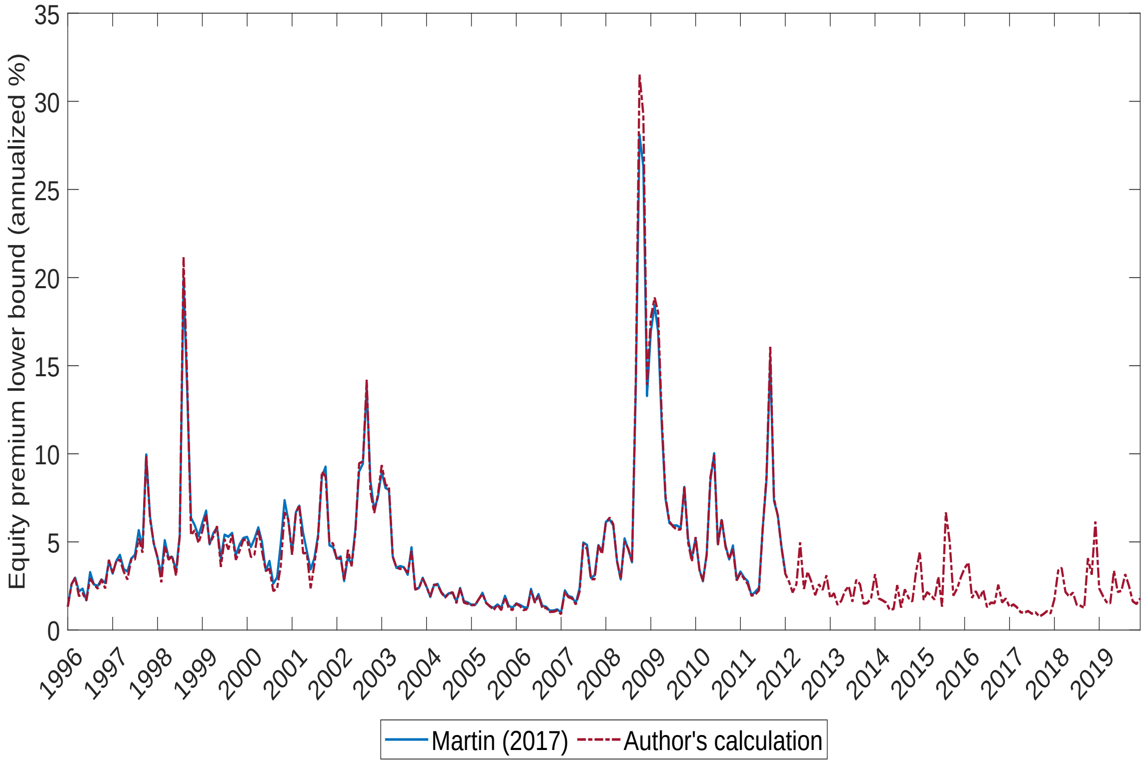
The OptionMetrics dataset includes the type of options contract, its expiration date, its forward price, strike price and closing price of the index. The following steps describe the construction for the period January 4, 1996- December 31, 2019:

1. Delete all options contracts with the following characteristic:
    (a) Highest closing bid of 0.
    (b) Quarterly option contracts since they are relatively less liquid.
    (c) Date to expiry is more than 550 days.
2. For all the options with non-zero value, construct mid price as the average of bid price and ask price.
3. Calculate the sum over discrete strike prices for each date-expiry date-strike price combination:

    The above expression provides a value for every date-expiry date combination.
4. Calculate the constant maturity premium for 30 days using linear interpolation.
5. The final numbers are annualized and the unit of measure is percentage points.

I utilized the above listed steps to extend the 30 day constant maturity equity premium lower bound series in Martin (2017) from 2012 up to 2019. I first compute the series for the same sample period (1996m1-2012m1) and visually compare them. Figure 7 shows that the two series are remarkably similar. There is one exception - the peak of the series during the financial crisis from my code is higher. In terms of numbers, the annualized average for both the series is about 5% and the correlation coefficient between them is 0.99.

Figure 7: Time series of lower bound of equity premium at 1 month horizon



Note: This figure plots the time-series of the lower bound on expected equity premium constructed using Martin (2017) (in blue) along with the same measure available with the original paper (in maroon) for the period Jan 4, 1996-Jan 1, 2012. The sample length was chosen to match the original paper's dataset. The two time series are remarkably similar. with a correlation coefficient of 0.99.

E External instrument approach

The identification requires exclusion restrictions on the contemporaneous relationships between variables in the model. The model has an instrumental variable interpretation in the sense that linear combinations of innovations act as an IV for identifying structural parameters (Stock and Watson, 2012). However, contemporaneous restrictions can be considered subjective. In this paper, I instead follow the "external" instruments approach (developed by Stock and Watson, 2008 and Mertens and Ravn (2013)). It utilizes information from outside the VAR model to create instrumental variables. Suppose the relationship between structural shocks (ε_t) and the reduced form innovations (u_t) is given by $\varepsilon_t = A_0 u_t$ where A_0 represents these contemporaneous relationships. Assuming that the shock of interest is ordered first, estimation of the monetary policy shock is done in three steps:-

1. Estimate the VAR model and obtain the residuals ($\hat{u}_t$).
2. In order to obtain elements of the column of the matrix (A_0^{-1}), say a_1, regress $\hat{u}_t$ on z_t.
3. Take the ratio of regression coefficients obtained from step 2 with the coefficient a_{11}.
4. Choose a normalization.

In order to transmit a unit shock in the system, I normalize such that a_{11}=1. Under these assumptions, the shock can be identified up to a scale by regressing the instrument on each innovation series.

F Instrument in presence of risk premium shocks

In this section, I discuss the assumptions required to eliminate risk premium shocks using a regression based approach. The idea is to isolate the variation in market surprises that are due to monetary policy shocks. A popular method following (Romer and Romer, 2000; Miranda-Agrippino and Ricco, 2021) is to first isolate the variation in market surprises due to other shocks via OLS and then use the residual as the instrument. To follow this approach for eliminating risk premium shocks, I will need a measure of risk premium surprises (Δrp_t). I have two measures for *daily* changes in risk - (1) Excess bond premium from Gilchrist et al. (2021), (2) risk appetite index from Bauer et al. (2023). Note that risk appetite is inverse of risk premium - higher the risk appetite, lower the premium required to hold an asset.

Think of these surprises as being generated due to 3 types of exogenous IID shocks $\varepsilon_t^j \sim \mathcal{N}(0,1)$, j - monetary policy shock (m), growth shock (g) and risk premium shock (rp):

$$\Delta f_t = \alpha_1^i \varepsilon_t^m + \alpha_2^i \varepsilon_t^g + \alpha_3^i \varepsilon_t^{rp} \tag{23}$$

$$\Delta s_t = \alpha_1^s \varepsilon_t^m + \alpha_2^s \varepsilon_t^g + \alpha_3^s \varepsilon_t^{rp}$$

$$\Delta rp_t = \alpha_1^{rp} \varepsilon_t^m + \alpha_2^{rp} \varepsilon_t^g + \alpha_3^{rp} \varepsilon_t^{rp} \tag{24}$$

where α_k^j is the impact of shock j on surprise in k. If we could isolate the variation in Δf_t which is due to monetary policy shocks, then it would be a good candidate for use as an external instrument in the VAR. Suppose we estimate the following regression equation:

$$\Delta f_t = b_0 + b_1 \Delta rp_t + \epsilon_t \tag{25}$$

Then, the parameter b_1 captures the variation in f_t that is explained by risk premium surprises. The OLS estimate can be shown to be a function of the parameters in the equations (23) and (24) above:

$$
\begin{aligned}
\hat{b_1} &= \frac{cov(\Delta f_t, \Delta rp_t)}{var(\Delta rp_t)} \\
&= \frac{\overbrace{\alpha_1^i \alpha_1^{rp}}^{+} var(\varepsilon_t^m) + \overbrace{\alpha_2^i \alpha_2^{rp}}^{-} var(\varepsilon_t^g) + \overbrace{\alpha_3^i \alpha_3^{rp}}^{-} var(\varepsilon_t^{rp})}{(\alpha_1^{rp})^2 var(\varepsilon_t^m) + (\alpha_2^{rp})^2 var(\varepsilon_t^g) + (\alpha_3^{rp})^2 var(\varepsilon_t^{rp})}
\end{aligned}
$$

where the sign on top of the brace is the expected sign of the product of α_k^j. The denominator is positive, so the sign of the coefficient depends on the numerator's product terms associated with each shock. If we assume that risk premium surprises do not respond to monetary and growth shocks, i.e., $\alpha_1^{rp} = \alpha_2^{rp} = 0$, then we can further obtain:

$$
\begin{aligned}
\hat{b}_1 &= \frac{\alpha_3^i \alpha_3^{rp} var(\varepsilon_t^{rp})}{(\alpha_3^{rp})^2 var(\varepsilon_t^{rp})} \\
&= \frac{\alpha_3^i}{\alpha_3^{rp}}
\end{aligned}
$$

Theoretically, we expect that a positive risk premium shock will result in a positive risk premium surprise, i.e., α_3^{rp} is positive. For the sake of convenience, I normalize it to 1. The coefficient estimate $\hat{b}_1$ isolates the variation in f_t due to risk premium shock ε_t^{rp}. I expect that a positive risk premium shock (or equivalently, a negative risk appetite shock) will decrease the LSAP factor. A residual $\hat{\epsilon}_t$ obtained by estimating equation (25) could be used as an external instrument for identifying the monetary policy shock. Note that the assumptions required to obtain such an instrument are extremely stringent. It is in contrast with studies that show a positive link between monetary policy and risk premium. For this reason, using a market surprise series for risk premium is unlikely to isolate variation in Δf_t *only* due to risk premium shocks.

To understand if this is likely to be an issue in the data, I estimate the regression equation (25) for different risk measures are presented in columns (1)-(5) of Table

8. The response of LSAP factor to risk appetite is positive, which is at odds with the expected sign, as discussed above. Estimates from regression of LSAP factor on other risk premium measures confirm this with the exception of the short term EBP measure (ΔEBP_{st})- it points towards a positive relationship, indicating that perhaps, the short maturity bonds are impacted more by a monetary policy shock while the longer maturity bonds are impacted more by risk premium shocks. The overall message from these estimates is that the LSAP factor is impacted by risk premium shocks.

Table 8: Regression of LSAP factor on different measures of risk

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ΔEBP_{agg}	-1.45					-2.27				
	(-1.04)					(-1.43)				
ΔEBP_{st}		1.36**					1.94**			
		(1.99)					(2.39)			
ΔEBP_{mt}			-2.30**					-1.75*		
			(-2.29)					(-1.80)		
ΔEBP_{lt}				-0.29					-3.21*	
				(-0.21)					(-1.91)	
Risk appetite					0.26***					0.21**
					(2.79)					(2.03)
Constant	-0.03	-0.05	-0.06	-0.03	-0.11	-0.48	-0.79	-0.32	-0.54	-0.47
	(-0.30)	(-0.57)	(-0.69)	(-0.31)	(-1.18)	(-0.42)	(-0.71)	(-0.27)	(-0.48)	(-0.42)
Greenbook forecasts and revisions						✓	✓	✓	✓	✓
Observations	85	85	85	85	85	85	85	85	85	85
R^2	0.01	0.05	0.06	0	0.09	0.57	0.6	0.58	0.58	0.59
Adjusted R^2	0.00	0.03	0.05	-0.01	0.08	0.42	0.45	0.43	0.44	0.44
F-test	1.07	3.97	5.24	0.04	7.81	3.79	4.17	3.92	3.96	4.01
Prob>F	0.30	0.05	0.02	0.83	0.01	0.00	0.00	0.00	0.00	0.00

Note: This table reports results for regression of the LSAP factor on different measures of risk premium, sourced from Bauer et al. (2023) and Gilchrist et al. (2021). The regressors are measured as change in risk measures at daily frequency on days of monetary policy decisions of the Federal Reserve Board. EBP_h is a measure of risk in the bond market at horizon h. The risk appetite measure is the first principal component of 14 financial indicators that capture risk across asset markets. Sample length is Dec, 2008-Dec, 2019. *p<0.1, **p<0.05,***p<0.01. Standard errors in parentheses.

In columns (6)-(10) of table 8, I re-run the above equation augmented with greenbook forecasts and revisions to control for information effects. The coefficient on change in risk measure is conditioned on the information set and thereby is the same coefficient as that of a regression of informationally robust factor on informationally robust version of change in risk measure (via Frisch-Waugh-Lovell Theorem). The estimates are unchanged in sign and show that the previous result holds despite controlling for information effects.

G Loadings on risk premium measure from PCA

The measure of risk premium index is based on nine financial market indicators whose common co-movement captures changes in risk premium (Bauer et al., 2023). All financial indicators enter the PCA in daily changes of their respective units. The common sample length is Jan 03, 2003-May 15, 2020. The loadings of the first principal components used to construct the risk premium measure are presented in Table 9 below.

Table 9: PCA loadings

Variable	Index loading	Unexplained
ICE BofA US high yield OAS index	0.46	0.29
ICE BofA US corporate OAS index	0.44	0.35
Moody's Baa corporate bond spread	0.33	0.62
3 month commercial paper spread	0.20	0.87
J.P. Morgan EMBI diversified sovereign spread	0.43	0.38
Bloomberg OAS for US fixed rate MBS index	0.15	0.92
ICE BofA MOVE index	0.26	0.77
S&P500 volatility index	0.32	0.66
CBOE 10-Year treasury note volatility futures index	0.28	0.72

Note: This table reports the loadings from principal components analysis of nine variables that reflect credit spreads and volatilities in financial markets. OAS denotes to Options Adjusted Spread, MBS denotes mortgage backed securities, and MOVE denotes Merrill Lynch Option Volatility Estimate.

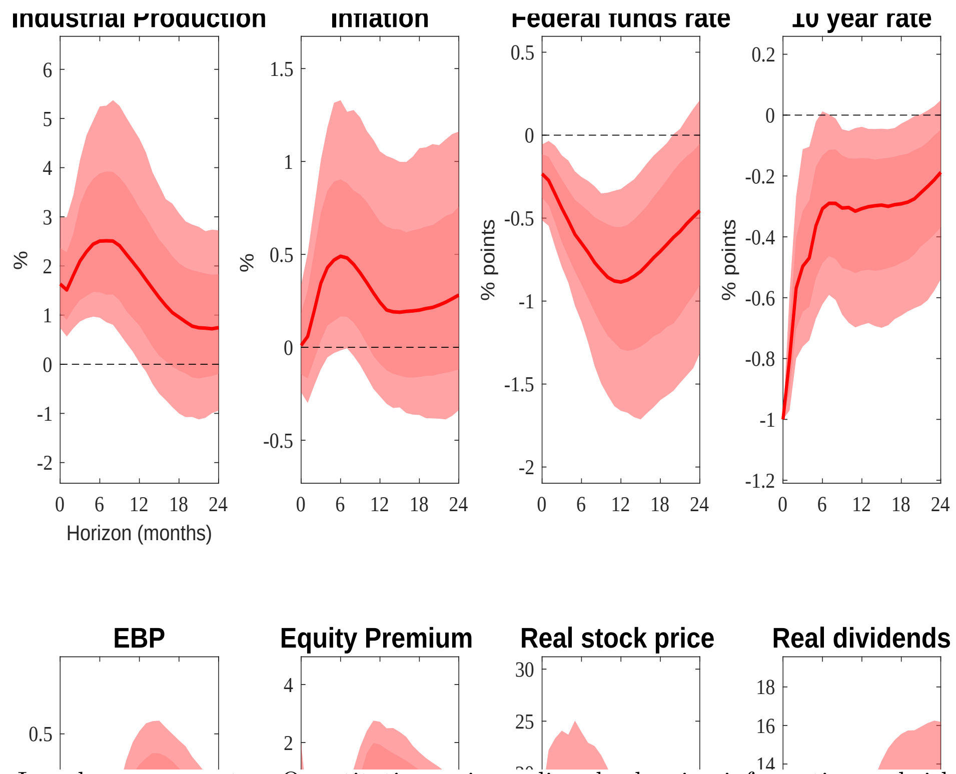
H Robustness checks

This section contains results to check robustness of IRFs from the VAR exercise.

H.1 Alternate instrumental variable

I construct an alternate instrument for identifying the QE policy shock using two steps. In the first step, I zero out all dates from the LSAP factor where surprises in stocks and LSAP factor co-move positively (Jarociński and Karadi, 2020). In the second step, I zero out dates where the co-movement between risk premium and the LSAP factor is negative. Hence, only those values of the LSAP factor are used which are consistent with co-movements generated by a monetary policy shock.

Figure 8: IRFs for QE policy shock using alternate identification strategy

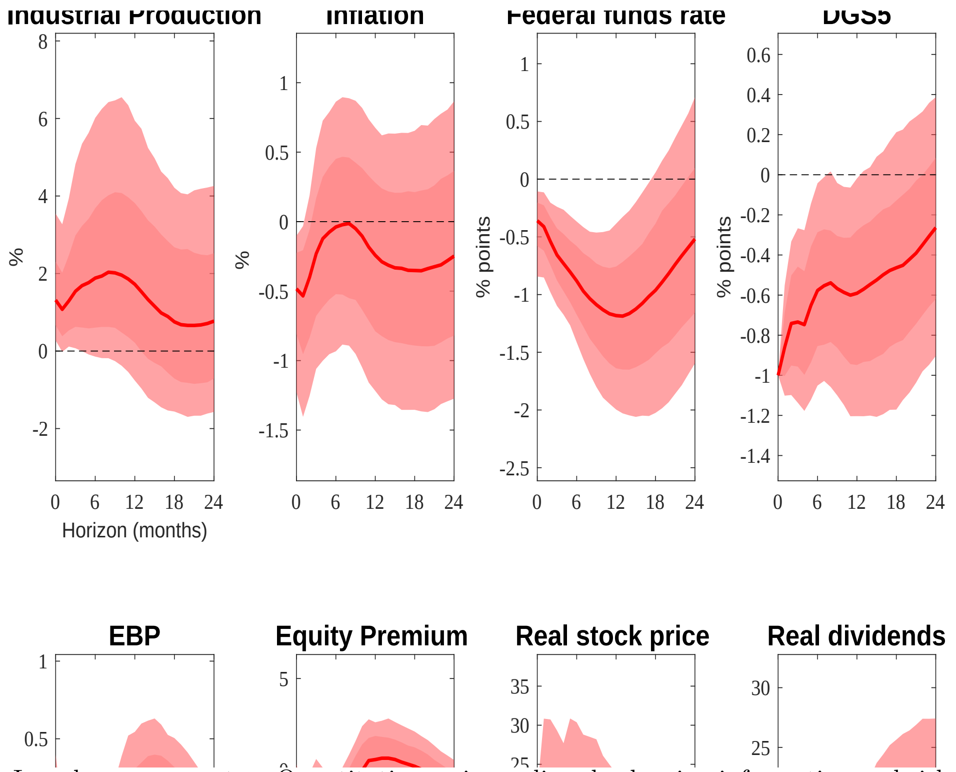


Note: Impulse responses to a Quantitative easing policy shock using information and risk-corrected instrument. The external instrument uses only those events where the co-movement between surprises in stocks, risk premium and yields is consistent with a monetary policy shock. The shock is normalised to induce a 1% decrease in the 10 year rate. Sample: 1996:1-2019:12. Dark and light shaded areas represent 68% and 90% posterior coverage bands respectively.

H.2 Alternate indicator of monetary policy

I use the 5 year treasury yield in place of the 10 year treasury yield as an indicator of monetary policy in the VAR model.

Figure 9: IRFs for QE policy shock using 5 year policy rate

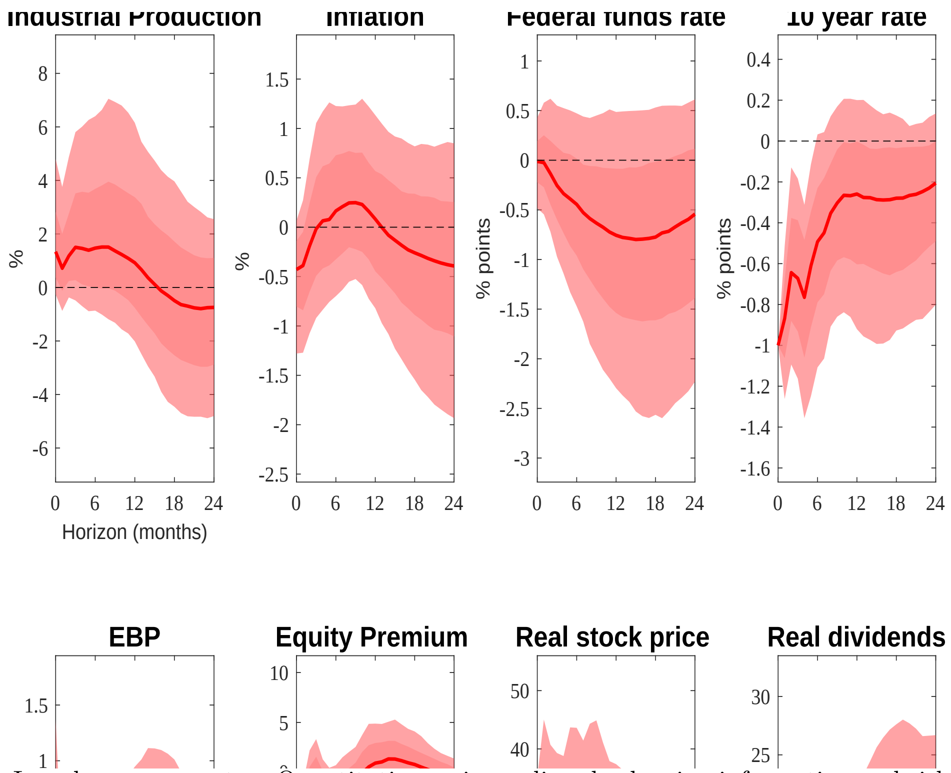


Note: Impulse responses to a Quantitative easing policy shock using information and risk-corrected instrument. The shock is normalised to induce a 1% decrease in the 5 year rate. Sample: 1996:1-2019:12. Dark and light shaded areas represent 68% and 90% posterior coverage bands respectively.

H.3 Alternate sample length

I use an a shorter sample length of November 2001-December 2019 for estimating the VAR model. The start date was chosen keeping in mind the end of recession after the dot com bubble.

Figure 10: IRFs for QE policy shock for the sample Nov 2001-Dec 2019

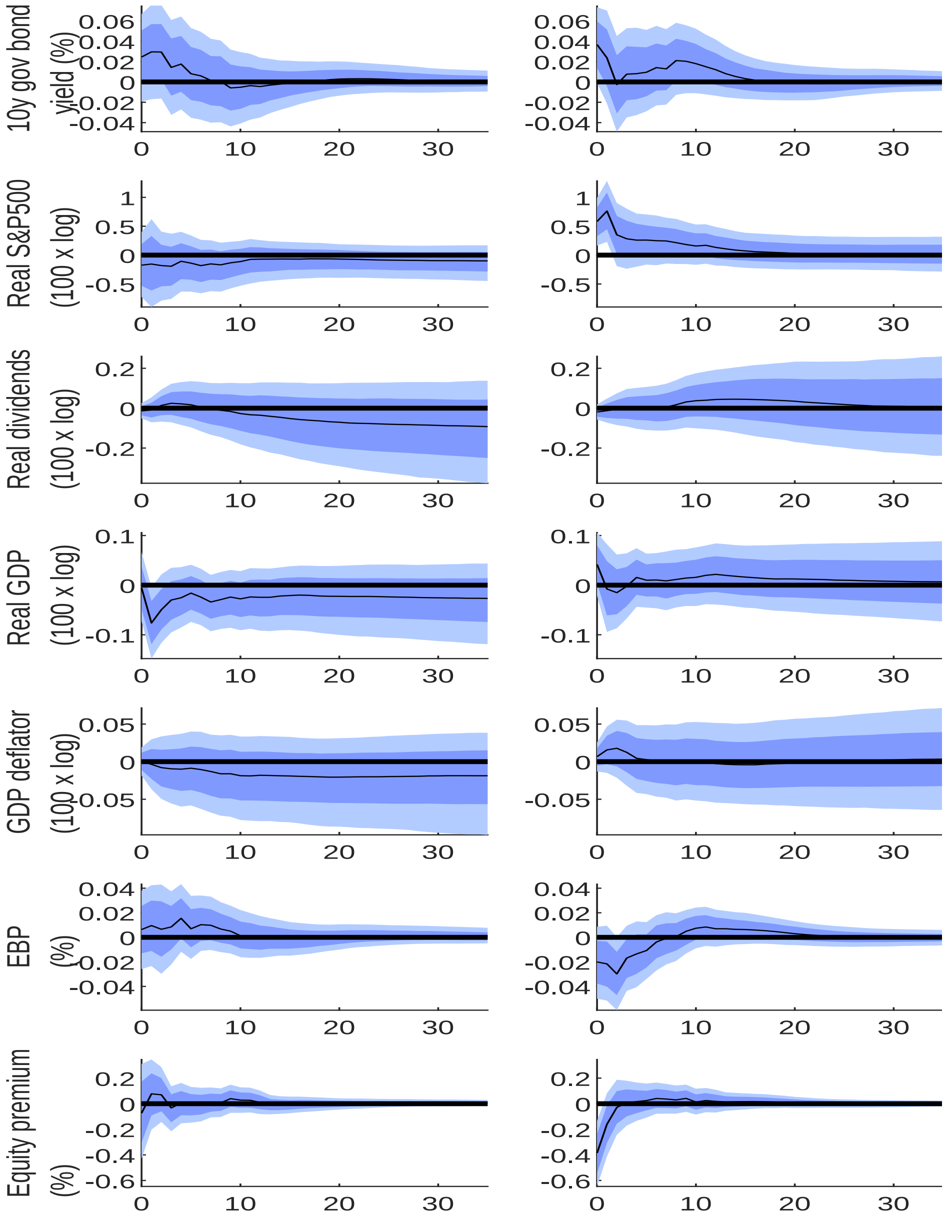


Note: Impulse responses to a Quantitative easing policy shock using information and risk-corrected instrument. The shock is normalised to induce a 1% decrease in the 10 year rate. Sample: 2001:11-2019:12. Dark and light shaded areas represent 68% and 90% posterior coverage bands respectively.

H.4 Alternate identification methodology

I use the sign restrictions identification approach to examine the effect of monetary policy shocks on stock prices and its components. The restrictions are based on Jarociński and Karadi (2020), who disentangle *conventional* monetary policy shocks and information shocks by placing restrictions on high frequency surprises on market data. The two restrictions are first, a QE policy shock should lead to negative co-movement in stock index surprises and LSAP factor, and second, a non-monetary shock should lead to positive co-movement in stock index surprises and LSAP factor. Note that the latter restriction identifies a mix of information and risk premium shocks. The sample length is 2008:11-2019:12 and the shock is normalized to have a 1 standard deviation change in the LSAP factor. The sample has been truncated relative to that in the main exercise since sign restrictions require the high frequency measures of LSAP factor and stock surprises to be included in the VAR. Figure 11 presents IRFs from this exercise using the replication code of (Jarociński and Karadi, 2020) with monetary policy shocks in the left column and non-monetary shocks on the right column. The two columns shows that placing sign restrictions disentangles two shocks with different implications for impact response of S&P500 index, real GDP, excess bond premium and equity premium. This shows that sieving out non-monetary shocks from the LSAP factor is important for correctly estimating the causal effect of monetary policy shock on equity premium.

Figure 11: IRFs for QE policy shock using sign restrictions



Note: Impulse responses to one standard deviation (contractionary) shocks using sign restrictions on high frequency surprises in stock index and LSAP factor. Sample: 2008:11-2019:12. Dark and light shaded areas represent 68% and 90% posterior coverage bands respectively.