The Time Horizon of Price Responses to Quantitative Easing

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Abstract

Studies of how quantitative easing (QE) impacts asset prices typically look for effects in one- or two-day windows around QE announcements. This methodology underestimates the impact of QE on asset classes whose responses happen outside of this short time frame. We document that QE announcements by the Fed, ECB, and the Bank of England are associated with: quick price reactions of medium- and long-term government bonds; but with reactions in equity and equity implied volatility that occur over several weeks. Robustness checks using past monetary policy episodes and the cross-section of US industry returns confirm these results.

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1 Introduction

In response to the financial crisis of 2008 and early-2009, central banks around the world conducted monetary policy primarily via large scale asset purchases, also known as quantitative easing (QE). The effects of QE on fixed income markets have received much attention with the general conclusion being that they were large and immediate. QE effects on less bond-like markets, such as equities and equity implied volatilities, have received less attention, probably because the effects that were found turned out to be small. A general feature of the literature has been to look for QE effects in very short time periods, either intraday or one to two days following QE announcements, with the implicit assumption being that because central bank policy announcements are very public and well-followed events, all impacted markets should incorporate the price implications of such announcements almost instantaneously. In this paper we present empirical evidence that this assumption and the focus on short-term effects that it engenders lead to a potential mismeasurement of the effects of QE.

In the traditional macro-finance interpretation, QE works its way into prices through three main channels: liquidity, signaling, and portfolio balance.[1] When a central bank reduces the supply of long-term, illiquid securities by replacing them with reserves, it drives down liquidity premia in the market. This should push lenders into making riskier loans as the "easy money" from owning safe but illiquid securities is no longer available. Securities, such as MBS and agency debt, which were directly targeted by the Federal Reserve should have had large and immediate price moves, while less liquid credit instruments should be impacted over time as lenders take on additional credit risk.

Likewise when a central bank credibly signals to the market its commitment to maintain accommodative short rates for a long period of time, discount rates fall and fixed income security prices rise. However, the effect on asset classes with greater cash flow variability may be ambiguous because of the endogeneity in the central bank's decision – it chooses to keep rates low exactly when economic, and hence cash flow, prospects are poor. It may take investors time to interpret the implications of such interest rate signals for cash flow prospects of risky securities.

The portfolio balance (or scarcity) channel encompasses either rational reallocation decisions

[1] The names and subtleties of meaning vary slightly from author to author: liquidity, signaling, and portfolio balance (Gagnon et al. (2011a) and Neely (2015)); signaling, scarcity, and duration (D'Amico et al. (2012)); signaling, duration, liquidity, safety, prepayment and default risk, and inflation (Krishnamurthy and Vissing-Jorgensen (2011)); preferred habitat (Modigliani and Sutch (1966,1967), Vayanos and Vila (2009)).

as the supply of certain assets is reduced by the central bank, or a preferred habitat (or clientele) effect where natural holders of a given asset class are forced into another asset class because the risk-adjusted returns on the former are not sufficiently attractive. In either case, the effect of central bank buying is to force market participants to deviate from their pre-buying asset allocations. For example, pension funds which may have been content to hold riskless securities at a certain yield, may be forced to compensate in credit spreads for loss in riskless yield and thus buy riskier securities in an attempt to meet return targets. As spreads tighten, asset allocation funds which may have been content with a conservative corporate bond to stock mix, may now be forced more into stocks. Due to a multitude of market and organizational frictions – limited liquidity which slows portfolio reallocation, decision making by consensus among multiple senior managers – it is unlikely that such portfolio flows, and the associated price responses, can take place quickly.

More recently, several papers have focused on the bank lending channel, which was one of the original motivations for QE – the conjecture being that QE would increase the availability of deposits, a cheap source of bank financing, and therefore induce banks to make more loans. The evidence here is mixed, with Butt et al. (2014) finding little evidence for the bank lending channel for Bank of England QE. Chakraborty, Goldstein and MacKinlay (2017) find limited evidence for a sizable bank lending channel response to Fed QE, while Darmouni and Rodnyansky (2017) find some evidence that banks with relatively more mortgage-backed securities increased their lending in response to the first and third rounds of Fed QE.

The key question is whether the effect of any particular channel on prices happens instantaneously or with a lag. This question has received little, if any, attention in the existing literature, and yet it is crucial for the proper identification of the effects of QE. We appeal to the asset pricing and market microstructure literatures to argue that informational frictions and capital constraints imply that the liquidity, signaling and portfolio balance channels are all likely to affect certain asset classes with a delay. We should note that the bank lending channel – relying as it does on an uncertain future increase in bank lending – would necessarily result in delayed real effects, though at a time horizon even longer than what we consider in this study.

The Sims (2003) theory of rational inattention conjectures that investors are unable to process *all* information that is salient for decision making, and therefore must choose some subset of information on which to base their decisions. There is ample empirical evidence that when investors are distracted, the market mechanism does not operate with its usual efficiency. For example, Dellavigna and Pollet (2009) find a stronger post earnings announcement drift for

Friday earnings, when many people on Wall Street leave the office early. Ehrmann and Jansen (2016) show that World Cup soccer matches in South Africa lower the correlation between the local and global stock markets, presumably because the local traders are distracted. Lucca and Moench (2015) argue that rational inattention may be a cause of their finding of a pre-FOMC announcement drift (which we discuss in Section 2.2). Glasserman and Mamaysky (2017) show that SP500 realized and implied volatility react to information from news articles about individual stocks with a lag of several months, and argue that capacity constrained investors may explain this finding. During the period of QE, investors were inundated with news, about the macro economy, failing banks, an unprecedented deterioration in the US mortgage market, and so on. QE announcements were only one of many news items that capacity constrained investors needed to absorb. Assets that were directly targeted by QE, and close substitutes, reacted to announcements very quickly because QE was the most salient information for investors who specialized in these asset classes. But those assets where the impact of QE was not immediately obvious, and whose investor bases were focused on other information besides QE, may have experienced delayed price reactions.

While the above rational inattention argument may apply to many investors, certainly some investors must have anticipated the effects of QE on the non-targeted asset classes. The second part of the story is to understand why they – presumably hedge funds or bank trading desks – didn't step in and accelerate the price adjustment process? To some extent, they did. However it is likely that hedge funds and similar levered actors did not have enough capital to make this process take place over the one- or two-day window of most QE event studies even if they understood the ultimate direction of the price effect. There is a large literature on the various constraints faced by arbitrageurs that leave them unable to fully exploit pricing discrepancies that arise in markets (Shleifer and Vishny (1997) is a classic paper, and Gromb and Vayanos (2010) is a recent overview). Such constraints are likely to be binding when the quantity of assets subject to pricing discrepancies is particularly large, as was the case with QE. Therefore it is possible that there wasn't enough arbitrage capital in the market to sufficiently expedite the propagation of QE into non-targeted asset classes over a one- or two-day time horizon, even if such effects were broadly anticipated by some market participants.

Recently Greenwood, Hanson, and Liao (2016) analyze a multi-asset market hit by a supply shock: Frictions, in the form of partially segmented markets with slow moving capital, impede the transmission of a supply shock in the primary market to prices in the secondary market; price dynamics in such a setting are characterized both by lead-lag effects, as well as short-term momentum with longer-run reversals.[2] The key assumption generating such effects is that specialists in a particular market (for example, Treasury investors) react to Treasury supply shocks very quickly, but transmission of those shocks to a secondary market (for example, credit) needs to happen via capital flows from generalists, which occurs slowly.[3]

The combination of attention capacity and investor capital constraints suggest that QE may not affect all asset classes at the same time horizon. Empirical work on QE however has largely ignored such market imperfections, and, with few exceptions, has operated under the dual assumptions that the effects of QE manifest very quickly (intraday, or in one- or two-day windows following QE announcements) and are persistent. The literature on QE can be classified into four broad categories. The first set of papers analyzes the stock and flow effects of QE on bond and MBS prices.[4] Event studies are the second category, and analyze one- and two-day (sometimes intraday) responses of different asset classes to QE.[5] Event studies typically find QE effects on Treasury and MBS yields between 70 and 150 basis points – a range we confirm in our analysis. Another key finding is that the security class that is being targeted by QE has an important effect on which yields are impacted, with Treasury bond purchases affecting Treasury and agency yields, and MBS purchases affecting credit sensitive products. The third strand of the literature examines QE, or more broadly monetary policy, effects on equities and currencies. The short-term effect of QE on equities was found to be very small. Bernanke and Kuttner (2005) is the classic work in this area, and Kiley (2014) is a recent investigation of the effect of QE on stocks – we discuss both in Section 4.[6] Finally, there is a literature on the real effects

[2]Lead-lag effects – in the case of QE the pattern that bonds moved first and stock moved later – have been documented in other contexts, for example between large and small stocks in the same industry (see Lo and MacKinlay (1990)). Also, short-term momentum of stocks around QE announcements fits into a very large literature on momentum in financial markets. For example, the Hong and Stein (1999) behavioral theory of momentum implies a delayed effect of QE on equity markets if information about the ramifications of QE was absorbed by market participants only slowly.

[3]A referee pointed out that other theories for delayed price reaction to news could also be at work. For example, Hou and Moskowitz (2005) attribute the delayed reaction of some stocks to market-wide news to those stocks' poor liquidity and lack of investor recognition. Frazzini (2006) argues that the disposition effect – the unwillingness of investors to sell stocks in which they have lost money – can explain delayed price reaction to earnings news. Whether stocks characterized by lack of liquidity or attention or Frazzini's capital loss measure reacted more slowly to QE announcements is an interesting area for future study.

[4]Papers include D'Amico et al. (2012), D'Amico and King (2013), Krishnamurthy and Vissing-Jorgensen (2012), and Gagnon et al. (2011a) which is also an event study. Greenwood and Vayanos (2012) and Modigliani and Sutch (1966,1967) look at how the amount outstanding and composition of government debt affect prices, though not in a QE context. Warnock and Warnock (2009) study the effect of international capital flows on Treasury pricing.

[5]These papers include Swanson(2011), Gagnon et al. (2011a), Krishnamurthy and Vissing-Jorgensen (2011), Neely (2015), and Bauer and Neely (2013).

[6]Other papers include Stehn and Weisberger (2013), Hooper, Slok, and Luzzetti (2013), Neely (2015), Glick and Leduc (2013), and Rosa (2012).

of QE or past monetary policy episodes.[7] These papers generally have a hard time identifying large macroeconomic effects. Bhattarai and Neely (2016) is an excellent survey of the extensive literature on the effects of QE.

In a notable departure from the majority of the literature, Wright (2012) and Neely (2016) analyze the dynamic impact of QE on government bond yields in the US, and find in their VAR specifications that the half-life of the initial QE impact ranges from several months (Wright) to perhaps a year (Neely).

Our empirical work relies heavily on Fawley and Neely (2013), who identify important QE announcements by the Federal Reserve (Fed), the European Central Bank (ECB), and the Bank of England from early 2008 to late 2012. For the most part, these announcements increase market expectations of quantitative easing, causing the prices of targeted and related securities to rise as a consequence.[8] Using the Fawley and Neely announcements, we first verify the results of prior studies that over one- or two-day windows around QE announcements, QE effects are large for government bonds, and are small for equities and equity implied volatilities. Furthermore, we show that similar effects to those found for Fed announcements in US markets exist for ECB and Bank of England announcements in European and UK markets respectively. We gauge the statistical significance of these results by bootstrapping announcement dates over the QE time period to calculate security return distributions under the null hypothesis that QE events are no different than randomly sampled event dates.

In Section 3 we extend the horizon over which we calculate QE effects to up to one month (21 business days) after policy announcements. We then look for the post-event horizon over which a given security's QE response is most statistically different from its distribution under randomly sampled event dates. We refer to this as the *maximal response horizon* (though perhaps *most unusual* response horizon would be more accurate). We show that at this horizon the null hypothesis that security returns following QE dates are no different than returns following randomly chosen dates can often be rejected. Our methodology allows for the impact of QE on a given asset class to consist of two dimensions: (i) a time horizon – not directly observable – following the QE announcement over which the behavior of a security is most different from its typical behavior over the same time horizon following randomly selected days; and (ii) the magnitude of the price reaction following QE announcements over this time horizon. Our

[7]See Bernanke (2011), Chung, Laforte, Reifschneider, and Williams (2012), Rudebusch (2010), Chen, Curdia, and Ferrero (2011), Williams (2012), and Fuhrer and Olivei (2011).

[8]See the discussion in Tables 1A, 1B, and 1C in the Fawley and Neely paper. Consideration of QE withdrawal would not begin until 2013, a time period which is not covered in our analysis.

maximal response horizon is an estimate of the unobserved time horizon in part (i), which then pins down the price response in part (ii). We can think of this as a non-parametric, dynamic analysis, similar in spirit to Wright (2012) and Neely (2016).

We demonstrate that the horizon of security responses following central bank policy announcements involves two time scales. The one- or two-day time scale of the existing literature is appropriate for analyzing QE responses of government bonds. Increasing the response horizon does not change the conclusion that QE had large effects on bond yields, in line with the 100 to 200 basis point range identified in prior literature. However, analyzing stock market index and equity implied volatility reactions over this short time frame leads to incorrect conclusions about the possible effects of QE. Stocks and equity implied volatilities do not seem to react strongly following QE in the short term, but do react strongly – with economic and statistical significance – at the maximal response horizon, which occurs several weeks after QE announcements took place. Over these longer time periods, credit spread, equity, and equity implied volatility responses following QE are economically very large. In the US, UK, and Europe stock returns in the weeks following QE range from 20% to 49%, and are statistically different from what would have been expected if QE dates were instead randomly sampled. QE announcements were also associated with drops in implied volatilities of between 45 and 60 percent, an effect that occurred three to four weeks after QE announcements. Our stock and implied volatility effects are far larger than those identified in prior event studies because these have not focused on the appropriate response horizons for this set of securities. As we argue in Section 3.2, these results are robust to different inference and bootstrap methodologies.

We cannot claim that our results definitively establish that QE caused the observed price responses. We show only that – once we look over an appropriate time horizon – the responses of equities and equity implied volatilities following QE announcements appear to be systematically different to those that occur under the null hypothesis of randomly chosen dates. In Section 4 we argue that two of the four channels discussed earlier (signaling and portfolio balance) could potentially explain the delayed responses of equity and equity volatilities to QE. First, we document that the delayed response of equities to QE is, in fact, also a feature of prior monetary policy episodes in the US and UK, suggesting that the signaling channel is at work. Furthermore, using ideas from Campbell and Shiller (1988), Campbell (1991), and Vuolteenaho (2002), we argue that the large observed QE effects on stocks are consistent with plausible changes in investor expectations about future cash flows and discount rates – again consistent with the signaling channel. Finally, we use a cross-section of US industry stock portfolios to show that more bond-like industries have stock prices that react to Fed QE announcements more quickly than do those of less bond-like industries, providing evidence of a portfolio balance effect. Section 5 concludes.

2 Data and summary statistics

We divide our analysis into three regions: US for Fed announcements, UK for Bank of England, and Euro for the ECB. We analyze local security responses to their respective bank's QE events.[9] Within each region we analyze six security types: a short-term bond, a 10-year government bond, a 30-year government bond, the local stock market index, a measure of local short-dated equity implied volatility, and a credit default swap (CDS) series. These are summarized in Table 1. Data for each security are obtained from Bloomberg. Bond data is expressed in basis points, volatility data in percent, and stock price data in continuously compounded percent returns.

Note that the CDS series have different interpretations across the three regions. The CDS series for the US is the Markit CDX North American Investment Grade Index, which references a basket of 125 individual companies (that are updated every six months), and measures the overall creditworthiness of large American corporations. For the eurozone, the CDS series is an average of the sovereign CDS spreads of Italy, Spain and Portugal (IPS Sov CDS), and thus measures the creditworthiness of peripheral eurozone countries. For the UK, we use the UK sovereign CDS spread.

Table 2 shows our list of QE dates, from Fawley and Neely (2013), for the three central banks. Events are labeled with the Fawley and Neely subgroups (e.g. QE1, LTRO1, etc.) though the subgroups are not used in the present analysis. Also shown are the changes in the respective 10-year bond yields for each region on the day of the QE announcement. For example, on November 25, 2008 – the day of the Fed's first QE announcement – the yield on 10-year US Treasuries fell by 21.5 basis points. Quantitative easing by the ECB was focused on ameliorating credit conditions for the peripheral eurozone countries, and was accompanied by large falls in the sovereign credit spreads of the targeted countries, but an *increase* in Bund yields – indicating a decrease in the demand for safe-haven assets. In the US and UK, QE focused directly on lowering the yields of government bonds. Most QE announcements in the US and UK are accompanied by drops in 10-year bond yields.

Not all QE announcements were interpreted by markets as easing credit conditions. For

[9] The response of a region to a different central bank's QE decisions is not analyzed in the present study.

example, the FOMC statement on January 28, 2009 did not announce any new programs and likely disappointed markets; this announcement was accompanied by a 13.9 basis point increase in 10-year Treasury yields. To focus on QE events that likely led to an expectation of more accommodative policy, we drop all QE dates from our sample in which 10-year government bond yields move by 10 basis points or more in the direction opposite of their typical QE response (down for the US and UK, and up for Bunds). These dates are labeled *[drop]* in Table 2. We are left with 18 QE events in the US, 8 events in the eurozone, and 10 events in the UK.[10]

2.1 Summary statistics

Table 3 shows the change in yield, volatility or log price for our 6 security types on the day of a QE announcement and on the following day, summed over all QE announcements. We refer to this as the *aggregate response* of a security to QE announcements with $Npre = 0$ (zero days before the event) and $Npost = 1$ (one business day after the event).[11] This event window, for which we use the notation $[t, t+1]$, matches that of many of the QE studies discussed in the Introduction. For example, the first Fed QE announcement happened on Tuesday, November 25, 2008. For the stock index response in the US we look at the log return on Tuesday and Wednesday of that week, then repeat this for the other QE dates, and sum across all these two-day responses. This yields a value of -3.5%. Since this is an aggregate response over 18 different QE events, for an average of roughly -20 basis points per event, the effect is economically small.

To gauge the statistical significance, we perform a block bootstrap – which we call the *inner* bootstrap – over the QE announcement dates.[12] The idea behind the bootstrap is to test whether yield and volatility changes, and stock returns, in windows around QE events are statistically different to security responses in windows around randomly chosen event dates. For each region, we divide the time period between the first and last QE announcement into thirds. We then count how many of the QE events fall into each third of the sample, say N_1, N_2, N_3.[13] A single draw of the bootstrap samples without replacement N_1 dates from the first third, N_2 dates

[10]Rerunning our analysis while retaining all QE dates in Table 2 leaves the results largely unchanged.

[11]We use the term *response* to refer to either changes in yields for bonds, changes in spreads for CDS, changes in implied volatility, or continuously compounded stock returns, depending on the security in question. Changes in volatility are measured as differences in percent volatility, e.g. a volatility response of 2 means a change in implied volatility from 11% to 13%.

[12]We refer to this as the inner bootstrap to differentiate it from the *outer* bootstrap discussed in Section 3.2. Also note that this is a slight abuse of the term "block bootstrap," which typically refers to the method originally proposed by Carlstein (1986) as a way of calculating the variance of a general statistic of stationary data with an unknown dependence structure. Our method is related.

[13]Note that $N_1 + N_2 + N_3$ is equal to 18, 8, and 10 for the US, Europe and UK respectively (see Table 2).

from the second third, and N_3 dates from the last third of the sample – and then computes security responses in two-day windows around these dates. Under the assumption that security price change distributions have multiple, but persistent states, the block bootstrap facilitates the comparison of price changes during QE times to price changes likely to be drawn from the same underlying distribution.[14] The p-values from this bootstrap, shown in brackets in Table 3, are the fraction of security responses from 5000 bootstrap draws that are smaller than the actual security response.[15] Since we are testing whether QE events impacted a given security in a particular direction, we use one-sided tests.[16] For series that increase around QE events (e.g. stock returns), we consider a response significant at the 10% (5%) level if its associated p-value is above 90% (95%). For series that decrease around QE (e.g. bond yields), the p-value would need to be below 10% (5%).

For example, the two-day aggregate returns of SP500 around Fed QE episodes of -3.5% is not statistically significant with a p-value of 0.24 – 24% of all bootstrap runs generated cumulative two-day returns that were less than -3.5%.

The takeaways from Table 3 are consistent with the existing literature. Because short rates were already low, their near term moves around QE announcements were small, except in the UK. Fed and Bank of England QE had large and immediate negative effects on 10- and 30-year rates, with the former falling 198 basis points in the US and 86 basis points in UK in two-day windows around QE announcements. In Germany, 10- and 30-year Bund yields increased between 50 and 70 basis points in two-day windows around QE announcements reflecting a sharp and highly significant drop of 197 basis points in Italian, Spanish and Portuguese sovereign credit spreads. The effects on 10- and 30-year bonds were highly statistically significant with p-values close to 0 (US and UK) or 1 (eurozone). Meanwhile, the effects on stock index returns and equity implied volatility were economically small and statistically insignificant. There was a small and statistically insignificant tightening of US investment grade credit spreads of 27.5 basis points.

[14]For example, the middle third of the UK sample has no Bank of England QE announcements. We do not want to contaminate our measure of the significance of QE responses by using returns during a time period where there were no QE announcements.

[15]We discuss the robustness of this bootstrap methodology in Section 3.2.

[16]Since the bootstrap procedure samples dates at random over the QE time period, our statistical inference accounts for the fact that stock prices rose and equity implied volatilities fell during this time.

2.2 The Lucca-Moench effect

Lucca and Moench (2015) document that from September 1994 through March of 2011, 80% of the US equity premium was earned in the 24-hour window prior to FOMC announcements.[17] As their Figure 1 shows, the pre-FOMC drift starts at around noon on the day prior to the announcement, at $t-1$, and continues up to the 2:15pm announcement event on the FOMC announcement day t.[18]

Anecdotal evidence suggests that the news media speculated about Fed quantitative easing measures ahead of scheduled FOMC announcements. For example, referring to the December 16, 2008 FOMC meeting, Market News International wrote on December 12, 2008: "The coming week starts with an FOMC meeting that should result in further Fed ease in the target Federal funds rate (economists look for -50 bps to 0.5%) and possibly a better explanation of how the Fed might execute quantitative ease, maybe by issuing its own debt." On December 15, 2008, Reuters wrote: "'Since there is precious little room between current target rates and zero, it will be more interesting to see if the FOMC statement begins to lay out any additional steps that might be undertaken in the new quantitative easing regime,' said Max Bublitz, chief strategist at SCM Advisors in San Francisco." Similarly, ahead of the March 18, 2009 FOMC announcement, the Associated Press wrote on March 17, 2009: "It's less clear whether the Fed will unveil new actions to battle the worst financial crisis since the 1930s. One option advanced at its last meeting in January is buying long-term Treasury securities. Doing so would help further drive down mortgage rates and help the crippled housing market, economists said. [...] Another option put forward in January is expanding a Fed program aimed at bolstering the mortgage market. The Fed could boost its purchases of debt issued or guaranteed by mortgage giants Fannie Mae and Freddie Mac." Given widespread media and investor speculation about what easing steps the Fed will take at upcoming meetings, it is possible that market anticipation of Fed QE announcements began prior to the actual announcement day.

To examine this further, we perform an event study of the intraday returns of SPY (an ETF which tracks the SP500 index) around the 18 Fed QE announcements.[19] The top chart in Figure 1 shows the cumulative log return of SPY from the first trade on the business day prior to Fed announcements ($t-1$) to the last trade on the business day following Fed announcements ($t+1$).[20]

[17] Cieslak, Morse, and Vissing-Jorgensen (2016) also examine US stock market performance around FOMC announcements, but focus on weekly cycles.

[18] The notation $t-1$ refers to the *business* day immediately prior to business day t.

[19] Our intraday data is obtained from the TAQ database on WRDS. We unfortunately do not have access to intraday data on UK and Euro stock indexes.

[20] The Lucca-Moench sample contains 131 FOMC announcements dates, while ours contains only 18 Fed QE

We see a phenomenon similar to the Lucca-Moench effect around Fed QE announcements. There appears to be an SP500 reaction on the day prior to the announcement. The average cumulative return on day $t-1$ across the 18 events is approximately 60 basis points. On the announcement day, the index reacts sharply around the time of the announcement (usually at the 2:15pm FOMC release), but then gives up most of that gain prior to the close. And on the day after the announcement, the SP500 index finishes slightly higher than its announcement day close. The three day SP500 cumulative return around QE announcements is roughly 55 basis points, with the majority of that return occurring on the day prior to the announcement. This is very similar to the Lucca and Moench (2015) finding, but even more stark – in their case approximately 40% of the total three day return happens on the day prior to the announcement.

We also investigate whether US Treasuries exhibit a similar pre-announcement drift. The bottom chart in Figure 1 shows the same event study for IEF (an ETF which holds a basket of 7- and 10-year US Treasuries). Just as in Lucca and Moench (2015, Table VIII) we find that Treasuries exhibit no pre-QE-announcement drift.[21]

To take into account the Lucca-Moench effect, in Table 4 we compute the QE responses of our 6 asset classes in three day windows $[t-1, t+1]$ around QE announcements. As expected, we find that short-, 10-yr and 30-yr bond yield changes are largely unaffected by this 1-day extension of the event window across the three regions. Also as expected, the US equity index response is now much larger – +11% vs -3.5% – though still statistically insignificant with a p-value of 0.80.[22] The reason that such a large equity response is not significant is because in the QE time period, from November 2008 to December 2012, the SP500 generally rose. In fact, 20% of our 5000 bootstrap runs (of 18 randomly sampled dates) produced returns that exceeded 11%. The stock market response in Europe is unchanged, suggesting no Lucca-Moench effect there, but in the UK the stock market response increases from 3.4% (insignificant) to 12.3% (significant at the 7% level). Equity implied volatility in the US falls by 9.3 percentage points, though this change is not statistically significant; while UK equity implied volatility falls by 15.7% (e.g. from 35.7 to 20) with a p-value of 0.06 (vs the two-day insignificant fall of 5.4%).[23]

events. Our standard errors are much larger than those in the Lucca and Moench (2015) paper, and therefore we do not show them in the chart.

[21]Because IEF returns are much less volatile than those of SPY, the bottom chart in Figure 1 shows 95% confidence bands.

[22]We again run a block bootstrap with three periods, and now calculate security responses in three day windows around the randomly chosen dates.

[23]In the UK, the Lucca-Moench effect is very pronounced for equity and equity implied volatility, though this is not the case in the eurozone. See also the Wall Street Journal article from March 13, 2017 entitled "New Data Suggest U.K. Government Figures Are Getting Released Early."

US investment grade credit spreads respond more than in two-day windows, tightening 43 basis points though with a p-value of 0.14.

3 Response horizon

Extending the start of QE event windows by one day from $[t, t+1]$ to $[t-1, t+1]$ has very little effect on bond yield and CDS spread changes, though it increases the stock and implied volatility reactions to QE in the US and UK, with the latter effects being statistically significant. We now turn to the core of our analysis, and look for the post-event horizon over which security reactions following QE announcements are most anomalous.

Let $Npost$ be the number of post-event days in an event window, and $Npre$ be the number of pre-event days. For a given QE announcement e, let us define t_e as the event date. We start with a list of candidate event windows given by $[t_e - Npre, t_e + Npost]$. We refer to $t_e - Npre$ as the window start date, and $t_e + Npost$ as the window end date. Given the chronological proximity of some QE events, it is possible that for a large enough $Npre$ or $Npost$ some of the candidate event windows will overlap. In this case, we use the following rules: (1) if a start date of a window is earlier than or equal to the event date of the prior window, set the start date to the business day after the prior event date; and (2) if an end date occurs on or after the start date of the following window, set the end date to one business day prior to the next event's start date. This scheme generates a sequence of non-overlapping event windows.[24]

Let us define $r_i(k)$ as the change in yield, implied volatility or the log price of security i on business day k, and let us define $r_i(s, s') = \sum_{k=s}^{s'} r_i(k)$. To take into account the Lucca-Moench effect, our event windows always start at $Npre = 1$, i.e. one day before the event day.[25] For a given $Npost$, each event window is given by $[t_e - 1, t_e + \nu(t_e, Npost)]$ where $\nu(t_e, Npost) = Npost$ most of the time, and $\nu(t_e, Npost) < Npost$ when condition (2) from the above paragraph binds. The aggregate response of security i around QE announcements is given by

$$AG_i(Npost) = \sum_{e \in \text{QE events}} r_i(t_e - 1, t_e + \nu(t_e, Npost)). \tag{1}$$

We note that the number of business days over which AG_i is calculated does not necessarily

[24] We do not perform a standard event study because overlap of event windows around QE announcements would lead to a double counting of some effects of quantitative easing.

[25] Condition (1) in the prior paragraph never binds in the case of $Npre = 1$.

grow linearly with $Npost$ because of the non-overlapping windows adjustment.

In this notation the responses considered in Table 4 were $AG_i(1)$. The response of a security to QE events calculated in windows $[t_e - 1, t]$ is given by $AG_i(0)$. For each security i in each of the three regions we now calculate the security responses to QE announcements in windows of up to one month after the announcement; that is we calculate $AG_i(0), \ldots, AG_i(21)$ (because there are on average 21 tradings days per month). For each $AG_i(Npost)$ we calculate a p-value using the block bootstrap methodology described in Section 2.1. Whereas before we calculated security responses in either $[t_r, t_r + 1]$ or $[t_r - 1, t_r + 1]$ windows around randomly drawn events (here t_r is the randomly drawn event date), we now calculate security responses in windows given by $[t_r - 1, t_r + \nu(t_r, Npost)]$ for $Npost = 0, \ldots, 21$. As before, for each bootstrap run we sample N_1, N_2, N_3 dates in each third of the sample, where the N_j corresponds to the number of actual QE event dates that took place in the j^{th} third of the sample.

Figure 2 shows the distribution of cumulative SP500 returns for 5000 draws from the block bootstrap with $Npre = 1$ for $Npost = 0, \ldots, 21$. For example, for $Npost = 0$ the mean two-day SP500 return, i.e. in $[t_r - 1, t_r]$, is 2.0% with a standard deviation of 8.1%. For $Npost = 21$, the mean cumulative SP500 return is 18.3%, with a standard deviation of 18.5%. Returns do not increase linearly with $Npost$ because of the overlapping windows adjustment discussed earlier.

The p-value for the SP500 aggregate response over $Npost$ business days after Fed announcements, which we write as $p_{SP500}(Npost)$, is the fraction of draws in Figure 2 that are lower than $AG_{SP500}(Npost)$. The p-values for any security i, $p_i(0), \ldots, p_i(21)$, are calculated in the same manner using security i's bootstrapped aggregate response distributions. The bootstrap therefore controls for the fact that stock prices (implied volatilities) rose (fell) during the time frame of central bank QE. The null hypothesis of randomly drawn event dates yields SP500 return distributions at different horizons that have very high means. For each $Npost$, the p-value computed for the actual SP500 return following QE dates is therefore measured against a distribution that already has a high mean return.

The top panel of Figure 3 shows aggregate responses to Fed QE announcements for the US securities from Table 1. The bottom panel shows the p-values, $p_i(0), \ldots, p_i(21)$, of each security's aggregate responses. Any aggregate response significant at the 10% level or better is marked with a circle in the top panel, with darker circles indicating p-values closer to 0% and 100% (recall these are one-sided tests). For example, cumulative log returns for SP500 start at just over 10% ($AG_{SP500}(0)$) and increase to over 50% ($AG_{SP500}(21)$). The p-values (bottom panel of Figure 3) start below 90%, but almost all p-values for $Npost > 10$ (excluding $p_{SP500}(15)$)

are significant at the 10% level or better. On the other hand, the aggregate change in 3-month T-bill rates oscillates between -10 and +10 basis points, and is never significant with p-values between 20% and 80%. Figures 4 and 5 show aggregate responses to ECB and Bank of England QE announcements respectively, as well as the associated p-values.

3.1 Maximal response horizons

Table 5 summarizes the information contained in Figures 3, 4, and 5. Let us define the *maximal response horizon* as

$$Npost_i^* \equiv \arg\max_n |p_i(n) - 0.5|. \tag{2}$$

By selecting the post-announcement horizon for which the associated p-value is furthest away from 0.5, we find the security response least likely to have occurred by chance relative to the block bootstrap. We don't select the post-event horizon with the largest security price change, but rather the one whose associated price change is least likely to have occurred under the null hypothesis that QE announcements behaved just like randomly sampled dates.[26]

For each region (US, Europe, UK) and each security type (short bond, 10-yr and 30-yr bond, stock index, index implied volatility, and CDS), Table 5 shows $Npost_i^*$, the aggregate response of each security at that horizon, i.e. $AG_i(Npost_i^*)$, and the associated p-value $p_i(Npost_i^*)$. It is useful to compare the results in this table to those in Table 4, which shows aggregate security responses in three day windows around QE announcements (i.e. $AG_i(1)$).

The short bond in the US doesn't react meaningfully to QE (because QE was undertaken once short rates hit the zero lower bound) even at the maximal horizon; while for the UK the maximal horizon is the same as in Table 4 with $Npost^* = 1$. However in Europe, the short Bund yield rises by close to 90 basis points nine days after QE announcements, an effect that is both statistically and economically significant. The 10-yr and 30-yr bond responses are very similar at the maximal response horizon as in three day windows around QE announcements, suggesting that the majority of the QE effect on bonds happened quickly, and was properly

[26]A referee pointed out that this test procedure is similar to the Andrews (1993) test for structural breaks when the change point is unknown. Andrews (1993) considers a test statistic TS which, if the break point π were known, would give a value $TS(\pi)$. However, since the break point π is not known, the test statistic Andrews considers is $\sup_\pi TS(\pi)$. Our inference procedure in Section 3.2 is also similar to the Andrews procedure, which calculates critical values by sampling the sup over π of the asymptotic null distribution.

identified in past studies.[27]

The most interesting results have to do with the stock index and equity implied volatility reactions. The maximal post-announcement response horizons for US and European stock indexes are 18 and 15 days respectively. The aggregate SP500 response 18 days after Fed QE announcements is a very large 49.1%, with a p-value of 0.97. From Figure 2, we see that the mean of the SP500 bootstrapped returns for $Npost_{SP500} = 18$ is 16.2%. This is the mean return under the null hypothesis that QE dates are no different from 18 randomly drawn dates in a block bootstrap. The actual return in $[t-1, t+\nu(t, 18)]$ windows around Fed QE announcements is larger than 97% of the boostrapped returns. In Europe the aggregate response of Euro Stoxx 50 at the maximal horizon of 15 days is 27.8% with a p-values of 0.97. Both responses are much larger than the $Npost = 1$ results from Table 4. In the UK, the maximal response horizon for the FTSE100 is 3 days, with an aggregate return of 19.7% and a p-value of 0.973 – larger than the $Npost = 1$ return, though not by nearly as big a margin as in the US and Europe.

The maximal response horizons for index implied volatility are 21, 15, and 16 days respectively for the US, Europe, and UK. The drops in implied volatility are all economically very large at 53%, 65% and 47% respectively, and all 3 p-values are very close to zero.

Recall that in Europe the CDS series is the average of the sovereign CDS spreads of Italy, Spain and Portugal (IPS Sov CDS). IPS Sov CDS, which proxies for the asset class targeted by the ECB – peripheral sovereign bonds in Europe – has a maximal response horizon of 1 day, a very fast reaction in line with that observed in 10- and 30-yr government bond yields. In the UK, the CDS series is UK sovereign CDS, and this again reacts very quickly to Bank of England QE with $Npost^*_{UK\ CDS} = 0$ though the effect is economically small and not statistically significant. In the US, the CDS series is the spread of an investment grade CDS index. The maximal response horizon is 3 days, with a tightening in credit spreads of 84 basis points and a p-value of 4.5% – again much larger than the effects for $Npost = 1$ shown in Table 4. In this case, the three day horizon hides the fact that US CDS spreads continued to tighten for the entire 21-day post event period that we analyze, as can be seen from the top panel of Figure 3; in fact, $p_{US\ CDS}(21)$ is very close to 5%. Corporate credit spreads in the US react to QE relatively quickly, but continue to tighten for weeks after the QE announcements took place.

[27] The UK 10-year Gilt has $Npost^*_{10-yr\ Gilt} = 9$ days, though as can be seen from Figure 5, $p_{10-yr\ Gilt}(n) < 0.10$ for $n \leq 12$ days, with $p_{10-yr\ Gilt}(1) = 2\%$ from Table 4. Similarly, though for the US 30-yr Treasury $Npost{*}_{30-yr\ Treasury} = 10$ days, we see from Figure 3 that almost all $p_{30-yr\ Treasury}(n) < 0.05$ for $n \leq 13$ with $p_{10-yr\ Gilt}(1) = 0.7\%$ from Table 4. Therefore the 10-yr Gilt and the 30-yr Treasury have large and almost instantaneous reactions to QE announcements, though the drop in yield remains highly significant for up to 13 days after QE announcements.

Table 5 contains the main result of the paper: While the most statistically anomalous response of 10-yr and 30-yr government bonds to QE announcements occurred either on the day of or on the business day immediately after the announcement, the most statistically anomalous response of stocks and stock implied volatility happened 15 to 21 days *after* the QE announcement. Furthermore, at this lag, the aggregate stock returns (of 49% for the US, 28% for Europe and 20% for the UK) and the aggregate drops in implied volatility (of 53% in the US, 65% in Europe and 47% in the UK) were (1) highly statistically significant, (2) very large in economic terms, and (3) much larger than the effects found in prior studies of QE. It should be emphasized that large and delayed responses of equity and equity implied volatilities to QE exist in *all three* of our geographical regions.

3.2 Robustness

We perform two robustness checks. First, we confirm that our maximal response horizon selection procedure in equation (2) does not bias the results. Next we repeat our analysis with a different version of the block bootstrap.

Full p-values

The p-values shown in Table 5, $p_i(Npost_i^*)$, are biased away from 0.5 by construction: Even under the null hypothesis that QE dates are no different than randomly chosen event dates, the choice of $Npost_i^*$ in (2) will generate p-values that systematically deviate from 0.5. To adjust for the bias introduced by this selection criterion, we look at *all* p-values, rather than looking at the one that is furthest away from 0.5. Taking the 22 p-values (one for each $Npost$) from Section 3.1 we examine the sum of all individual p-values $P_i \equiv \sum_{n=0}^{21} p_i(n)$ for a given security i.

To come up with a distribution for P_i under the null hypothesis of randomly chosen dates, we perform the *outer* bootstrap. A single draw m of the outer bootstrap proceeds as follows: (1) using the block bootstrap, choose N_1, N_2, N_3 dates in each third of the sample period; (2) for a security i, calculate its aggregate response $AG_i^m(Npost)$ for each $Npost$ using these as the event dates (the m superscript emphasizes that a new aggregate response is calculated for each outer bootstrap run); (3) for each $AG_i^m(Npost)$ calculate the associate p-value $p_i^m(Npost)$ using the security response distribution from the inner bootstrap (e.g. those shown in Figure 2 for the SP500); (4) sum these individual p-values for this one outer bootstrap run to get

$P_i^m \equiv \sum_{n=0}^{21} p_i^m(n)$. We define the *full* p-value for security i as

$$\pi_i = \frac{1}{M} \sum_{m=1}^{M} \mathbf{1}[P_i^m < P_i], \tag{3}$$

where M is the number of outer bootstrap runs (in our case, $M = 5000$).[28]

The full p-value is a comparison of the average p-value (i.e. $P_i/22$) of a security's responses to actual QE announcements to the distribution of average p-values of security responses to randomly drawn event dates. For example, if actual QE announcements resulted in a persistent (over the next 21 business days) decrease in bond yields, then the p-values of these aggregate yield changes would on average be close to zero. When we compare these to the p-values generated for randomly drawn event dates, we would see that the average p-value for yield changes after QE announcements was lower than a majority of the outer bootstrap average p-values – π_i measures how many of the randomly drawn average p-values are lower than the actual average p-value.

Table 6 reproduces the maximal response horizons and associated p-values from Table 5, and also shows the full p-values from (3). It is informative to consider the case of the short bond response to QE announcement in the US, where the maximal response horizon is 0 days, and the associated p-value is 0.895 – suggesting the effect is significant at the (almost) 10% level. However, when we examine the aggregate response of short bond yields to Fed QE (top panel of Figure 3), we see that they zigzag from +10 to -10 basis points, in a pattern that appears random. While, $p_{T-bill}(0)$ is quite high, at close to 0.9, the full p-value π_{T-bill} is 0.443 – confirming the intuition that the T-bill response to QE in the US was not statistically different from its response to randomly drawn dates. Since QE was implemented only after short rates in the US hit the zero lower bound, this finding is to be expected.

Looking at the full p-values for 10- and 30-yr bonds in Table 6, we see that longer term government bond yields had a significant and persistent response to QE announcements (with the exception of 30-yr Gilt yields in the UK, which now have a full p-value of 0.25 which reflects a lack of persistence in the initial QE response, see Figure 5). Stock index and implied volatility

[28] A previous version of this paper defined P_i as $\max_n p_i(n)$ (and similarly for P_i^m) rather than the sum. This test ignores the information contained in the other p_i's (i.e. they also may be close to 0 or 1). The present test, with P_i defined as the sum of p_i's, is more powerful. For example, take Case A where 21 of the 22 p-values are 0.5 and one p-value is 0.95, versus Case B where 21 p-values are 0.9 and one p-value is 0.95. Intuitively, Case B is more anomalous than Case A. Our current $P_i \equiv \sum_n p_i(n)$ clearly distinguishes between Cases A and B, whereas $\max_n p_i(n)$ does not.

responses remain significant at the 10% level or better (with the exception of stock responses in Europe, with a p-value of 0.85) suggesting that QE had a significant effect on these markets that did not materialize immediately (as we have already argued) but that was persistent (as measured by the average p-value). Finally, CDS spread moves in the US and Europe remain highly significant.

We conclude that the selection criterion introduced in (2) did not bias our conclusions in Section 3.1, though the adjusted results using full p-values are slightly weaker.

Bootstrap robustness

We ran a version of the block bootstrap where all event dates were chosen to be consecutive, i.e. we randomly selected the first event date and then assumed the remaining $N-1$ events occurred over the ensuing $N-1$ business days. Table 7 shows the maximal response horizon, the associated p-value, and the full p-value for this version of the bootstrap. All results are consistent with what we have seen before, but are generally stronger (i.e. have more extreme p-values). In unreported results, we reran our analysis with a single block and with a four block bootstrap, and found that neither method meaningfully changed our findings. Note that a block bootstrap with a single block is a standard bootstrap that uniformly samples from all dates in the QE period.

4 Interpretation

Our empirical results thus far have shown that equity and equity implied volatilities have economically and statistically significant reactions in the weeks following QE announcements. We now turn to an analysis of our results. First, we investigate stock index and bond yield reactions to past (non-QE) Fed and Bank of England monetary easing and tightening episodes, and show that a similar delayed stock price reaction occurred historically. Then we perform a simple model calibration to argue that the large stock returns we observe around QE announcements are economically plausible. And finally, we analyze a set of US industry portfolios and show that how bond-like an industry is can forecast its maximal response horizon to QE announcements. We interpret these findings in light of the causal channels discussed in the Introduction.

4.1 Behavior in other monetary policy regimes

Our evidence suggests that while government bond markets reacted very quickly to QE announcements, equities and equity implied volatilities didn't fully reflect the announcement effect for several weeks. We now investigate whether this pattern can be caused by the signaling channel – that is, does the delayed effect of QE on equity prices and equity implied volatilities operate through a revision in investor expectations about the path of future interest rate policy? To address this question we examine historical, pre-QE episodes of monetary easing and tightening. We show that government bond yields have anticipated past central bank policy rate changes, whereas equity markets reacted to these changes with a lag even though these same changes were partially anticipated by bond markets. The sizable stock and bond reactions to policy rate changes suggest that market participants interpret these as signals about the path of future monetary policy, rather than one off events, soon to be reversed. The delayed stock reaction to policy rate changes therefore suggests that the signaling channel affects stock prices with some delay. Our approach is closely related to Dimson, Marsh and Staunton (2016), who perform event studies of stock index and government bond returns in 20-day windows before and after Fed and Bank of England policy rate changes. Our results are qualitatively very similar to theirs.

We obtain data on the Fed funds target rate (starting January 1971) from Bloomberg, and the Bank of England's official bank rate (starting January 1975) from the Bank of England's website. Our 10-year Treasury (starting January 1962) and 10-year Gilt (starting January 1989) nominal yield series are obtained from WRDS and Bloomberg respectively. Our SP500 total return series (in dollars, starting July 1962) is obtained from CRSP, and the FTSE100 total return series (in pounds, starting January 1986) is obtained from Bloomberg. All data are at a daily frequency.

We define an event as a day on which the Fed's or the Bank of England's target policy rate changes. Unlike Bernanke and Kuttner (2005), who analyze Fed fund surprises, we are interested in the simple case of actual central bank rate changes, even when these may have been partially anticipated. First, this formulation is most comparable to the QE events we analyze – as we have argued, these were partially anticipated by the market, and we do not study QE surprises. Second, we are interested in understanding *when* markets begin to respond to partially anticipated interest rate policy announcements. Do some markets anticipate these events, while others seem to react only with a lag?

We analyze the cumulative yield changes in 10-yr Treasuries and Gilts and the cumulative

SP500 and FTSE100 continuously compounded returns in 43 business day windows around monetary policy rate changes (21 days before the event, the event itself, and 21 days after the event). We subtract from daily yield changes and returns the lagged change or return calculated over the eleven months immediately prior to the first day ($t-21$) in the event window.[29] This adjustment ensures that we are not simply capturing the tendency of stocks to increase and of bond yields to fall over our sample period. Because there is very little overlap in our event windows we do not apply any window adjustments as we did in the QE analysis in Section 3. Furthermore, whereas in the QE analysis we analyzed the aggregate response for *all* QE announcements, in this event study we report the average *per event* response.

Figure 6 analyzes the effects of Fed and Bank of England policy rate cuts on local government bond yields and stock index returns. The top row of the figure shows the 10-yr Treasury and Gilt responses to Fed and Bank of England rate cuts respectively. Treasuries anticipate the policy rate decision. Treasury yields drop on average by 22 basis points in the month prior to a Fed rate cut, and show no meaningful movement following the policy rate decision. Gilts also appear to anticipate Bank of England rate cuts, though in a much less pronounced way than Treasuries do for Fed cuts, but then revert back to their pre-event-window level. On the other hand, as can be seen from the bottom row, neither the SP500 nor the FTSE100 exhibit significant price moves prior to central bank policy rate changes, but they do so afterwards. The SP500 rises by approximately 2.3% in the 21 business days after Fed rate cuts, and the FTSE100 rises by 1.3%. Both moves appear to be statistically significant at the 5% level. Figure 7 shows the bond and stock responses to pre-QE monetary policy tightening. As before, Treasuries seem to fully anticipate Fed rate hikes, though Gilts do not appear to either anticipate or react to policy tightening by the Bank of England. The SP500 exhibits a post-tightening negative drift, though of a smaller magnitude than the post-easing drift; while the FTSE100 again neither anticipates nor reacts to Bank of England rate hikes.[30]

In summary, pre-QE monetary policy easing appears to have been largely anticipated by government bond markets, but not by equity markets – which react to the rate decision with a pronounced lag of (at least) 21 business days. This pattern is exactly in line with what we find in our QE response analysis in Section 3, suggesting that the signaling channel affects stock

[29]Normalizing by subtracting the full sample daily yield changes or returns does not affect the results.

[30]As can be seen from Figures 6 and 7, there is evidence that the SP500 has a positive return both on days when the Fed cuts and hikes rates. Our sample period is 1971–2008 for the Fed-SP500 event study, and our events are target rate changes. Lucca and Moench (2015) analyze SP500 performance around scheduled FOMC announcements from 1994–2011. The different time periods and event definitions make the results not directly comparable.

prices with a lag both during QE and non-QE monetary policy easing.

4.2 Magnitude of stock returns following QE announcements

One surprising finding of this study is the magnitude of the response of stock market returns to QE at the maximal response horizon.[31] As can be seen from Table 5, US stocks experience an aggregate continuously compounded return of 49% in 20-day windows $[t-1, t+18]$ around the 18 Fed QE announcements (for an average per announcement effect of 2.7%). The stock responses in Europe (28%) and the UK (20%) were also large, though smaller than in the US (but spread over fewer QE announcements, and thus having a similar per announcement effect). Having established that the signaling channel is likely involved in the delayed equity response to QE, we would like to examine whether the magnitude of the observed stock price reaction is also consistent with the signaling channel. If what changed during Fed QE announcement windows were investor expectations about the path of future monetary policy, how large a change would need to have occurred in order to be consistent with a 49% aggregate stock return?

Using data from 1989 to 2002, Bernanke and Kuttner (2005) show that a 100 basis point surprise drop in the Fed funds rate leads to a same day return of roughly 8% in the CRSP value-weighted index (their Table IV). In a recent paper, Kiley (2014) analyzes the short-term responses of SP500 to FOMC announcements. From July 1991 to December 2008, a 100 basis point decline in 10-yr Treasury yields is associated with a 6-9% increase in SP500 prices in half-hour windows around FOMC announcements. From December 2008 to December 2012 (which is almost the same as the time period of our analysis) the magnitude of this effect falls to 1.5-3%.

As we see from Table 4, in $[t-1, t+1]$ windows around Fed QE announcements, 10-yr Treasury yields fell 183 basis points, and the SP500 returned 11% – in-line with the Bernanke and Kuttner (2005) and the Kiley (2014) estimates.[32] Therefore, when measuring short-term moves, our results are consistent with prior work. The question, though, is whether the longer term stock price reaction that we document can plausibly have resulted from the Fed QE actions.

As Campbell and Shiller (1988) and Campbell (1991) have argued, unexpected returns reflect

[31] Implied volatility changes and stock returns are highly correlated, and the implied volatility response is largely consistent with the observed stock returns.

[32] Note that the QE announcements we analyze are a subset of the 12/2008–12/2012 FOMC announcements analyzed by Kiley 2014, and are likely associated with larger SP500 reactions. We map to the Bernanke and Kuttner (2005) surprise drops in the Fed funds rate by assuming the change in the 10-yr Treasury yield represents the magnitude of easing unanticipated by the market prior to the QE announcement.

changes in expectations about future discount rates and cash flows. We use their framework to do a back-of-the-envelope calculation about the possible impact of QE on stock returns. Let us assume that the change in 10-yr and 30-yr Treasury yields around Fed QE announcements (see Table 4) was accompanied by a revision in investor expectations about the path of future discount rates. We will discuss the potential effect on cash flow expectations momentarily. As discussed in the Introduction, the Greenwood et al. (2016) slow moving capital mechanism can delay the transmission of supply shocks from the Treasury market to the equity market. We assume therefore that the equity market incorporated this change in expectations about discount rates with a lag of 18 business days, as documented in Table 5.

Using the decomposition in Vuolteenaho (2002), it is straightforward to show that the change (in event time) in the SP500 log price to book ratio in the event window $[t-1, t+18]$ is given by

$$\ln \frac{M_{18}}{B_{18}} - \ln \frac{M_{-1}}{B_{-1}} = \sum_{y=1}^{\infty} \rho^{y-1} \Delta_E e_y - \sum_{y=1}^{\infty} \rho^{y-1} \Delta_E h_y, \tag{4}$$

where h_y is the year y continuously compounded stock return, e_y is the continuously compounded annual return on book value, i.e. $\ln(1 + \text{Net income}_y/\text{Book value}_{y-1})$, and $\Delta_E x_y \equiv E_{18}[x_{18+y}] - E_{-1}[x_{-1+y}]$ is the change in expectations of x that took place from the start of the event window to the end of the event window across *all* QE announcements. Here $\rho = 1/(1+\eta)$ where η is the long-run ratio of the dividend to the average of the book and market value of the stock. Following Vuolteenaho (2002) we use $\rho = 0.967$. If we further assume that the SP500 book value did not change in the 20-day event windows, then the right hand side of (4) gives us the aggregate continuously compounded SP500 return over all Fed QE windows.

Let us set that

$$\Delta_E h_y = \begin{cases} -150 \text{ basis points} & \text{for } y \leq 20, \\ 0 & \text{for } y > 20. \end{cases} \tag{5}$$

In other words, we assume that over all of the QE event windows $[t-1, t+18]$ market participants revised their expectations about future discount rates down by 1.5% for the next 20 years, but did not change their beliefs about discount rates after that. We discuss whether this is a reasonable assumption shortly. In this case, the h_y term in (4) implies a continuously compounded return of 22.2% (i.e. $1.5 \times \sum_{y=0}^{19} 0.967^y$). Bernanke and Kuttner (2005, Table XI) show that roughly half of contemporaneous stock excess returns due to Fed funds rate surprises are due to changes in expectations about future discount rates, and half of the contemporaneous excess returns are due to changes in expectations about future dividends. Therefore, if $\Delta_E e_y$ is of the same order of magnitude as $\Delta_E h_y$, this simple calculation can produce a return in QE windows of a similar magnitude to the observed 49%.

Is the assumption in (5) about the change in investor expectations about discount rates plausible? From Table 5, we see that Fed QE announcements were associated with a 183 (211) basis point fall in 10-yr (30-yr) rates, though as Wright (2012) and Neely (2016) argue these changes were at least partially mean reverting. On November 24, 2008, the day before our first Fed QE announcement, the 10-yr Treasury yield was 3.33%, and since the final QE announcement (December 12, 2012), 10-yr Treasury yields have averaged 2.2%. The drop in interest rates that took place around the time of Fed QE has been very persistent. Furthermore, many authors (for example, Laubach and Williams 2015, and Gourinchas and Rey 2016) have argued that interest rates experienced a secular move down around the time of the financial crisis, and are likely to remain low indefinitely. Laubach and Williams (2015) write: "Since the start of the Great Recession, the estimated natural rate of interest fell sharply and shows no sign of recovering." They estimate the natural rate fell from 2% to 0% around the financial crisis (their Figure 5).

Coupled with a possible contemporaneous drop in the equity risk premium, a 150 basis point drop in expectations of equity discount rates for the next 20 years could well have occurred around the time of Fed QE announcements. The arguments in this section can be made rigorous by modeling investor expectations of future discount rates and cash flows in a VAR framework, but this is beyond the scope of the present paper. Our heuristic argument is only intended to illustrate that an equity increase of the observed magnitude is consistent with plausible assumptions about how investors may have revised their discount rate and cash flow expectations in response to Fed QE signals about the path of future monetary policy.

4.3 Industry analysis

The portfolio balance channel involves the reallocation of investor portfolios from asset classes directly targeted by QE (such as government bonds and mortgage backed securities whose risk-return trade-off was impacted by central bank policy) into related asset classes. We conjecture this process operates sequentially: as central banks buy government bonds and MBS, previous holders of these bonds are now left holding cash; they then switch out of cash into the most bond-like, still unaffected asset class; after this the prior owners of the secondarily-affected asset class switch into the next most bond-like and still unaffected asset class and so on. Thus more bond-like asset classes will react to QE more quickly than less bond-like asset classes.

Baker and Wurgler (2012) document that bond-like stocks, for example stocks of large, profitable, low-volatility, high-dividend firms, covary more with government bonds than less bond-like stocks. Their measure of "bondness" is b_p in a regression of stock portfolio returns on a set of factors that includes the excess bond return:

$$r_{pt} - r_{ft} = \alpha_p + \beta_p(r_{mt} - r_{ft}) + b_p(r_{bt} - r_{ft}) + s_p SMB_t + h_p HML_t + m_p MOM_t + \epsilon_{pt}, \quad (6)$$

where r_{mt} is the return on the CRSP value-weighted index, r_{bt} is the return on 10-year US Treasuries obtained from CRSP, r_{ft} is return from holding a 1-month T-bill, and SMB, HML, MOM are the size, value and momentum factors from Fama and French (1993) and Carhart (1997), available on Ken French's website.[33] We estimate this regression for 49 value-weighted industry stock portfolios from Ken French's website.

If the portfolio balance channel operates in the conjectured way, we should see more bond-like industries react to QE more quickly, and less bond-like industries react more slowly. To test for this, we estimate each industry's bond beta b_p, as well as its other factor betas, in (6) using non-overlapping weekly returns in 1 to 5-year windows leading up to but not including the first QE announcement by the Fed (on November 25, 2008).[34] Using the methodology from Section 3, we calculate the $Npost^*_p$ using $Npre = 1$ for each industry portfolio – that is we calculate over which time horizon each industry experiences its maximal response to Fed QE announcements.[35] The mean and median maximal response horizons across industries are 8.1 and 7 days respectively, which further supports our finding that stocks experience their maximally significant reactions following QE with a lag. We then run the following cross sectional regression:

$$Npost^*_p = \gamma_0 + \gamma_\alpha \hat{\alpha}_p + \gamma_\beta \hat{\beta}_p + \gamma_b \hat{b}_p + \gamma_s \hat{s}_p + \gamma_h \hat{h}_p + \gamma_m \hat{m}_p + \gamma_\sigma \hat{\sigma}_{\epsilon,p} + u_p, \quad (7)$$

[33] We use SMB and HML from the "Fama/French 5 Factors" version of the model. Using the "3 Factors" version does not change the results.

[34] Because day end prices for Treasuries and equities do not occur at the same time, 3pm vs 4pm, daily estimates of (6) are noisy. We can't compute weekly returns for weeks that are missing any daily returns, which represent approximately 3% of the sample.

[35] We use a 3 block bootstrap with 5000 draws for each industry portfolio. When we exclude the dropped dates from Table 2, we calculate that $Npost^*_p = 21$ (its maximum value) for nearly half of the industry portfolios. Rather than deal with the associated econometric issues, we include all 20 Fed event dates from Table 2, which produces only two portfolios with $Npost^*_p = 21$.

using coefficient estimates and the estimated annualized idiosyncratic volatility $\hat{\sigma}_{\epsilon,p}$ from (6). We estimate this model using regressors from each of the five horizons over which (6) was estimated to make sure our results are robust. Note that the estimated factor betas and volatility in (7) are known as of November 25, 2008, and $Npost^*_p$ is estimated using data on and after November 25, 2008. By including an industry's alpha, all its factor betas and its idiosyncratic volatility, we control for many characteristics which may have affected how quickly a given industry responded to Fed QE announcements.

Table 8 reports the results of this regression for the five different time horizons used to estimate (6). We see that the bond beta loading γ_b in (7) (labeled "Treasury 10yr") is always negative, and statistically significant for the 2-, 3- and 5-year estimation windows. When significant, the magnitude of γ_b is large, between 6.5 and 8.5. The estimated bond betas, $\hat{b}_p$'s, across the 49 industries range from -1 to +0.5 depending on the estimation window. The spread of 1.5 in industry bond betas implies a difference in $Npost^*_p$ of over 10 days between the lowest and highest bond-beta industries – a large economic effect. While other betas enter (7) significantly for some estimation windows, the bond beta is associated with the largest and most pervasive effect. This evidence supports a portfolio balance channel for the delayed QE response of some asset classes: more bond-like industries have maximal response horizons to QE that are 10 days shorter than less bond-like industries, suggesting they were earlier recipients of portfolio rebalancing flows.

5 Conclusion

We have shown that the prices of stocks (at the country and industry levels) and equity implied volatilities react over the course of several weeks following QE announcements. We also showed that the Lucca and Moench (2015) finding of an anticipatory reaction starting on the day prior to FOMC announcements occurs as well during the Fed's QE announcement period, thus suggesting that the day prior to the announcement day should be included in the QE event window. Focusing only on the traditional intraday or one- or two-day windows around QE announcements misses large impacts of QE on less bond-like asset classes. These results are consistent across our three geographical regions. Furthermore, we have shown that similar lagged stock price reactions occurred in past monetary policy episodes in the US and UK. The size of the observed QE effect in US stocks is large, but is consistent with plausible revisions in investor expectations about cash flows and discount rates that may have occurred during QE announcement windows. Finally, our finding that the bond beta of industry portfolios negatively forecasts the time horizon of industry responses to QE is further evidence that more bond-like securities react to QE more quickly.

We argued that the signaling and portfolio balance channels can explain part of the delayed response of equity returns and equity implied volatility to QE announcements. We did not examine how the delayed response interacts with the liquidity or bank lending channels. A unified theoretical explanation of why events as widely publicized as QE may have affected stocks and equity implied volatilities with a lag remains an important research question that will shed insights into market frictions and investor behavior.

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List of securities by region and category

	US	Euro	UK
Short Bond	T-bill 3mo	Bubill 3mo	Gilt 1yr
10-yr Bond	Treasury 10yr	Bund 10yr	Gilt 10yr
30-yr Bond	Treasury 30yr	Bund 30yr	Gilt 30yr
Stock index	SP500	Euro Stoxx 50	FTSE100
Index implied vol	VIX	VSTOXX	VFTSE
CDS	US InvGrade CDS	IPS Sov CDS	UK Sov CDS

Table 1: This table lists the securities we use in our QE analysis, organized by region and category of security. The stock implied volatility indexes, VIX, VSTOXX, and VFTSE, are short-term equity implied volatilities for the SP500, Euro Stoxx 50, and FTSE100 stock indexes respectively. *IPS Sov CDS* refers to the average CDS spread on Italian, Spanish and Portuguese sovereign CDS contracts. *UK Sov CDS* is the sovereign CDS contract on UK government debt. *US InvGrade CDS* is the spread of the on-the-run Markit CDX North American Investment Grade Index. Bond yield and CDS spread changes are expressed in basis points; stock index log returns are expressed percent; and changes in implied volatility are expressed in percent (e.g. 5 means an increase in implied volatility from 12% to 17%).

QE event dates and bond yield changes

Group Name	Subgroup	Date	10-yr Rate Change
FedQE	QE1	2008-11-25	-21.5
FedQE	QE1	2008-12-01	-18.9
FedQE	QE1	2008-12-16	-25.7
FedQE	QE1	2009-01-28	13.9 [drop]
FedQE	QE1	2009-03-18	-47.3
FedQE	QE1	2009-08-12	4.9
FedQE	QE1	2009-09-23	-2.6
FedQE	QE1	2009-11-04	5.9
FedQE	QE2	2010-08-10	-7.0
FedQE	QE2	2010-08-27	16.9 [drop]
FedQE	QE2	2010-09-21	-13.0
FedQE	QE2	2010-10-12	3.9
FedQE	QE2	2010-10-15	5.2
FedQE	QE2	2010-11-03	-1.6
FedQE	QE2	2011-06-22	-0.1
FedQE	Twist	2011-09-21	-8.1
FedQE	Twist	2012-06-20	3.7
FedQE	QE3	2012-08-22	-10.7
FedQE	QE3	2012-09-13	-3.4
FedQE	QE3	2012-12-12	4.4
ECBQE	LTRO1	2008-03-28	1.4
ECBQE	FRFA	2008-10-15	0.7
ECBQE	CBPP/LTRO	2009-05-07	14.0
ECBQE	SMP	2010-05-10	15.8
ECBQE	CBPP	2010-06-30	1.8
ECBQE	CBPP2	2011-10-06	10.3
ECBQE	LTRO2	2011-12-08	-8.8
ECBQE	OMT	2012-08-02	-14.1 [drop]
ECBQE	OMT	2012-09-06	8.0
BoEQE	2009	2009-01-19	13.2 [drop]
BoEQE	2009	2009-02-11	-24.1
BoEQE	2009	2009-03-05	-28.5
BoEQE	2009	2009-05-07	7.3
BoEQE	2009	2009-08-06	-9.5
BoEQE	2009	2009-11-05	6.2
BoEQE	2010	2010-02-04	-1.8
BoEQE	2011	2011-10-06	3.8
BoEQE	2011	2011-11-29	-3.9
BoEQE	2012	2012-02-09	3.4
BoEQE	2012	2012-07-05	-6.8

Table 2: Fed, ECB, and Bank of England QE announcement dates. Note that August 10, 2010 is classified in Fawley and Neely (2013) as QE1, but we re-classify this date as QE2 (Krishnamurthy and Vissing-Jorgensen (2011) also classify this date as QE2.) All Bank of England announcements are placed into subgroup by year. The table also shows the change, in basis points, in the 10-year government bond yield (shown in Table 1 for each region) on the day of each of the domestic central bank's QE announcements. Event dates that do not satisfy the 10 basis point test described in Section 2 are dropped from the analysis, and are labeled *[drop]*.

Aggregate responses for QE announcements with $Npre = 0$ and $Npost = 1$ day

Field	US	Euro	UK
		Short Bond	
Response	-4.6	-2.5	-50.2
p-value	[0.268]	[0.535]	[0.016]
		10-yr Bond	
Response	-198.1	53.0	-85.5
p-value	[0.000]	[0.991]	[0.006]
		30-yr Bond	
Response	-133.7	66.9	-79.7
p-value	[0.001]	[0.997]	[0.004]
		Stock index	
Response	-3.5	2.6	3.4
p-value	[0.242]	[0.658]	[0.643]
		Index implied vol	
Response	1.1	4.8	-5.4
p-value	[0.620]	[0.729]	[0.299]
		CDS	
Response	-27.5	-196.7	5.5
p-value	[0.188]	[0.001]	[0.678]

Table 3: For each security type and region, this table shows the the aggregate security response and associated p-value with $Npost = 1$ day. The response windows are calculated starting at $t-0$ where t is the event date. All p-values come from a block bootstrap that divides the sample into 3 equally sized intervals. All bootstraps were conducted with 5000 draws.

Aggregate responses for QE announcements with $Npre = 1$ and $Npost = 1$ day

Field	US	Euro	UK
		Short Bond	
Response	3.3	6.1	-57.7
p-value	[0.657]	[0.719]	[0.016]
		10-yr Bond	
Response	-182.9	74.4	-75.8
p-value	[0.000]	[0.997]	[0.021]
		30-yr Bond	
Response	-119.6	93.5	-61.8
p-value	[0.007]	[0.999]	[0.025]
		Stock index	
Response	11.0	2.7	12.3
p-value	[0.799]	[0.634]	[0.930]
		Index implied vol	
Response	-9.3	8.5	-15.7
p-value	[0.307]	[0.802]	[0.064]
		CDS	
Response	-43.1	-236.5	-6.2
p-value	[0.140]	[0.001]	[0.392]

Table 4: For each security type and region, this table shows the the aggregate security response and associated p-value with $Npost = 1$ day. The response windows are calculated starting at $t-1$ where t is the event date. All p-values come from a block bootstrap that divides the sample into 3 equally sized intervals. All bootstraps were conducted with 5000 draws.

Aggregate responses for QE announcements with $Npre = 1$ and the maximal Npost

Field	US	Euro	UK
		Short Bond	
Response	9.6	88.6	-57.7
Npost*	0	9	1
p-value	[0.895]	[0.998]	[0.016]
		10-yr Bond	
Response	-182.9	64.6	-152.2
Npost*	1	0	9
p-value	[0.000]	[0.998]	[0.009]
		30-yr Bond	
Response	-210.7	81.7	-61.8
Npost*	10	0	1
p-value	[0.005]	[1.000]	[0.025]
		Stock index	
Response	49.1	27.8	19.7
Npost*	18	15	3
p-value	[0.970]	[0.970]	[0.973]
		Index implied vol	
Response	-53.0	-64.8	-46.6
Npost*	21	15	16
p-value	[0.028]	[0.000]	[0.001]
		CDS	
Response	-84.0	-236.5	-14.9
Npost*	3	1	0
p-value	[0.045]	[0.001]	[0.173]

Table 5: For each security type and region, this table shows the the aggregate security response at the maximal horizon $AG_i(Npost_i^*)$ (labeled "Response"), the maximal response horizon $Npost_i^*$, in days, and the associated p-value $p_i(Npost_i^*)$. The response windows are calculated starting at $t-1$ where t is the event date. All p-values come from a block bootstrap that divides the sample into 3 equally sized intervals. All bootstraps were conducted with 5000 draws.

Adjusted p-values for QE announcements with $Npre = 1$ and the maximal Npost

Field	US	Euro	UK
	Short Bond		
Npost*	0	9	1
p*	[0.895]	[0.998]	[0.016]
Full p-value	[0.443]	[0.982]	[0.078]
	10-yr Bond		
Npost*	1	0	9
p*	[0.000]	[0.998]	[0.009]
Full p-value	[0.020]	[0.944]	[0.025]
	30-yr Bond		
Npost*	10	0	1
p*	[0.005]	[1.000]	[0.025]
Full p-value	[0.027]	[0.948]	[0.250]
	Stock index		
Npost*	18	15	3
p*	[0.970]	[0.970]	[0.973]
Full p-value	[0.939]	[0.848]	[0.943]
	Index implied vol		
Npost*	21	15	16
p*	[0.028]	[0.000]	[0.001]
Full p-value	[0.096]	[0.034]	[0.003]
	CDS		
Npost*	3	1	0
p*	[0.045]	[0.001]	[0.173]
Full p-value	[0.058]	[0.006]	[0.353]

Table 6: For each security type and region, this table shows the maximal response horizon $Npost_i^*$, in days, the associated p-value $p^* = p_i(Npost_i^*)$, and the adjusted p-value π_i (labeled "Full p-value"). The response windows are calculated starting at $t-1$ where t is the event date. All p-values come from a block bootstrap that divides the sample into 3 equally sized intervals. All bootstraps were conducted with 5000 draws.

Consecutive date bootstrap:
Aggregate responses for QE announcements with $Npre = 1$ and the maximal Npost

Field	US	Euro	UK
		Short Bond	
Response	11.5	78.4	-70.1
Npost*	4	8	4
p*	[0.933]	[0.999]	[0.000]
Full p-value	[0.412]	[0.969]	[0.062]
		10-yr Bond	
Response	-206.4	74.4	-136.3
Npost*	9	1	7
p*	[0.000]	[0.996]	[0.000]
Full p-value	[0.014]	[0.888]	[0.009]
		30-yr Bond	
Response	-202.6	93.5	-63.6
Npost*	9	1	5
p*	[0.000]	[1.000]	[0.012]
Full p-value	[0.030]	[0.934]	[0.166]
		Stock index	
Response	40.8	27.8	21.6
Npost*	13	15	7
p*	[1.000]	[0.998]	[1.000]
Full p-value	[0.975]	[0.860]	[0.993]
		Index implied vol	
Response	-47.7	-52.2	-20.6
Npost*	16	13	2
p*	[0.000]	[0.000]	[0.000]
Full p-value	[0.036]	[0.044]	[0.002]
		CDS	
Response	-154.0	-236.5	-45.0
Npost*	21	1	16
p*	[0.002]	[0.000]	[0.040]
Full p-value	[0.026]	[0.006]	[0.233]

Table 7: For each security type and region, this table shows the aggregate response at the maximal response horizon, the maximal response horizon $Npost_i^*$, in days, the associated p-value $p_i(Npost_i^*)$, and the adjusted p-value π_i (labeled "Full p-value"). The response windows are calculated starting at $t-1$ where t is the event date. All p-values come from a *consecutive date* bootstrap. All bootstraps were conducted with 5000 draws.

Cross-sectional regression of $Npost^{*}$ on industry factor betas

	T = 1	T = 2	T = 3	T = 4	T = 5
Intercept	8.22**	10.41***	11.84***	6.85*	11.47***
Alpha	2.15	2.78	-2.07	-0.38	-2.90
Mkt - RF	-1.49	-3.00	-4.14	0.42	-3.33
Treasury 10yr	-3.32	-6.47**	-7.55**	-2.04	-8.65**
SMB	0.43	1.75	4.92	4.07	5.07*
HML	-4.79*	-4.57	-0.08	-1.52	0.59
MOM	2.51	1.84	0.85	4.47	6.64*
SD Residual	0.06	-0.02	-0.05	-0.03	-0.12
Adj R2	0.133	0.139	0.101	0.0438	0.122

Table 8: This table shows the coefficient estimates from (7). The regression contains 49 value-weighted industry stock portfolios. The columns correspond to different estimation windows (in years), all using weekly data, for the factor loadings in (6). Weeks with any missing Treasury returns are dropped (approximately 3% of the sample). "SD Residual" gives the value of $\hat{\gamma}_{\sigma}$, the estimated loading on the idiosyncratic volatility for industry p from (6). $Npost^{*}_{p}$ is calculated using $Npre = 1$ in a bootstrap with 3 blocks, that retains all US QE dates from Table 2, and uses 5000 draws. Standard errors are computed using White's adjustment for heteroskedasticity. Significance at the 1%, 5%, and 10% levels is indicated by ***, **, and * respectively.

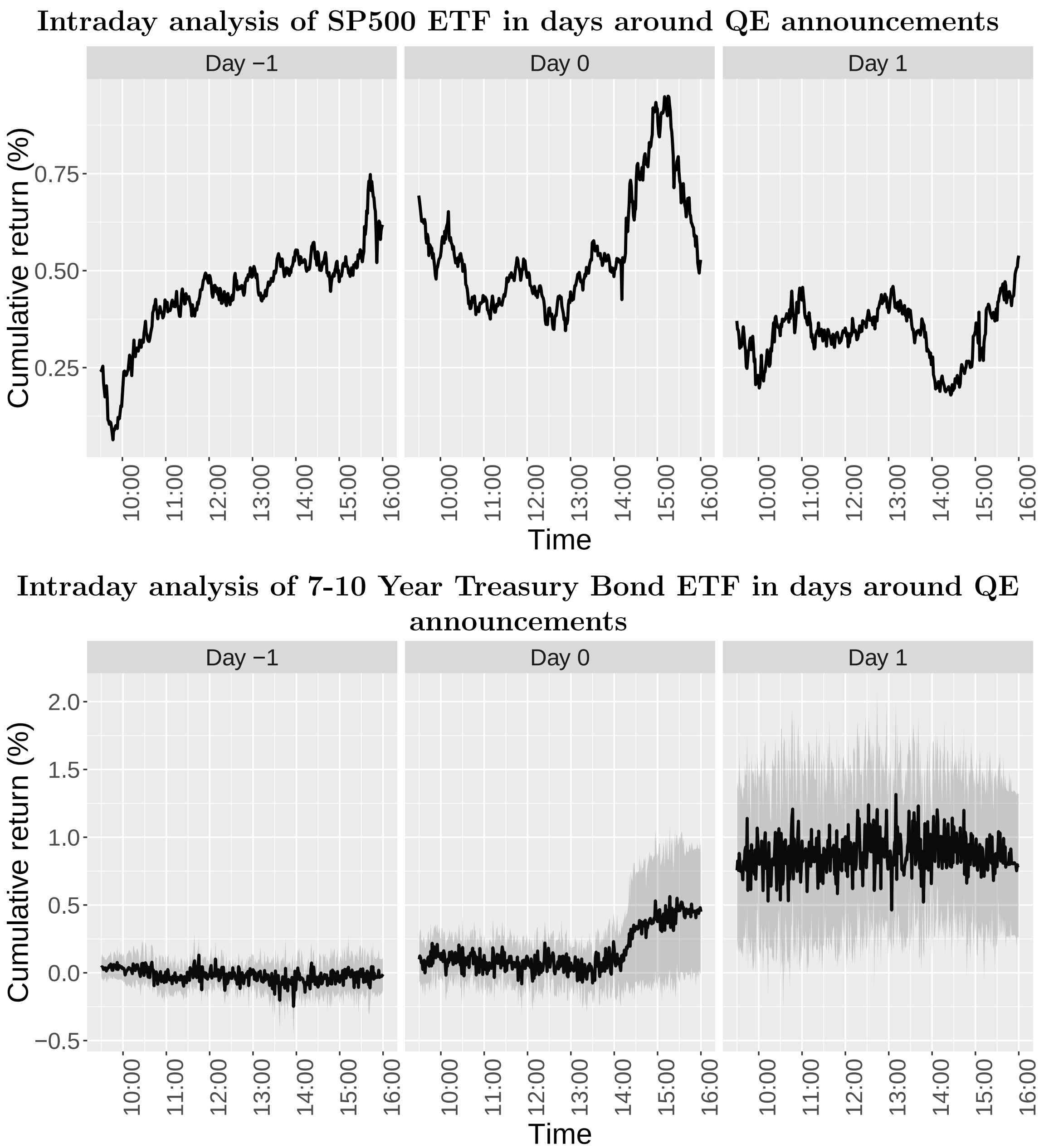


Figure 1: The top chart shows the cumulative log returns of SPY, an SP500 ETF, in the day prior to, the day of, and the day after the Federal Reserve QE announcements shown in Table 2. The bottom chart shows the cumulative log returns of IEF, an ETF that owns 7-10 year US Treasuries, over the same event dates. The final cumulative returns on Day 1 is the log of the last trade price on Day 1 minus the log of the first trade price on Day -1. Standard errors are only shown for IEF (bottom chart), and are calculated using Newey-West with 1 lag.

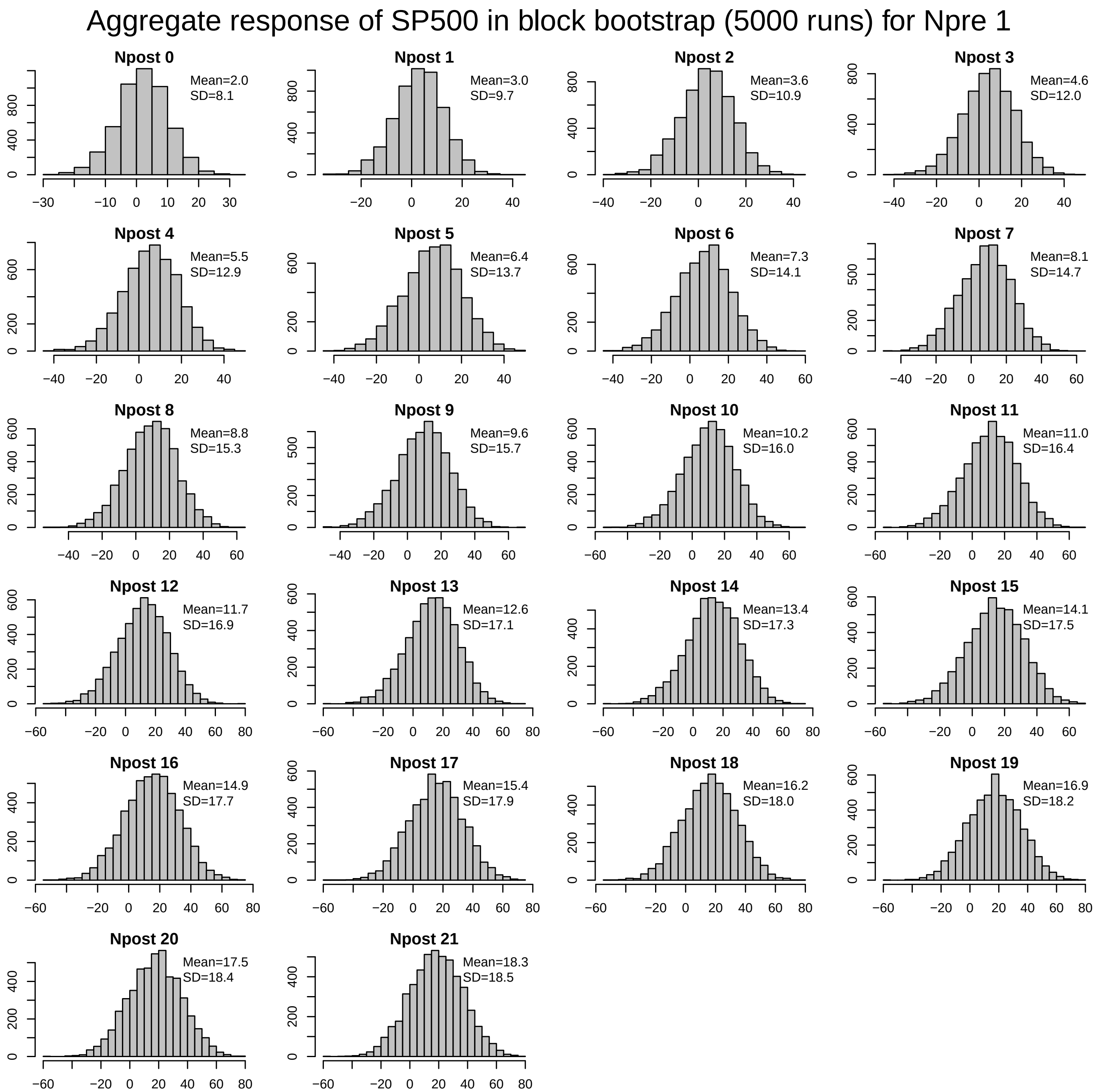


Figure 2: This figure shows the distribution of aggregate responses of the SP500 index for 18 random dates chosen using the block bootstrap (with 3 blocks and 5000 draws) described in the text. For a given $Npost$, each graph also shows the mean and volatility of the corresponding aggregate return.

Aggregate responses for Federal Reserve QE announcements

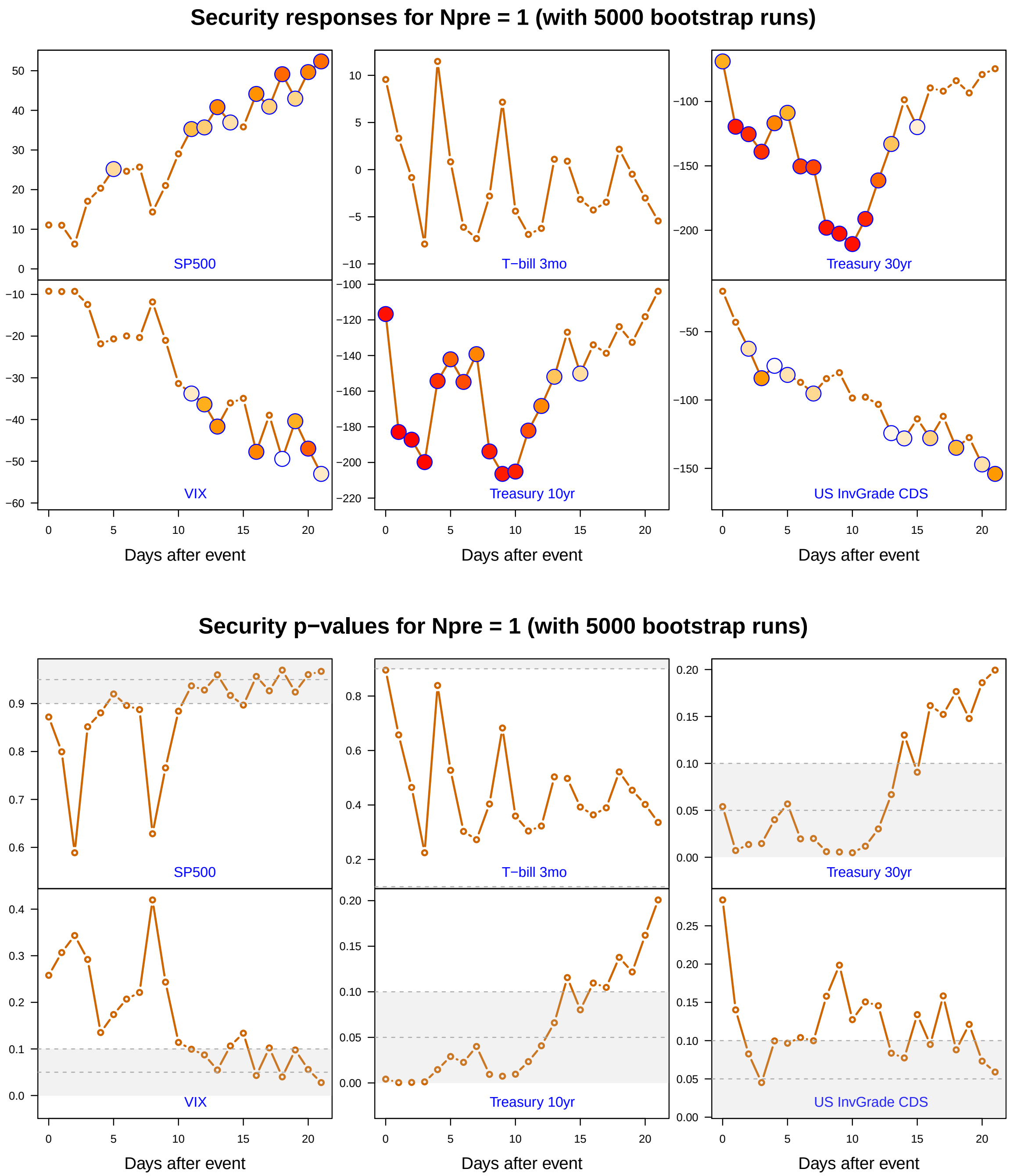
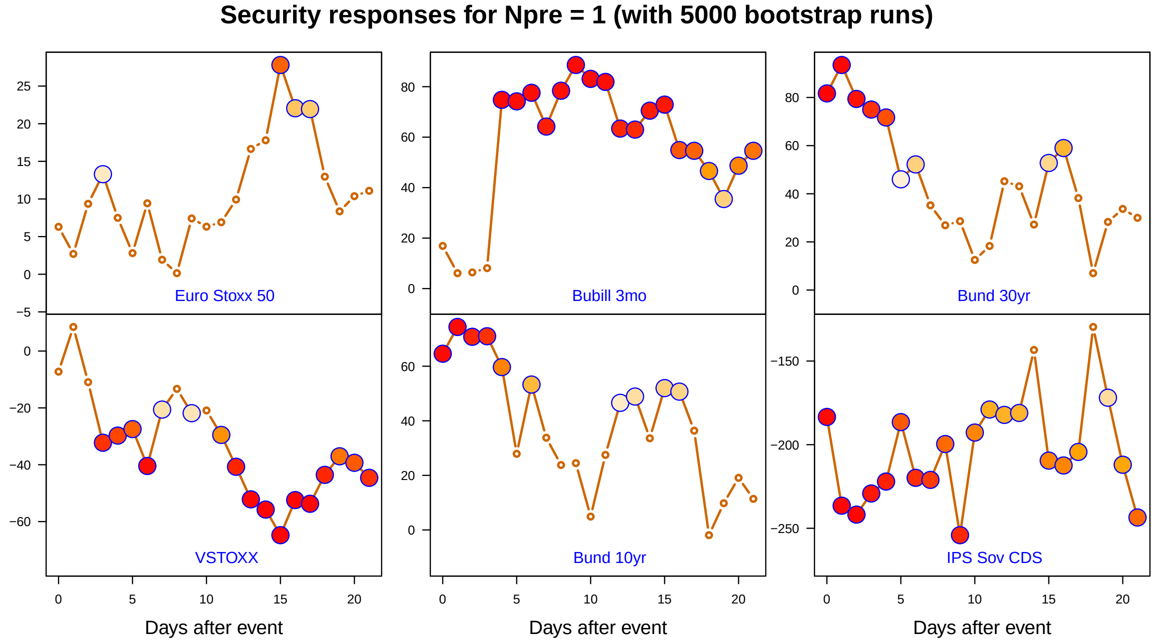


Figure 3: The top figures show the cumulative response, $AG_i(Npost)$, of each security to all Federal Reserve QE announcements. The x-axis shows $Npost$, labeled "Days after event." Circles indicate responses that are significant at the 10% level or better using the inner bootstrap p-values. Darker circles indicate more extreme p-values. The bottom figures show the corresponding p-values. The 10% and 5% significance regions are indicated by the shaded area and the dashed lines. The p-values were computed using a bootstrap with 3 blocks and 5000 draws.

Aggregate responses for ECB QE announcements



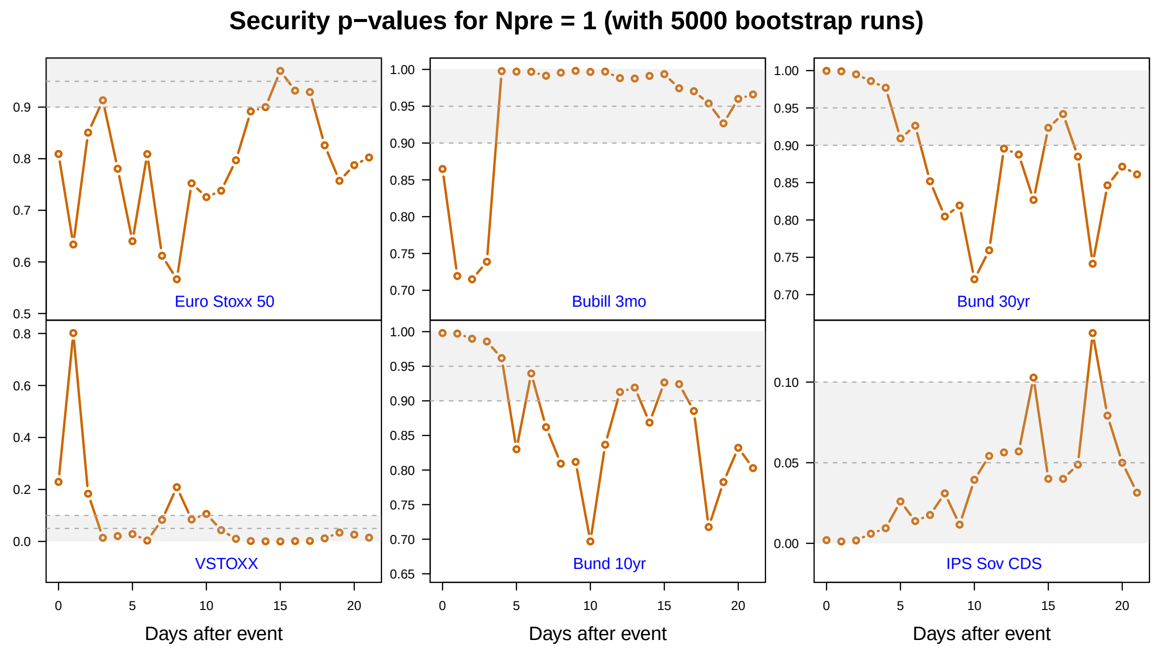


Figure 4: The top figures show the cumulative response, $AG_i(Npost)$, of each security to all ECB QE announcements. The x-axis shows $Npost$, labeled "Days after event." Circles indicate responses that are significant at the 10% level or better using the inner bootstrap p-values. Darker circles indicate more extreme p-values. The bottom figures show the corresponding p-values. The 10% and 5% significance regions are indicated by the shaded area and the dashed lines. The p-values were computed using a bootstrap with 3 blocks and 5000 draws.

Aggregate responses for Bank of England QE announcements

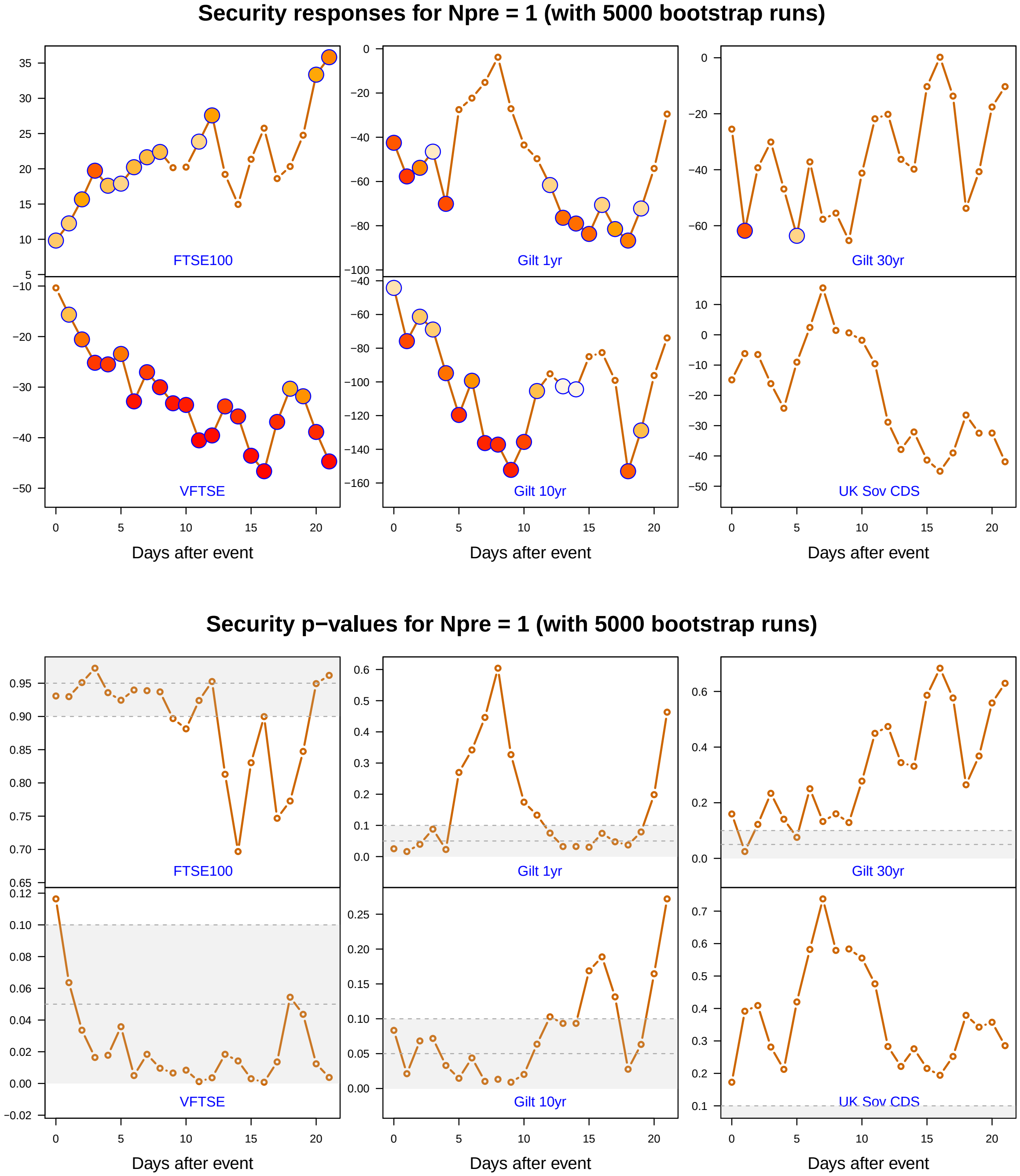


Figure 5: The top figures show the cumulative response, $AG_i(Npost)$, of each security to all Bank of England QE announcements. The x-axis shows $Npost$, labeled "Days after event." Circles indicate responses that are significant at the 10% level or better using the inner bootstrap p-values. Darker circles indicate more extreme p-values. The bottom figures show the corresponding p-values. The 10% and 5% significance regions are indicated by the shaded area and the dashed lines. The p-values were computed using a bootstrap with 3 blocks and 5000 draws.

Local stock index and interest rate responses around pre-QE monetary easing

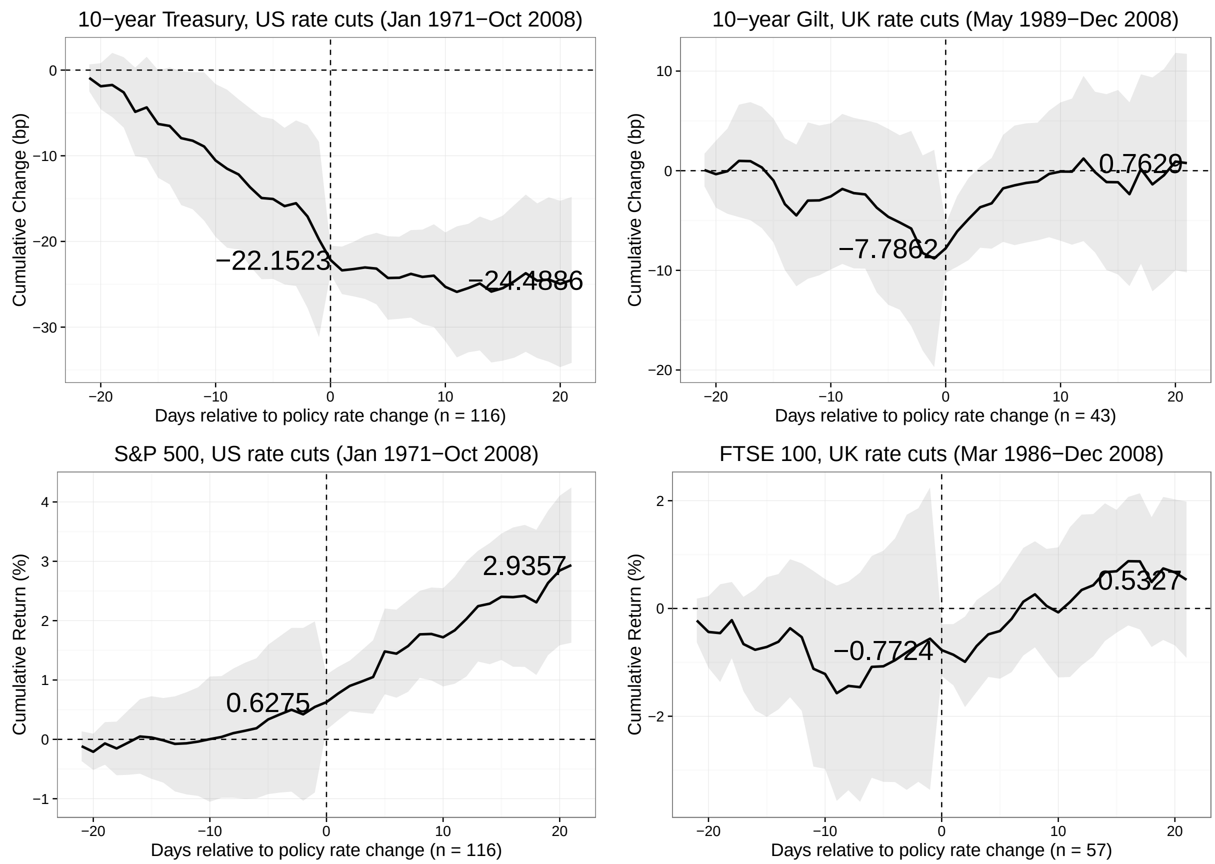


Figure 6: This figure shows the responses of the SP500 and FTSE100 (continuously compounded cumulative returns) and 10-year Treasury and Gilt yields (in basis points) for Federal Reserve and Bank of England policy target rate cuts respectively, in the pre-QE era. The time period of the first and last central bank policy rate change in our sample and the number of central bank policy events (labeled $n =$) are shown in each plot. We analyze a 43 day event window, with 21 days before and after policy rate changes. The numbers indicate the cumulative return or yield change on the event date (day 0), and on day 21. The first 12 months of each time period are used to calculate the first rolling mean return or yield change. The 95% confidence interval is calculated using Newey-West standard errors with 1 lag. The confidence interval is calculated separately for the pre- and post-event periods.

Local stock index and interest rate responses around pre-QE monetary tightening

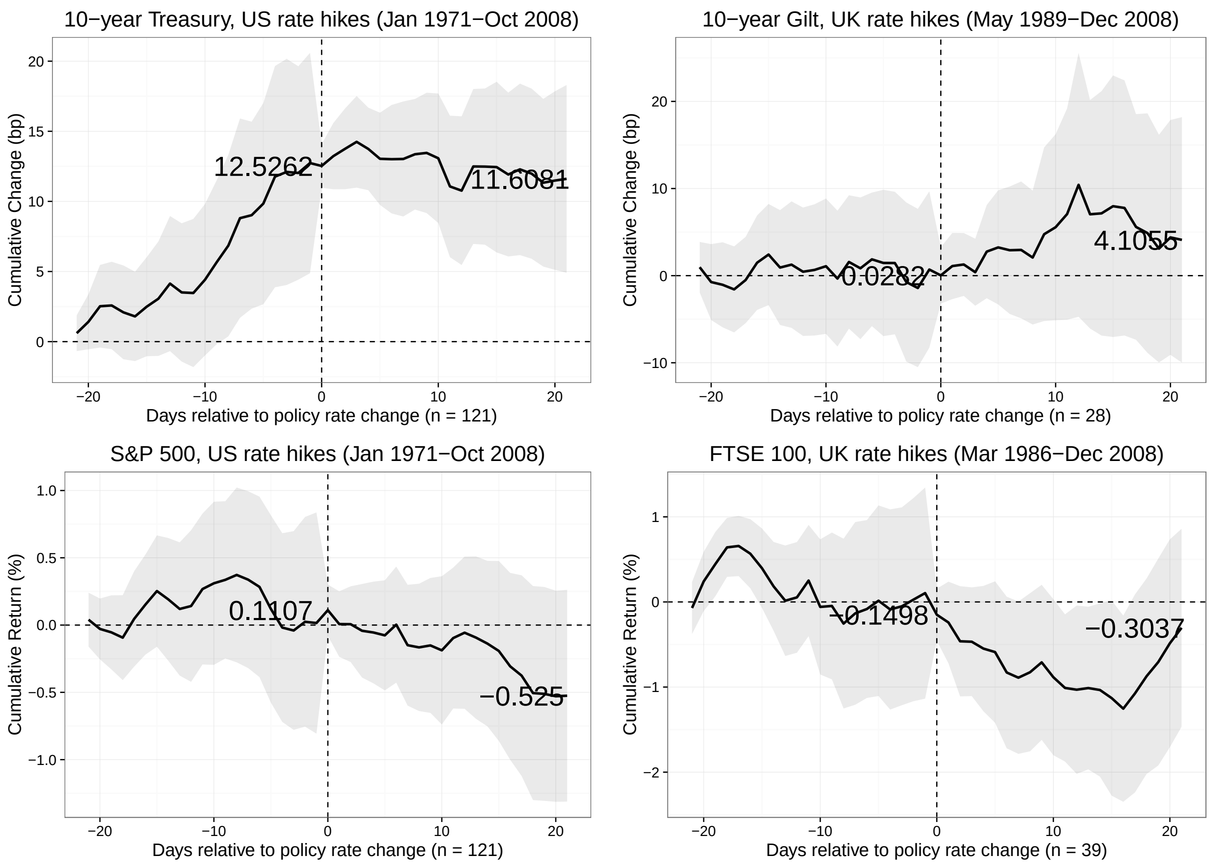


Figure 7: This figure shows the responses of the SP500 and FTSE100 (continuously compounded cumulative returns) and 10-year Treasury and Gilt yields (in basis points) for Federal Reserve and Bank of England policy target rate hikes respectively, in the pre-QE era. The time period of the first and last central bank policy rate change in our sample and the number of central bank policy events (labeled $n =$) are shown in each plot. We analyze a 43 day event window, with 21 days before and after policy rate changes. The numbers indicate the cumulative return or yield change on the event date (day 0), and on day 21. The first 12 months of each time period are used to calculate the first rolling mean return or yield change. The 95% confidence interval is calculated using Newey-West standard errors with 1 lag. The confidence interval is calculated separately for the pre- and post-event periods.