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Danmarks Nationalbank

**Has the Fed Reacted Asymmetrically
to Stock Prices?**

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Resumé

Eksisterende studier af aktivprisers potentielle rolle i pengepolitiske beslutninger bygger på en implicit antagelse om, at centralbanker reagerer fuldstændig symmetrisk på bevægelser i aktivpriser. Denne artikel tilføjer et nyt perspektiv til debatten ved at tillade, at den pengepolitiske reaktion på henholdsvis stigninger og fald i aktiepriser ikke nødvendigvis er den samme. For at undgå endogenitetsproblemer benytter jeg en metode, som sikrer identifikation ved at udnytte heteroskedasticiteten i de stød, som rammer aktiemarkedet. På denne måde demonstrerer jeg, at The Federal Reserve (den amerikanske centralbank) i perioden 1998-2008 netop har reageret asymmetrisk på aktiepriser. Et fald på 5 pct. i aktieindekset S&P 500 forøger sandsynligheden for en efterfølgende rentenedsættelse på 25 basispoint med $1/3$. Derimod fører en tilsvarende aktieprisstigning ikke til nogen signifikant renteændring.

Has the Fed Reacted Asymmetrically to Stock Prices?*

Søren Hove Ravn[†]

October 2011

Abstract

Yes. Existing studies of the possible role of asset prices in monetary policy implicitly assume that central banks respond to asset price movements in a fully symmetric way. This paper offers a new perspective by allowing for different policy reactions to stock price increases and decreases, respectively. To avoid endogeneity problems, I employ the method of identification through heteroskedasticity. I then demonstrate that the reaction of the Federal Reserve has indeed been asymmetric during the period 1998-2008. While a 5% drop in the S&P 500 index is shown to increase the probability of a 25 basis point interest rate cut by 1/3, no significant reaction to stock price increases can be identified.

Keywords: Monetary Policy, Asset Prices, Asymmetries.

JEL classification: E44, E52, E58.

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1 Introduction

The recent financial crisis has highlighted the importance of the link between financial markets and the macroeconomy, as well as the implications for monetary policy thereof. As a consequence, the crisis has led to a revival of the debate about the possible role of asset prices in monetary policy. The 'pre-crisis consensus' view prescribed that monetary policy should not lean against the wind with respect to asset prices, but rather be ready to clean up in case of a rapid drop in asset prices by cutting interest rates aggressively.¹ In the wake of the crisis, however, this view has come under critique for involving an inherent asymmetry in the sense that it calls for central banks to react only when asset prices go down.

The present paper contributes to the recent debate by assessing the empirical relevance of this asymmetry. I study the monetary policy reaction to stock price movements, but contrary to common practice, I allow for different monetary policy reactions to stock price increases and decreases, respectively. In this way, I investigate the hypothesis that the Federal Reserve (Fed) has been reacting asymmetrically to stock prices; cutting the interest rate in response to stock market drops, but not raising the interest rate correspondingly when stock prices go up. I build on the framework of Rigobon and Sack (2003), who use the method of identification through heteroskedasticity. This identification strategy exploits the heteroskedasticity of the shocks hitting the stock market and the fact that when the volatility of stock prices changes, so does the covariance between stock prices and interest rates. Using daily data, Rigobon and Sack (2003) show that the Fed has been reacting to stock price movements. Expanding their model allows me to investigate whether this reaction is symmetric.

The results indicate that the Fed has indeed been pursuing an asymmetric policy over the period 1998-2008. I find that the reaction to stock price drops turns out to be significant, while no reaction to an increase in stock prices is found. The way to interpret this result is not necessarily that small, daily changes in stock prices lead to small, daily adjustments of monetary policy. Indeed, the Federal Open Market Committee (FOMC) only meets every six weeks, and the Federal Funds Target rate is usually changed by at least 25 basis points at a time. Instead, one can think of these small daily movements as reflecting the change in the probability of a discretionary change in the policy rate at the next FOMC meeting. When interpreted this way, the results of the paper indicate that a 5 % drop in the S&P 500 index increases the probability of a 25 basis point interest rate cut by 33 %, while a rise in stock prices leads to no significant monetary policy reaction.

Importantly, detecting a response of monetary policy to stock prices does not necessarily imply that the Fed is targeting stock prices *per se*. Instead, the reason for the response could be that stock prices affect the actual target variables of the Fed; inflation and economic activity. Indeed, this is the explanation provided by Rigobon and Sack (2003). Along these lines, I discuss how the asymmetric policy found in this paper could reflect a response to a

¹The term 'pre-crisis consensus' is coined by Bini Smaghi (2009).

possible asymmetry in the way the stock market impacts the macroeconomy.

The paper is related to other studies of the monetary policy reaction to asset prices. Rigobon and Sack (2003) find that for the period 1985-1999, a 5 % drop in the S&P 500 index increases the probability of a 25 basis point interest rate cut by 57 %. More recently, Furlanetto (forthcoming) finds that the magnitude of the response of US monetary policy to stock prices has been declining over time. My results are in line with this finding, as the size of the response found in the present paper is smaller than what is found by Rigobon and Sack (2003) for their earlier sample. On the contrary, using real-time data, Fuhrer and Tootell (2008) find no reaction to stock prices during the Greenspan era (1987-2006). Finocchiaro and Queijo von Heideken (2009) identify a policy reaction to housing prices in the US, the UK and Japan. These studies all share the common feature that no asymmetries or non-linearities in monetary policy are considered. In contrast, D'Agostino *et al.* (2005) allow for the size of the monetary policy reaction to stock prices to depend on the concurrent volatility of the stock market. They find that the Fed's reaction is substantially larger in periods of high volatility in the stock market than when volatility is low.

The rest of this paper proceeds as follows: Section 2 reviews the debate about the link between stock prices and monetary policy and, in particular, the hypothesis of an asymmetric policy reaction. Section 3 covers methodological issues and describes the identification strategy in detail. Results are presented in section 4 and discussed in section 5, while section 6 concludes.

2 Monetary Policy, Asset Prices and Asymmetries

The debate about the role of asset prices in monetary policy goes back at least to Bernanke and Gertler (1999, 2001). They argue that asset prices should not enter the monetary policy rule, except insofar as these can be regarded as signals about future macroeconomic conditions. This view has been supported by, among others, Gilchrist and Leahy (2002) and Tetlow (2005), as well as in speeches by leading Fed officials (Kohn 2006, Mishkin 2008). Cecchetti *et al.* (2000) reach the opposite conclusion, as they find that the optimal monetary policy rule does include a reaction to the stock market, although this reaction is usually quite small. The activist position of Cecchetti *et al.* has also been advocated by Bordo and Jeanne (2002), Borio and White (2003), and, recently, Pavasuthipaisit (2010).

Despite some enduring disagreement, it has been argued that a certain degree of consensus seemed to have been reached before the crisis.² According to this consensus, central banks should not try to lean against perceived asset price bubbles, partly because these are extremely hard to identify in real time, and partly because of the difficulties in using monetary policy to 'prick' such bubbles. Instead, central banks should stand ready to cut

²See Bini Smaghi (2009), Issing (2009), and Yellen (2009).

interest rates aggressively after the bursting of these bubbles in order to contain the effects on real economic activity and price stability. As described by Bini Smaghi (2009), part of the explanation behind this consensus is that the New-Keynesian model framework, which has become the dominant theoretical workhorse for monetary policy analysis over the last decade, has until recently failed to pay sufficient attention to financial markets. When financial markets play only a small (or no) role in the model economy, the potential gains from reacting to asset prices are reduced markedly. The recent crisis, however, has drawn substantial attention to this shortcoming of previous macroeconomic models, and a new strand of literature is emerging, in which financial intermediation, credit conditions, and other sources of fluctuations in financial markets have important macroeconomic implications. Notable contributions to this literature include Christiano *et al.* (2010), Gertler and Kiyotaki (2010), and Woodford (2010).

Moreover, the crisis also seems to have reopened the debate on the role of asset prices in monetary policy. Bini Smaghi (2009), Issing (2009), and Yellen (2009) all question the validity of what used to be conventional wisdom in light of the crisis, while White (2009) argues that central banks should not only deal with asset prices after the bursting of a bubble, but also before. Posen (2009) even claims that opposing that central banks should take asset prices directly into account 'is now an embattled position to take'. Kohn (2009), however, remains skeptical towards the activist view. Pavasuthipaisit (2010) demonstrates how leaning against the wind can be optimal when asset prices contain signals about the future state of the economy.

One particular feature of the recent debate has been the acknowledgement of an inherent asymmetry in the pre-crisis consensus view. The notion that monetary policy should remain passive during the build-up of an asset price bubble, and then step in to clean up after the bursting of the bubble, gives rise to an asymmetric monetary policy towards the stock market, as recognized by Bini Smaghi (2009), Issing (2009), and White (2009). The asymmetric approach is criticized by Issing (2009), who points out that this might lead to moral hazard problems for investors. Issing advocates that monetary policy should be 'leaning against headwind' (asset price declines) as well as 'tail wind' (increases). White (2009) accuses the Fed of having conducted an asymmetric policy during the Greenspan era and, in line with Issing, calls for monetary policy to be symmetric in the future. The present paper evaluates the empirical relevance of such an asymmetry in the recent past.

3 Methodology

Estimating the response of monetary policy to changes in stock prices involves a number of difficulties. Due to endogeneity problems, it is not immediately possible to estimate a monetary policy rule with a distinct reaction to stock prices. As stock prices and interest rates are determined simultaneously, the *ceteris paribus*-interpretation of the parameters

breaks down, and the results are likely to be misleading, as also illustrated by Rigobon and Sack (2003). One technique that is often used to avoid endogeneity problems is the instrumental variable (IV) method. However, it is hard to find an appropriate instrumental variable for this problem, since it is extremely difficult to think of any variable that is correlated with stock prices but uncorrelated with the interest rate. Other authors have used GMM to estimate the parameters of Taylor rules, including Clarida *et al.* (2000) and Fuhrer and Tootell (2008).

In the present paper, I instead follow the identification method proposed by Rigobon and Sack (2003). This involves working with daily data.³ Hence, it is not meaningful to estimate a standard monetary policy rule augmented with a term capturing stock prices, as these rules involve variables such as output and inflation, for which no daily observations exist. Instead, the asymmetry hypothesis is incorporated into a system of two equations describing the dynamics and the interaction between the interest rate and stock prices on a daily basis. This system closely resembles the setup in Rigobon and Sack, except for the asymmetric part. The system is the following:

$$i_t = \beta_j s_t + \lambda x_t + \gamma z_t + \varepsilon_t, \quad (1)$$

$$s_t = \alpha i_t + \phi x_t + z_t + \eta_t, \quad (2)$$

where

$$\beta_j = \begin{cases} \beta_1 & \text{if } s_t \geq 0 \\ \beta_2 & \text{if } s_t < 0. \end{cases}$$

The variables are the following: i_t represents daily observations of the interest rate as measured by the 3-month Treasury Bill rate. This choice is discussed below. s_t is the daily percentage change in the closing value of the S&P 500 index. x_t is a matrix capturing surprises about key macroeconomic indicators. More specifically, for each of the variables in x_t , the daily observation is set to zero on days when no news about this variable is released. On release dates, the value equals the surprise in the news, measured as the actual release minus the market expectation of the given release, which is collected from Bloomberg. The following six variables are included in x_t : Output growth (GDP), nonfarm payrolls (NFPAY), consumer price index (CPI), producer price index (PPI), retail sales (RETL), and the purchasing managers index (ISM). I use daily observations of the interest rate, the stock price change, and each of the six macroeconomic news variables for the sample period January 1998 to December 2008.⁴ Note that while the system presented above does not

³At least, using lower-frequency data, e.g. monthly observations of stock prices and interest rates, would exclude many of the rich patterns in the comovement between these variables that is found using daily data and is essential for identification.

⁴The reason for not using a longer sample is lack of data, as I did not have access to Bloomberg data on market expectations for all the macroeconomic variables further back than 1998. The end of the sample,

include lags of the variables, I do include five lags of i_t and s_t when I regress (a rewritten version of) the equations in subsection 3.2.

Further, the system contains three unobserved shocks. Given that these are structural or fundamental shocks, as opposed to reduced-form innovations, I follow Rigobon and Sack (2003, 2004) and Furlanetto (forthcoming) in assuming that they are mutually uncorrelated, as discussed below. z_t is a common shock to both equations (with the effect on s_t normalized to one) and can be interpreted as macroeconomic shocks not captured by the six variables in x_t , as well as shocks to the risk or liquidity preferences of investors, or any other shock affecting both stock prices and interest rates. The inclusion of a common shock plays a key role in obtaining a correct estimate of the policy reaction, as discussed below. ε_t represents a monetary policy shock in the standard interpretation from the New Keynesian literature.⁵ The final shock parameter, η_t , measures shocks to the stock market; i.e., changes in stock prices not driven by macroeconomic factors or interest rate movements. Given the interpretation of the common shock, the stock market shock can be interpreted as capturing bubbles or 'fads' in the stock market.

Essentially, (1) is supposed to capture any daily movements in the 3-month T-Bill rate. The equation states that these movements could be driven by macroeconomic news, general macroeconomic shocks, monetary policy shocks or stock price changes. In particular, the effect on the interest rate of stock price movements is allowed to differ depending on whether stock prices are increasing or decreasing. If the central bank reacts in an asymmetric way to the stock market, market participants will realize this and act accordingly. Thus, daily drops or jumps in stock prices will lead to asymmetric effects on the daily 3-month T-Bill rate. Note that the parameters multiplying the shocks in (1) are the same no matter the sign of s_t . By assuming that the shocks hitting the interest rate are the same no matter if the stock market is rising or falling, the shocks are excluded as a possible source of asymmetry in the monetary policy reaction.

Similarly, (2) implies that daily stock price changes are driven by macroeconomic factors, interest rate movements and shocks. Rigobon and Sack show that this equation is in essence a version of Gordon's growth formula if it is assumed that expectations of future dividends are driven by macroeconomic news, and that expectations of future interest rates are shaped by this news as well as by the current interest rate. Thus, (2) is derived from the fundamental value of an asset.

The assumption of mutually uncorrelated shocks is key in obtaining identification, and therefore merits discussion. Rigobon and Sack (2004) point out that this assumption is

December 2008, is chosen so as to correspond to the time when the Federal Funds Target rate reached its lower bound of zero.

⁵Christiano *et al.* (1999) offer three possible interpretations of this type of shock. First, it may reflect changes in the preferences of individual FOMC members or in the process of aggregating their views. Second, the Fed may sometimes find itself in so-called 'expectation traps' (Chari *et al.*, 1998), in which changes in private agents' policy expectations warrant a deviation from systematic monetary policy in order not to disappoint these expectations. Measurement error in real-time data may be a third source of exogenous variations in the policy process

not directly testable in the present setup. As will become evident in section 3.2, what is actually assumed is that the three shocks are mutually uncorrelated *conditional on* each of the four covariance regimes into which I divide the observations. This is similar to Rigobon and Sack (2003). To justify this assumption, recall that the presence of the common shock z_t is supposed to capture *any* shock that affects both stock prices and interest rates. This includes, for example, shocks to investors' preferences for risk or liquidity that shift their relative appetite for stocks versus Treasury bills. In the absence of the common shock, either the assumption that ε_t and η_t are uncorrelated would have to be abandoned, or the estimates of β_1 and β_2 would be biased. Once the common shock is included, the two remaining shocks are much more likely to be orthogonal to each other.⁶ Moreover, the common shock z_t needs to be orthogonal to each of ε_t and η_t . Given the interpretation of η_t as reflecting non-fundamental stock price shocks or bubbles, it seems reasonable to assume that at the daily level, this shock is exogenous to the more fundamental movements underlying the common shock. With low-frequency data, one might suspect that these two shocks could be correlated; for instance that positive macroeconomic shocks could lead to overoptimism in the stock market. At the daily frequency, however, the orthogonality assumption is likely to hold. As for the monetary policy shock, ε_t is treated as entirely exogenous by most of the New Keynesian literature (e.g., Christiano *et al.*, 1999; Clarida *et al.*, 2000), and is therefore assumed to be orthogonal to z_t also in this setup.⁷

Furthermore, in the context of the present paper, I also need to assume that the shocks are mutually uncorrelated *conditional on* the sign of s_t as well as on the covariance regime. That is, the shocks must be orthogonal for the subsample of decreasing stock prices as well as for the subsample of non-decreasing stock prices. Given that s_t is a linear function of the structural shocks, this implies that the shocks must be uncorrelated on given truncations of their distributions. One might suspect that conditioning on some linear function of the shocks being smaller or larger than zero could induce some (positive) correlation. This concern is likely to be related primarily to the possible correlation between z_t and η_t , as these two shocks affect the (sign of the) change in the stock price directly, whereas ε_t affects stock prices only indirectly through its impact on the interest rate. If s_t had been determined only by the shocks, these would likely be correlated on each subsample. However, s_t is a function not only of the shocks, but also of the interest rate and macroeconomic news, according to (2). Moreover, as already mentioned, five lags of stock price changes and interest rates are

⁶Recall the three possible interpretations of ε_t suggested by Christiano *et al.* (1999). It seems reasonable to assume that shocks deriving from noise in the data collection process or 'institutional shocks' to the position of the FOMC are uncorrelated with non-fundamental shocks to the stock market. As for the third interpretation of the monetary policy shock; given that monetary policy is already allowed to react (systematically) to stock prices, it seems plausible that stock market shocks are unrelated to the emergence of 'expectation traps' in the sense of Chari *et al.* (1998), and hence also uncorrelated with the (unsystematic) monetary policy responses to such traps.

⁷To stick with the interpretation in Christiano *et al.* (1999): Given that monetary policy can react to the factors driving z_t , there is no reason to believe that these factors should then be correlated with the emergence of expectation traps and unsystematic policy responses. Moreover, the institutional factors and measurement errors underlying ε_t are likely to be exogenous also to the common shock.

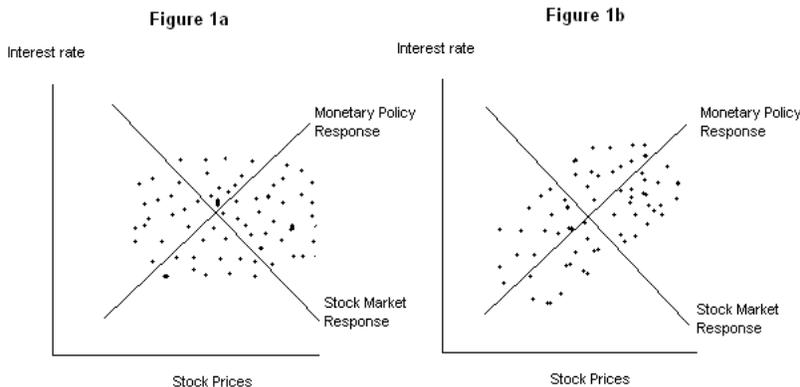
included when regressing the system. In other words, each shock is only one among many factors affecting the sign of each observation of s_t . Based on this insight; conditioning on, say, $s_t < 0$ does not imply that the structural shocks at time t must be negative (and hence, correlated). Dividing the observations into two subsamples should thus induce little (if any) correlation between the structural shocks, provided these are truly structural. Assuming mutually orthogonal shocks on each subsample therefore does not seem too harsh.

I follow existing literature on the topic (Rigobon and Sack, 2003; Furlanetto, forthcoming) and use the 3-month T-Bill rate in the analysis. As discussed by Rigobon and Sack (2003), this rate will adjust on a daily basis to reflect expectations of future monetary policy decisions. As the identification method relies on the use of daily data, the Federal Funds Target rate would be an inappropriate measure, as it is changed less frequently; usually no more often than every six weeks. The Federal Funds rate does change on a daily basis, but only fluctuates within a very small band around the target rate. As also acknowledged by Furlanetto (forthcoming), the use of the T-Bill rate is not entirely unproblematic, as this rate can also be affected by factors not directly related to monetary policy, such as changes in the term premium or in the risk appetite of investors. However, Furlanetto argues that the inclusion of a common shock in the model exactly captures many of these factors, as also discussed above. As a result, much of the 'noise' affecting the T-Bill rate (but not the Federal Funds rate) is taken into account, largely isolating the movements in the T-Bill rate that reflect monetary policy expectations, namely those driven by changes in the macroeconomic environment and shocks to the monetary policy process. In particular, the common shock accounts for the part of this noise that is related to stock price movements. This implies that any remaining noise in the T-Bill rate (relative to the Federal Funds rate) is likely to be exogenous with respect to stock prices. To further confirm the validity of using the 3-month T-Bill rate, I calculate the correlation between daily observations of the levels of the Federal Funds rate and the T-Bill rate lagged by 3 months (recall that the interest rate enters the system (1) – (2) in levels). This gives a correlation coefficient as high as 0.97.⁸ In other words, the market does seem to forecast quite precisely the short-term policy rate. Finally, using the 6-month T-Bill rate produces largely the same estimate of the policy reaction, as demonstrated in section 4.1. This confirms the finding of Rigobon and Sack (2003) that the results are not very sensitive to the choice of interest rate variable.

3.1 Identification through heteroskedasticity

To obtain identification, Rigobon and Sack (2003) apply the method of identification through heteroskedasticity described below. As it turns out, this method is also applicable in order to address the question of this paper. This study builds heavily on the work of Rigobon and Sack, but they do not allow for any asymmetries in the monetary policy rule.

⁸Even after using a band pass filter to filter out low-frequency movements (frequencies lower than six years), the correlation only drops to 0.96.



To understand the method of identification through heteroskedasticity, consider Figure 1a. The upward sloping schedule illustrates the hypothesis that the Central Bank reacts to a stock price increase by raising the interest rate, giving rise to a positive relation between the two variables. The downward sloping curve, labelled Stock Market Response (SMR), captures the effect that a rise in the interest rate will cause a drop in stock prices, all else equal, as future dividends are discounted more heavily. Initially, no particular pattern emerges from the cloud of artificial observations.

Consider an increase in the volatility of the daily stock price changes. In terms of the system (1) – (2) above, this amounts to an increase in the variance of η_t . If stock prices become more volatile, so does the monetary policy response to them. As a result, the causal link going from stock prices to interest rates will be stronger than before, as stock prices do now account for a larger share of the movement in interest rates. On the other hand, as stock price changes will now largely be driven by the shocks, the causal link going from interest rates to stock prices becomes weaker. One can think of this in terms of variance decomposition of equations (1) and (2).

Graphically, this means that the Monetary Policy Response (MPR) will account for a larger part of the comovement between stock prices and interest rates than before. Correspondingly, the SMR will now have relatively less explanatory power. As a consequence, the observations of daily stock prices and interest rates will now to a larger extent than before be distributed along the MPR-schedule, as illustrated in Figure 1b. Hence, the observations now trace out the slope of the MPR-curve. The slope is exactly the parameter of interest, as it measures the reaction of monetary policy to stock prices.⁹

In other words, the identification method exploits the fact that when the variance of stock prices changes, so does the covariance between stock prices and interest rates. This seems to be supported by empirical observations, as testified by figure A2 in Appendix A,

⁹The illustrations in figure 1 are caricatures of the empirical scatterplots, which are shown in figure A1 in Appendix A. While the pattern described above is much less obvious in these empirical scatterplots than in figure 1, the same, rough picture emerges.

which displays the relationship between the volatility of stock prices and the covariance between stock price changes and interest rate changes. The figure illustrates a substantial, positive comovement between the two curves, and the correlation coefficient between the two is 0.60 for the period 1998-2008; the sample period considered in this paper.

The identification method relies on the insight that the reaction of monetary policy to the stock market accounts for a larger share of the comovement between asset prices and interest rates in periods of high volatility in the stock market. This can be exploited by comparing the covariance matrix between stock price changes and interest rates in periods of high and low volatility. The method is developed by Rigobon (2003) and applied in order to estimate the reaction of monetary policy to stock prices by Rigobon and Sack (2003). They assume that monetary policy reacts linearly to stock prices, so that the response to a 1 % rise in stock prices is the exact opposite of the response to a 1 % fall. However, as explained below, the same method allows me to relax this assumption and investigate if there is any asymmetry in the reaction to stock market hikes and drops, respectively.

3.2 Obtaining Identification

Due to the endogeneity problems pointed out above, as well as the presence of unobserved shocks, the system (1)-(2) cannot be regressed. Instead I run the following structural VAR:

$$\begin{pmatrix} i_t \\ s_t \end{pmatrix} = \Theta x_t + \begin{pmatrix} v_t^i \\ v_t^s \end{pmatrix}, \quad (3)$$

By inserting (1) and (2) into each other and solving for i_t and s_t , it follows that the residuals v_t^i and v_t^s are given by the following system:

$$\begin{pmatrix} v_t^i \\ v_t^s \end{pmatrix} = \begin{cases} \begin{pmatrix} \frac{1}{1-\alpha\beta_1} [(\beta_1 + \gamma) z_t + \beta_1 \eta_t + \varepsilon_t] \\ \frac{1}{1-\alpha\beta_1} [(1 + \alpha\gamma) z_t + \eta_t + \alpha\varepsilon_t] \end{pmatrix} & \text{if } s_t \geq 0 \\ \begin{pmatrix} \frac{1}{1-\alpha\beta_2} [(\beta_2 + \gamma) z_t + \beta_2 \eta_t + \varepsilon_t] \\ \frac{1}{1-\alpha\beta_2} [(1 + \alpha\gamma) z_t + \eta_t + \alpha\varepsilon_t] \end{pmatrix} & \text{if } s_t < 0. \end{cases} \quad (4)$$

Note that λ does not appear in these expressions, as it is included in the expression for the matrix Θ multiplying x_t in (3). The only difference between the residuals with rising or falling stock prices arises from β_1 or β_2 appearing. Therefore, in the following analysis I will work only with the system with β_1 , as the analysis with β_2 is entirely analogous.

When running the regression in (3), I include five lags of each of i_t and s_t . I discuss this choice in subsection 4.1. The regression then produces the residuals which must satisfy (4).

As stressed above, the identification method relies on changes in the variance and covariance of stock prices and interest rates. Hence, the covariance matrix of v_t^i and v_t^s is computed. This matrix looks as follows:

$$\Omega = \frac{1}{(1 - \alpha\beta_1)^2} \cdot \begin{bmatrix} (\beta_1 + \gamma)^2 \sigma_z^2 + \beta_1^2 \sigma_\eta^2 + \sigma_\varepsilon^2 & (1 + \alpha\gamma) (\beta_1 + \gamma) \sigma_z^2 + \beta_1 \sigma_\eta^2 + \alpha \sigma_\varepsilon^2 \\ (1 + \alpha\gamma) (\beta_1 + \gamma) \sigma_z^2 + \beta_1 \sigma_\eta^2 + \alpha \sigma_\varepsilon^2 & (1 + \alpha\gamma)^2 \sigma_z^2 + \sigma_\eta^2 + \alpha^2 \sigma_\varepsilon^2 \end{bmatrix} \quad (5)$$

In order to compute the covariance matrix, the assumption that the shocks z_t , η_t and ε_t are mutually orthogonal for each of the two subsamples is central, as it implies that the covariance terms cancel out in the above expression. However, the covariance matrix is not enough to identify the variables, as it provides a system of three equations in six variables (α , β_1 , γ and the variances of the three shocks). Instead, dividing the observations into four variance-covariance regimes based on their variance yields four covariance matrices.¹⁰ I then follow Rigobon and Sack in assuming that while the variance of z_t and η_t is allowed to vary across regimes, the variance of the monetary policy shock ε_t is constant over time and across regimes. This can be motivated in the following way: remember that z_t and η_t measure macroeconomic shocks and stock market shocks, respectively. It seems unlikely that the variances of these shocks remain constant as the variance of v_t^i and v_t^s shifts. Indeed, shifts in the variance of v_t^i and v_t^s are likely to be driven in large part by shifts in the variance of the stock market shock η_t as well as the macroeconomic shock z_t . On the contrary, the monetary policy shock ε_t reflects changes in or deviations from the systematic monetary policy process, as argued above. These types of 'institutional' disturbances are more likely not to change over time. Hence, it is assumed that σ_ε^2 is constant across all regimes.

With this assumption, each new covariance matrix adds three equations and two variables (σ_z^2 and σ_η^2) to the system.¹¹ Thus, starting out with one covariance matrix (i.e. three equations) and six variables, the system will be just identified with four covariance matrices, as this gives 12 equations in 12 variables. However, as it turns out, the parameter of interest (β_1) can actually be identified from just three covariance matrices. In this case, while the system as such is underidentified, β_1 is just identified as the system of equations can be shown to collapse into two equations in two variables due to the symmetry of the equations. This is shown explicitly in Appendix B.

¹⁰In this step, I impose the assumption that the structural shocks are orthogonal *conditional* on each regime, as discussed above.

¹¹An implicit assumption is that the parameters α , β and γ are also constant across regimes. Apart from being essential in obtaining identification, this allows me to avoid conducting a VAR with time-varying parameters, which is not the focus of this paper. This could be an interesting extension.

Once the system is broken down into two equations in two variables, it can be shown (see the appendix) that β_1 will solve the following equation:

$$a\beta_1^2 - b\beta_1 + c = 0, \tag{6}$$

where

$$\begin{aligned} a &= \Delta\Omega_{41,22}\Delta\Omega_{21,12} - \Delta\Omega_{21,22}\Delta\Omega_{41,12}, \\ b &= \Delta\Omega_{41,22}\Delta\Omega_{21,11} - \Delta\Omega_{21,22}\Delta\Omega_{41,11}, \\ c &= \Delta\Omega_{41,12}\Delta\Omega_{21,11} - \Delta\Omega_{21,12}\Delta\Omega_{41,11}. \end{aligned}$$

In this system, $\Delta\Omega_{xy,zv}$ denotes the difference between element zv in covariance matrices x and y , with $x, y = \{1, 2, 3, 4\}$ and $zv = \{11, 12, 22\}$.

4 Results

The residuals are obtained by regressing (4). Rigobon and Sack (2003) include five lags in their regression, but do not give any reasons for their choice of this number of lags. To address this issue, I carry out an analysis of the optimal number of lags in the VAR-model. To this end, I perform a likelihood ratio test, and I calculate Schwarz's Bayesian Information Criterion for the model with p lags, where $p = \{1, 2, \dots, 10\}$. As it turns out, both of these methods lend support to the use of five lags. As the conclusion is not clear, however, changing the number of lags is included in the robustness tests below.

The next step is to divide the residuals into four different covariance regimes. For v_t^i and v_t^s , the 30-day rolling variance is calculated throughout the sample. I then follow Rigobon and Sack (2003) and define periods of high variance as periods in which this rolling variance exceeds its sample average by more than one standard deviation. While this definition is somewhat arbitrary, Furlanetto (forthcoming) points out that the same criterion has previously been used in the literature to separate periods of high and low asset price volatility. Moreover, Rigobon and Sack (2003) demonstrate that the identification strategy yields consistent estimates even if the regimes are misspecified. Finally, as discussed in section 4.1, my results are quite robust to alternative values for this threshold.

Four regimes result: When the variance of both v_t^i and v_t^s are high, when one is high and one is low, and when both are low. The share of observations falling under each regime is shown in Table 1, which clearly shows that the large majority of observations are in the "low,low"-regime.

Table 1: Separating the observations into different covariance regimes

	Share of obs., $s_t < 0$	Share of obs., $s_t \geq 0$
Regime 1 (l,l)	88.3 %	82.6 %
Regime 2 (l,h)	4.3 %	5.3 %
Regime 3 (h,l)	5.1 %	10.0 %
Regime 4 (h,h)	2.3 %	2.1 %

Having separated the observations into four regimes, the covariance matrix of each regime is then calculated. Subtracting the elements in these from one another as illustrated in the previous section then yields an estimate of β_1 (resp., β_2). As it is not possible to calculate their standard deviations and perform regular statistical inference, the raw estimates of β_1 and β_2 are difficult to interpret as such. Instead, I apply bootstrap methods (see Appendix C for details) in order to obtain 10,000 estimates for β_1 and β_2 . The distribution of these can then be used to draw more robust conclusions about the parameters.

Tables 2 and 3 display the results of the estimation. The parameter estimate for β_1 (the parameter governing the reaction to stock price increases) is -0.0134 when calculated using regimes 1, 2 and 3. While the sign is surprising, it is important to note that this parameter is clearly insignificant, as illustrated by the distribution of the probability mass. 16.68 % of the probability mass falls to the right of zero. On the other hand, β_2 is rather precisely estimated at 0.0123. With 96.75 % of the probability mass to the right of zero, this parameter is significant and has the expected sign. Interpreting these results in economic terms, it seems that the Fed has indeed reacted asymmetrically to stock price changes. When stock prices go up, no significant reaction from the Fed is found. On the other hand, as stock prices fall, the Fed reacts by cutting the interest rate. I also tested whether the two parameter estimates are significantly different from each other. This turns out to be the case, though only at the 10 % level.

If instead β_1 and β_2 are calculated using regimes 1,2 and 4, the results change quantitatively, but not qualitatively. While the parameter estimate for β_1 is now -0.0387, it is still highly insignificant. On the contrary, β_2 is still positive and significant, though now only at the 10 % level. The parameter estimate is as high as 0.0737, but this is mainly due to a few extremely large observations. Indeed, the median of β_2 is estimated at 0.019. Hence, this regime also lends support to the hypothesis of an asymmetric policy rule.

The results do change, however, when regimes 1, 3 and 4 are used. As can be seen from the table, the estimate for β_2 becomes very small numerically and highly insignificant. β_1 is still small and insignificant. Thus, while this regime is still not able to detect a reaction to stock price increases, it is now also impossible to identify any reaction to stock price drops, and hence also any asymmetry in the policy rule.¹²

¹²The likely explanation of this has to do with the regime being excluded. The difference in volatility between the high and low regime is larger for the stock price residual v^s than for the interest rate residual v^i . When regime 2 (low volatility of v^i , high volatility of v^s) is excluded, only regime 4 (which has a low number of observations) represents high volatility of v^s . As a result, the combination of regimes 1, 3 and 4 does not

The results using regimes 2, 3 and 4 are not shown. Recall that around 85 % of all observations were counted under regime 1. Thus, when discarding this regime, the analysis builds on very few observations, which in general makes it very difficult to obtain any significant or useful results. Indeed, none of the parameters could be precisely estimated under this regime.

Table 2: Estimates for β_1 ; the parameter measuring the reaction to stock price increases

β_1	Regime 1,2,3	Regime 1,2,4	Regime 1,3,4
Mean	-0.0134	-0.0387	0.0050
Median	-0.0144	-0.0616	-0.0038
Probability mass above 0	16.68 %	25.73 %	44.97 %

Table 3: Estimates for β_2 ; the parameter measuring the reaction to stock price decreases

β_2	Regime 1,2,3	Regime 1,2,4	Regime 1,3,4
Mean	0.0123	0.0737	-0.0046
Median	0.0109	0.019	-0.0052
Probability mass above 0	96.75 %	92.74 %	36.22 %

To give an interpretation of the economic significance of the estimated reaction to stock price drops above, one needs to figure out how to interpret the parameter estimate of β_2 . The estimate of 0.0123 implies that if stock prices drop by 5 %, the 3-month T-Bill rate drops by 6.15 basis points.¹³ Strictly speaking, this should reflect a market expectation that the Federal Funds Target rate should be cut accordingly¹⁴. However, the Federal Funds Target rate is usually changed only with certain time intervals (the FOMC meets every six weeks), and usually in integers of 25 basis points at a time. Thus, the results should not be interpreted as implying that any small, daily change in stock prices leads to a small monetary policy move by the Fed. Rather, it is the *accumulated* stock price change over a given period (say, between two adjacent FOMC meetings) that has an effect on the (market's perceived) *probability* of a discretionary interest rate move by the Fed. This interpretation bridges the high-frequency result and the lower-frequency institutional characteristics of the monetary policy process. Moreover, it also ensures that no arbitrary threshold needs to be imposed on the size of the daily stock price changes, below which stock price changes are assumed to be too small to affect monetary policy. While one might think that the Fed would only react to stock price changes of a certain size, even very small daily stock price movements are relevant for the accumulated change during a given period, and hence for the probability of a discretionary policy move by the Fed.

Rigobon and Sack (2003) demonstrate how to reinterpret the parameter estimate of β_2 in terms of its effect on the probability of a discretionary change in the Federal Funds Target

capture very well the differences in volatility of v^s that is crucial to obtain identification.

¹³If instead I use the alternative parameter estimate ($\beta_2 = 0.0737$), the drop in the 3-month T-Bill rate equals 36.85 basis points.

¹⁴To be exact, the Federal Funds Target rate should be cut by 8.20 basis points, as shown below.

rate. As the FOMC meets every six weeks, there is on average three weeks until the next meeting. The 3-month T-Bill rate expresses the expectations to monetary policy over the next 12 weeks, but since the Federal Funds Target rate will on average stay unchanged for the next three weeks (until the next FOMC meeting), only 3/4 of the expected change in the Federal Funds Target rate will carry through to the 3-month T-Bill rate. Thus, the reaction of the T-Bill rate (6.15 basis points) equals only 3/4 of the reaction of the Federal Funds Target rate, which then must equal 8.20 basis points. This is equivalent to a 5 % daily drop in the S&P 500 index increasing the probability of an interest rate cut of 25 basis points by 32.8 %, or roughly one third.¹⁵ This effect is somewhat smaller than that found by Rigobon and Sack, who estimate that a 5 % drop in stock prices increases the probability of a 25 basis point interest rate cut by about a half. This might seem surprising at first. Since Rigobon and Sack are in a sense measuring the average of the reaction to stock price drops and the (zero) reaction to increases, one should expect ex ante that the asymmetric reaction in the present study should be numerically larger than the reaction found by Rigobon and Sack. However, Furlanetto (forthcoming) finds that the Fed's response to stock prices has been sharply decreasing over time. Thus, as my sample covers a more recent period than that of Rigobon and Sack, the quantitatively smaller response reported here is in line with the findings reported by Furlanetto.

In principle, the results above imply that if the S&P 500 index drops by 50 %, the 3-month T-Bill rate goes down by 61.5 basis points. This might seem like a very small reaction to a stock market crash of this magnitude. With the specification of an asymmetric policy rule chosen in this paper, the monetary policy response to a 50 % drop in stock prices equals ten times the reaction to a 5 % drop. In practice, this is not very likely. Large stock price drops pose a threat to the entire financial stability of the economy. In response to stock price decreases of this magnitude, central banks are likely to cut the interest rate promptly and aggressively. In fact, it can be argued that in such cases, monetary policy is not reacting to the stock price drop *per se*, but to the financial instability caused by the drop. In the present paper, the destabilizing effects of very large stock price drops are not properly taken into account. As a consequence, the results are not able to explain monetary policy reactions to drops of this size. Hence, the results of this paper should only be interpreted as describing the response of the Fed to moderate stock price changes.

4.1 Robustness

It can be argued that given the relatively high degree of transparency in US monetary policy, changes in expected future policy will not affect the 3-month T-Bill rate, since such

¹⁵In other words, if the perceived probability of a 25 basis point interest rate cut was initially 25%, the probability will then increase to almost 58% after a 5 % drop in the S&P 500 index.

changes are not likely to materialize within only 3 months.¹⁶ If monetary policy is believed to be known almost with certainty for the next 3 months, a longer interest rate is needed to capture changes in expected future monetary policy. Hence, the 6-month or even the 12-month T-Bill rate could be used instead.¹⁷ The entire analysis is therefore conducted with the 6-month rate entering the VAR equation. The results (which are shown in Appendix D) indicate that altering the choice of interest rate does not overturn the conclusion of an asymmetric policy reaction. The parameter estimate of β_1 turns out highly insignificant in all three regime combinations. On the other hand, when evaluated at the 10 % significance level, two of the three combinations of regimes identify a significant drop in the interest rate when stock prices fall. This is similar to the results using the 3-month T-Bill rate. The parameter estimate for β_2 in the baseline scenario is 0.0131, i.e. quite close to the result when the 3-month T-Bill rate was used. This renders the economic significance of the results more robust.

As the choice of the number of lags in the VAR was not obvious, it is interesting to change the number of lags and investigate how this changes the results. While six lags did not seem to improve the model based on the likelihood ratio tests, the hypothesis that five lags are sufficient was just rejected against the alternative that seven lags are needed. Thus, I run the system with seven lags. In short, this does not change the results in any important way. β_2 is now estimated at 0.0133, i.e quite close to the estimate with five lags. This number is significant at the 5 % level. On the contrary, the parameter estimate for β_1 is small (-0.007) and insignificant. Using the other regimes, the results from the five lag specification carry over quantitatively, with the parameter estimates changing only slightly. Running the regression with four lags also leads to no major changes.

When dividing the observations into different covariance regimes, it is not obvious that 'high variance' should be defined as when the rolling variance exceeds its sample average by more than one standard deviation. As a robustness check, this threshold is changed to the sample average plus 0.5 and 1.25 times the standard deviation, respectively. Once again, the results (not reported) seem robust to this change. Specifically, the asymmetry in the policy reaction to stock prices is still present in the baseline scenario. Changing the threshold to 0.5 times the standard deviation leads to only minor changes in the parameter estimates, whereas setting it to 1.25 times the standard deviation increases the numerical value of the parameter estimates somewhat. In terms of statistical significance, the results are the same as in the baseline specification. Setting the threshold to two times the standard deviation, however, does change the results. In this case, only very few observations fall outside regime 'low,low', leaving too few observations in the other regimes for the results to become significant.

¹⁶Rigobon & Sack (2003) use the 3-month T-Bill rate, but it can be argued that the transparency of US monetary policy is higher in my sample period (1998-2008) than in theirs (1985-1999). For instance, since 1994 most decisions about interest rate changes have been made at regularly scheduled FOMC meetings.

¹⁷Of course, on the other hand, longer interest rates are in general likely to be less influenced by monetary policy.

Even though many lags were included in the original VAR, it is relevant to test for unit roots in the dependent variables. As the variable s_t measures daily changes in the S&P 500 index, one would expect this series to be stationary. This is confirmed when testing for a unit root. The null hypothesis of non-stationarity is easily rejected at all conventional significance levels. On the other hand, the above analysis was done with i_t measured in levels, i.e. the daily observation of the interest rate. For this variable, the null hypothesis that the series has a unit root cannot be rejected. I therefore carry out the analysis with i_t measured in daily changes instead. Testing for a unit root in this series also leads to a rejection of the null of non-stationarity. Using regimes 1, 2 and 3, the estimate for β_1 is once again insignificant, while β_2 is now borderline insignificant. However, the difference between β_1 and β_2 is still significant at the 10% level, lending some support to the hypothesis of an asymmetric policy response.

The specification of asymmetric monetary policy used in this paper is just one of many possible candidates. Another option would be to impose a threshold, capturing the idea that as long as stock prices do not move by 'too much', the Fed does not react. However, as discussed above, when the effects of stock price changes on monetary policy are interpreted in terms of changes in the probability of a discretionary policy move, a threshold becomes unnecessary. Moreover, it would be impossible to impose a threshold in the setup of this paper. If it is assumed that the Fed only reacts to daily stock price changes exceeding, say, 2 %, then almost all of the observations would fall under the same covariance regime. Obviously, on days when the S&P 500 index increases or decreases by more than 2 %, the volatility of the stock market is also relatively high, placing this observation in the 'high' covariance regime. When almost all of the observations fall in the same regime, the identification method becomes unreliable. Thus, investigating alternative definitions of the asymmetric reaction function is left for future research.

In conclusion, the apparent robustness of the asymmetric monetary policy reaction to various other model specifications and assumptions is reassuring.

5 Discussion

At a first glance, the results above might seem to indicate that the Fed has at least partly been acting in accordance with the activist view promoted by some authors. It is, however, important to keep in mind that the results do not imply that the Fed is targeting stock prices. Indeed, Rigobon and Sack (2003) use back-of-the-envelope calculations to argue that the magnitude of their estimated response is roughly in accordance with the effects of stock price changes on the macroeconomy through wealth effects on aggregate demand. In other words, the Fed might well be following the prescriptions of Bernanke and Gertler (1999, 2001); that is, reacting to stock prices only to the extent that these contain additional

information about the future course of the economy. This is also acknowledged by Furlanetto (forthcoming).¹⁸

Continuing along these lines, at least two possible explanations of the asymmetry discovered in the present study exist. First, because of inherent asymmetries in the functioning of the stock market itself, an analysis of this kind might detect an asymmetric monetary policy even if the policy reaction is in fact perfectly symmetric. Second, even if the monetary policy reaction to stock prices is indeed asymmetric, this might just be the central bank's attempt to correct for asymmetries in the way the stock market affects the macroeconomy.

An example of the first explanation is related to technological progress. This increases the earnings potential of firms, and hence the fundamental value of their shares, which is given by the discounted value of expected future dividends. As firms continuously put new and better machines to use, it seems that most technology shocks are positive in nature. A company might switch from one machine to a new and better model that enhances productivity, while a switch to a poorer machine that lowers productivity is not very likely. Hence, the possibility of a drop in the fundamental stock price caused by a technological step backwards seems quite small. Whenever the stock market index is increasing, a central bank with a fully symmetric reaction to stock prices has to decide whether this movement is due to non-fundamentals, or whether it reflects a fundamental increase based on continuous technology improvements and productivity growth. Separating fundamental and non-fundamental increases in stock prices is extremely difficult, especially when conducted real-time. However, when the central bank observes a fall in stock prices, there is a larger probability that this movement is due to non-fundamentals, as the probability of this drop being caused by technological regress (i.e., a fundamental technology-driven change) is not very large. As a consequence, policymakers are more likely to identify as non-fundamental (and hence, to react to) a stock market drop than a jump, implying that even a symmetric monetary policy might appear asymmetric in an analysis of the present kind.¹⁹ Another inherent asymmetry in the stock market is the tendency that large drops in stock prices sometimes happen very suddenly, while increases usually take place over extended periods of time. If a researcher was looking for an asymmetry of the Greenspan Put-type, i.e. a policy where *large* and *sudden* drops in stock prices lead to *large* interest rate cuts, this could be a potential driver of his results. In that case, even if monetary policy was perfectly symmetric; involving also a reaction to large and sudden stock price *increases*, this reaction would never be called for, and the researcher would identify an asymmetric policy. While this is a relevant concern, it is likely to be less important for the results in the present study,

¹⁸In fact, when interpreted in this way, the results of Rigobon and Sack (2003) and Furlanetto (forthcoming) are no longer in opposition to those of Fuhrer and Tootell (2008).

¹⁹Exceptions from this tendency are the drops in stock prices that occur after the bursting of a bubble, as these are likely to reflect movements towards the fundamental stock value. Moreover, one might argue that if the market expects continuous technological progress, a period of slower progress than expected might be sufficient to cause a (fundamental) stock price drop.

where also small changes in stock prices are allowed to affect monetary policy.²⁰

As for the second interpretation, an asymmetric reaction of monetary policy to stock prices could reflect an attempt of the central bank to correct for various asymmetries in the way stock price movements affect the macroeconomy. While an exhaustive discussion of the literature on the link between stock prices and the macroeconomy is beyond the scope of this study, I discuss two of the most illuminated channels, and how these might exert asymmetric effects on the macroeconomy. The first channel is the wealth effect of stock prices on aggregate demand. If individuals are loss averse; valuing decreases in wealth more than equivalent increases, one might suspect that stock price drops have a larger impact on consumption than equivalent increases. In other words, the wealth effect would be stronger when stock prices fall. This hypothesis seems to be supported by empirical evidence (Shirvani and Wilbratte (2000); Apergis and Miller (2006)), and is also discussed by Poterba (2000). The second channel is the famous financial accelerator of Bernanke and Gertler (1989), which works through the balance sheet of firms. A spike in asset prices increases the value of firms' net worth or collateral, giving them cheaper access to external finance (by reducing the agency problem between borrower and lender) and allowing them to expand their business. As discussed by, among others, Bernanke and Gertler (1989) and Peersman and Smets (2005), the financial accelerator is likely to be stronger in economic downturns than during booms, as small changes in net worth are likely to be more costly for firms with low collateral value and high agency costs of borrowing. Ultimately, this might even lead to a credit crunch. To the extent that stock prices are procyclical, this asymmetry implies that stock price drops may have larger effects on the economy than stock price increases. Together, these two channels might give rise to a potentially important asymmetry in the way stock prices influence the economy. This asymmetry might in turn rationalize the asymmetric reaction of monetary policy found in this study. This idea is investigated in some detail by Ravn (2011), who finds that even a modest asymmetry in the financial accelerator over the business cycle is sufficient to 'cancel out' an asymmetric policy reaction of the size found in the present paper.

On the other hand, it also cannot be excluded that the asymmetry discovered in this study is an example of exactly the type of policy that Issing (2009) and White (2009) have warned against. If the asymmetric policy was not an attempt to correct for market asymmetries, but rather was intended to support economic booms and counteract contractions in an asymmetric way, this policy might have run the risk of creating moral hazard problems. This risk can be illustrated as follows. Consider a central bank which systematically reacts to stock price decreases, but not to increases. Investors will sooner or later realize that in effect, the central bank is covering part of their downside risk from investments in the stock

²⁰To confirm this, I estimate the AR(1)-coefficients for stock price increases and decreases, respectively. If these were different, this would suggest that asymmetries in stock price dynamics could be a driving force behind my results. However, the AR(1)-coefficients are not significantly different from each other at the 5 % level, indicating that while this problem is a valid theoretical objection, it does not seem very relevant empirically in this context.

market, without claiming any of their potential gains. As a result, shares will be a more attractive investment, and so the decision of the investor will be distorted in favor of buying more stock. In this way, the central bank induces more risky investments as compared to the case when monetary policy is fully symmetric. This part of the discussion is closely related to the earlier debate about the possible existence of the so-called Greenspan Put. Miller *et al.* (2001) demonstrate how market perception about the existence of a Greenspan Put will push stock prices above their fundamental level, as investors' perceived downside risk is reduced considerably. Based on the above discussion, however, no clear conclusion as to whether or not the policy detected in this paper did cause moral hazard problems can be drawn.

6 Conclusion

In this paper, I have demonstrated that the Federal Reserve has been responding in an asymmetric way to stock price movements during the period 1998-2008. In an augmented version of the framework of Rigobon and Sack (2003), I show that a drop in stock prices increases the probability of a discrete interest rate cut, whereas a rise in stock prices does not bring about any policy response.

The study contributes to the recent revival of the debate about the possible response of monetary policy to asset prices. Being one of the few studies on the topic using more recent data, it sheds light on the role played by asset prices in monetary policy in the years leading up to the recent crisis. More fundamentally, the present study is to my knowledge the first to empirically identify an asymmetric response of monetary policy to stock price increases and decreases. This result illustrates that the inherent asymmetry in the pre-crisis consensus approach, as pointed out by Bini Smaghi (2009), Issing (2009), and White (2009), seems also to be an empirically relevant concern. The results of the paper do, however, not lead to a clear answer as to whether the Fed has been actively leaning against the wind with respect to stock prices, as recommended by some, or has been responding to stock prices only because these are signals about the future state of the economy, as others have advocated.

I have abstained from taking a normative stand on the appropriateness of this type of asymmetric monetary policy. On one hand, the asymmetric response runs the risk of creating moral hazard problems. On the other hand, it might be seen as an attempt to make up for possible inherent asymmetries in the way stock price movements affect the macroeconomy. In any case, evaluating the general equilibrium effects of such a policy, including whether (and under what circumstances) it could be optimal, requires a much richer model framework and is left for future research. A first step in this direction is taken by Ravn (2011).

In general, more research is needed in order to fully understand the link between monetary policy and asset prices. An interesting extension of the asymmetric approach of this paper would be to include quadratic terms in the monetary policy reaction function, allowing large stock market fluctuations to cause a much larger monetary policy reaction than small fluctuations. This idea is related to the discussion in section 4 about the possible inclusion of a threshold. Finally, in this paper, the threshold separating the monetary policy reactions (i.e., a zero change in stock prices) was imposed by the researcher. Using a threshold VAR (TVAR) model, it would be possible to estimate this threshold from the data.

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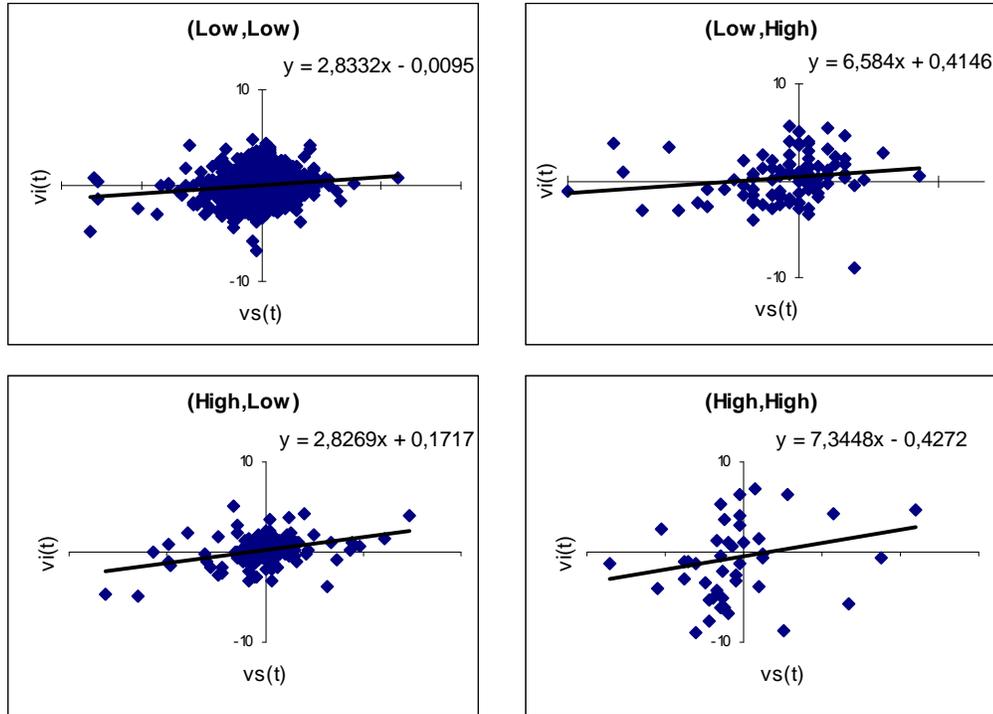
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Appendix A

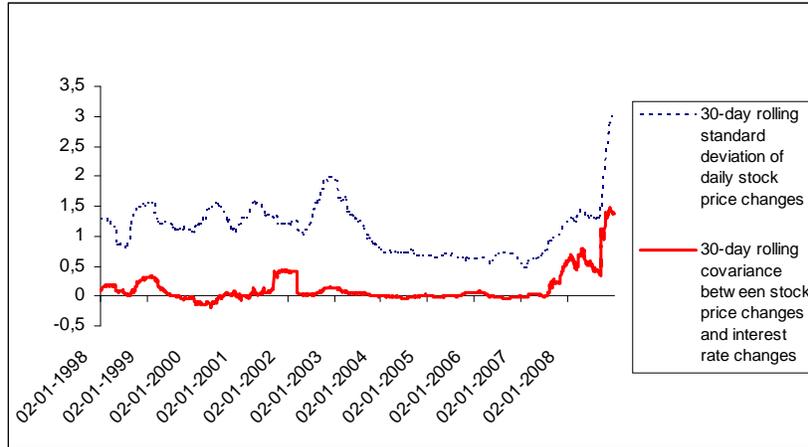
Figure A1: Scatterplots for each of the four covariance regimes of the residuals.



The figure above illustrates the scatterplots of the residuals v_t^i and v_t^s for each of the four regimes. Viewed in isolation, each of the upper and the lower panel constitutes an empirical equivalent of the theoretical scatterplots in figure 1a and 1b in the main text. The upper left panel displays the regime where both residuals have low variance, while the upper right panel illustrates the regime with low variance of the interest rate residual but high variance of the stock price residual. In other words, the upper right panel illustrates an increase in the volatility of stock price residuals, holding fixed the volatility of interest rate residuals, relative to the upper left panel; exactly as in figure 1. The same is true for the lower panels. Indeed, there seems to be a vague tendency for the residuals in the upper right panel to be distributed along an upward-sloping line, while no clear picture seems to emerge from the upper left panel. This is supported by the slope of the trend line, which is much larger for the upper right panel. For the lower panels, the slopes of the tendency lines tell the same story, whereas the pattern is not really clear graphically; partly because of the lower number of observations. In other words, the residuals do tend to display the pattern described in section 3.1, even if the picture is a lot less pronounced in the empirical scatterplots above than in the 'slanted' illustrations in figure 1.²¹

²¹On the other hand, one should expect to see a move towards a lower slope of the tendency lines when

Figure A2: Link between volatility of stock prices and covariance between stock prices and interest rates.



comparing the upper and lower panels. Fixing the volatility of the stock price residuals, an increase in the volatility of the interest rate residuals should cause the residuals to better trace out a downward-sloping curve. This pattern does not emerge in the scatterplots. As the interest rate residuals are in general a lot less volatile than the stock price residuals, the shift in volatility of the former simply seems to be of too little importance to alter the picture.

Appendix B: Mathematical derivations

As in the main text, the calculations in this appendix are shown for β_1 . Solving for β_2 proceeds in the exact same way.

In section 3, I showed what the covariance matrix for v_t^i and v_t^s looked like for a given regime. The covariance matrix for regime i is repeated here for convenience:

$$\Omega_i = \frac{1}{(1-\alpha\beta_1)^2} \cdot \begin{bmatrix} (\beta_1 + \gamma)^2 \sigma_{i,z}^2 + \beta_1^2 \sigma_{i,\eta}^2 + \sigma_\varepsilon^2 & (1 + \alpha\gamma) (\beta_1 + \gamma) \sigma_{i,z}^2 + \beta_1 \sigma_{i,\eta}^2 + \alpha \sigma_\varepsilon^2 \\ (1 + \alpha\gamma) (\beta_1 + \gamma) \sigma_{i,z}^2 + \beta_1 \sigma_{i,\eta}^2 + \alpha \sigma_\varepsilon^2 & (1 + \alpha\gamma)^2 \sigma_{i,z}^2 + \sigma_{i,\eta}^2 + \alpha^2 \sigma_\varepsilon^2 \end{bmatrix} \quad (A1)$$

As already described, the identification involves subtracting the covariance matrices of different regimes from each other. Subtracting covariance matrices i and j from each other yields:

$$\Delta\Omega_{ij} = \frac{1}{(1-\alpha\beta_1)^2} \cdot \begin{bmatrix} (\beta_1 + \gamma)^2 \Delta\sigma_{ij,z}^2 + \beta_1^2 \Delta\sigma_{ij,\eta}^2 & (1 + \alpha\gamma) (\beta_1 + \gamma) \Delta\sigma_{ij,z}^2 + \beta_1 \Delta\sigma_{ij,\eta}^2 \\ (1 + \alpha\gamma) (\beta_1 + \gamma) \Delta\sigma_{ij,z}^2 + \beta_1 \Delta\sigma_{ij,\eta}^2 & (1 + \alpha\gamma)^2 \Delta\sigma_{ij,z}^2 + \Delta\sigma_{ij,\eta}^2 \end{bmatrix} \quad (A2)$$

Note in this step how, due to the assumption of homoskedasticity of the monetary policy shock ε_t across regimes, the terms involving σ_ε^2 cancel out.

As noted in the main text, all four covariance regimes are needed for the system to be fully identified. However, for my purposes, identifying β_1 is enough. For this, only three different regimes are needed, as shown below. Therefore, fix $j = 1$ and let $i = \{2, 3\}$. Moreover, I follow Rigobon and Sack (2003) in rewriting the covariance matrix in the following way:

Define:

$$\theta = \frac{(1+\alpha\gamma)}{(\beta_1+\gamma)} \text{ and } \varpi_{z,i} = (\beta_1 + \gamma) \Delta\sigma_{i1,z}^2$$

Using this notation, (A2) can be rewritten as:

$$\Delta\Omega_{i1} = \frac{1}{(1-\alpha\beta_1)^2} \begin{bmatrix} \varpi_{z,i} + \beta_1^2 \Delta\sigma_{i1,\eta}^2 & \theta \varpi_{z,i} + \beta_1 \Delta\sigma_{i1,\eta}^2 \\ \theta \varpi_{z,i} + \beta_1 \Delta\sigma_{i1,\eta}^2 & \theta^2 \varpi_{z,i} + \Delta\sigma_{i1,\eta}^2 \end{bmatrix} \quad (A3)$$

Writing out the equations contained in (A3) for $i = 2$ explicitly yields:

$$\Delta\Omega_{21,11} = \frac{1}{(1-\alpha\beta_1)^2} [\varpi_{z,2} + \beta_1^2 \Delta\sigma_{21,\eta}^2] \quad (A4)$$

$$\Delta\Omega_{21,12} = \frac{1}{(1-\alpha\beta_1)^2} [\theta \varpi_{z,2} + \beta_1 \Delta\sigma_{21,\eta}^2] \quad (A5)$$

$$\Delta\Omega_{21,22} = \frac{1}{(1-\alpha\beta_1)^2} [\theta^2 \varpi_{z,2} + \Delta\sigma_{21,\eta}^2] \quad (A6)$$

A similar system of three equations can be written for $i = 3$. Together, these are six equations in the following seven variables: $\alpha, \beta_1, \gamma, \varpi_{z,2}, \Delta\sigma_{21,\eta}^2, \varpi_{z,3}$ and $\Delta\sigma_{31,\eta}^2$. Rewriting the system (A4) – (A6) in the following way, I am able to exploit the obvious symmetry in these three equations. First, insert (A4) into (A5):

$$\begin{aligned} \theta(1 - \alpha\beta_1)^2 \Delta\Omega_{21,11} - \theta\beta_1^2 \Delta\sigma_{21,\eta}^2 + \beta_1 \Delta\sigma_{21,\eta}^2 &= (1 - \alpha\beta_1)^2 \Delta\Omega_{21,12} \iff \\ \Delta\Omega_{21,12} - \theta\Delta\Omega_{21,11} &= \frac{\beta_1(1-\theta\beta_1)}{(1-\alpha\beta_1)^2} \Delta\sigma_{21,\eta}^2 \quad (A7) \end{aligned}$$

Similarly, insert (A5) into (A6):

$$\begin{aligned} \theta(1 - \alpha\beta_1)^2 \Delta\Omega_{21,12} - \theta\beta_1 \Delta\sigma_{21,\eta}^2 + \Delta\sigma_{21,\eta}^2 &= (1 - \alpha\beta_1)^2 \Delta\Omega_{21,22} \iff \\ \Delta\Omega_{21,22} - \theta\Delta\Omega_{21,12} &= \frac{(1-\theta\beta_1)}{(1-\alpha\beta_1)^2} \Delta\sigma_{21,\eta}^2 \quad (A8) \end{aligned}$$

$$\text{Next, divide } \frac{(A7)}{(A8)}: \quad \frac{\Delta\Omega_{21,12} - \theta\Delta\Omega_{21,11}}{\Delta\Omega_{21,22} - \theta\Delta\Omega_{21,12}} = \beta_1 \iff \theta = \frac{\Delta\Omega_{21,12} - \beta_1 \Delta\Omega_{21,22}}{\Delta\Omega_{21,11} - \beta_1 \Delta\Omega_{21,12}} \quad (A9)$$

Remember that a system similar to (A4) – (A6) can be written for $i = 3$. Solving that system for θ then yields:

$$\theta = \frac{\Delta\Omega_{31,12} - \beta_1 \Delta\Omega_{31,22}}{\Delta\Omega_{31,11} - \beta_1 \Delta\Omega_{31,12}} \quad (A10)$$

As it turns out, (A9) and (A10) are two equations in just two variables, β_1 and θ . This illustrates how the underidentified system of six equations collapses to a smaller system where β_1 is now identified. To solve the system for β_1 , equalize the right hand sides of (A9) and (A10) and cross-multiply:

$$\begin{aligned} \Delta\Omega_{21,12} \Delta\Omega_{31,11} - \beta_1 \Delta\Omega_{21,12} \Delta\Omega_{31,12} - \beta_1 \Delta\Omega_{21,22} \Delta\Omega_{31,11} + \beta_1^2 \Delta\Omega_{21,22} \Delta\Omega_{31,12} &= \\ \Delta\Omega_{31,12} \Delta\Omega_{21,11} - \beta_1 \Delta\Omega_{31,12} \Delta\Omega_{21,12} - \beta_1 \Delta\Omega_{31,22} \Delta\Omega_{21,11} + \beta_1^2 \Delta\Omega_{31,22} \Delta\Omega_{21,12} & \\ \iff 0 = \beta_1^2 [\Delta\Omega_{31,22} \Delta\Omega_{21,12} - \Delta\Omega_{21,22} \Delta\Omega_{31,12}] & \\ - \beta_1 [\Delta\Omega_{31,22} \Delta\Omega_{21,11} - \Delta\Omega_{21,22} \Delta\Omega_{31,11}] + [\Delta\Omega_{31,12} \Delta\Omega_{21,11} - \Delta\Omega_{21,12} \Delta\Omega_{31,11}] & \\ \iff 0 = a\beta_1^2 - b\beta_1 + c \quad (A11) & \end{aligned}$$

- where:

$$a = [\Delta\Omega_{31,22} \Delta\Omega_{21,12} - \Delta\Omega_{21,22} \Delta\Omega_{31,12}]$$

$$b = [\Delta\Omega_{31,22} \Delta\Omega_{21,11} - \Delta\Omega_{21,22} \Delta\Omega_{31,11}]$$

$$c = [\Delta\Omega_{31,12} \Delta\Omega_{21,11} - \Delta\Omega_{21,12} \Delta\Omega_{31,11}]$$

This solves the system for the parameter of interest; β_1 . As noted above, the exact same method is used to solve for β_2 .

It should be noted that the quadratic equation (A11) has two roots. Rigobon and Sack (2003) describe how the system of two equations in two variables (A9) and (A10) is solvable for β and θ whenever one of these roots is real. This condition is ensured by the positive definiteness of the covariance matrices. Rigobon and Sack then show that one set of solutions to the system gives the correct values of β and θ , while the other set gives the inverse of these values.

Appendix C: The Bootstrap

For the purpose of this paper, I do not have to bootstrap the actual observations that enter the original VAR. (Remember that this VAR has 2 dependent variables and 16 regressors). Instead, I can bootstrap the residuals from the VAR (see Efron and Tibshirani (1994,) or Johnston and DiNardo (1997) for a treatment of bootstrapping residuals). Usually, in order to bootstrap the residuals, these first need to be standardized, as emphasized by Johnston and DiNardo (1997). However, this is only necessary when the residuals are used for computing fitted values of the dependent variable in the original regression. The fitted values can then be regressed on the regressors to obtain a large number of estimates of the regression coefficients.

However, estimating the regression coefficients of the VAR is not the primary purpose of this paper. Instead, I am interested in the residuals from the VAR themselves, as I want to impose theoretical restrictions on these. Therefore, standardizing the residuals before implementing the bootstrap is not appropriate in the current context.

Following the above discussion, I use the raw residuals from the VAR to do the bootstrap. This gives me 10,000 realizations of the covariance matrix for each regime. With these in hand, it is easy to obtain 10,000 estimates of β_1 and β_2 , the parameters of interest.

References:

Efron, Bradley, and Robert J. Tibshirani. 1994. *An Introduction to the Bootstrap*. First edition, Chapman and Hall/CRC.

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Appendix D: Robustness checks

Table 4: Estimates for β_1 ; the parameter measuring the reaction to stock price increases; using the 6-month T-Bill rate.

β_1	Regime 1,2,3	Regime 1,2,4	Regime 1,3,4
Mean	-0.0077	0.0553	-0.0080
Median	-0.0083	0.0013	-0.0163
Probability mass above 0	29.97 %	50.41 %	32.14 %

Table 5: Estimates for β_2 ; the parameter measuring the reaction to stock price decreases; using the 6-month T-Bill rate.

β_2	Regime 1,2,3	Regime 1,2,4	Regime 1,3,4
Mean	0.0131	0.0768	0.0109
Median	0.0122	0.0276	0.0105
Probability mass above 0	91.90 %	73.46 %	90.10 %