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Has the Fed Reacted Asymmetrically to Stock Prices?*

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Abstract

This paper presents an empirical study of a potential asymmetry in the response of monetary policy to stock prices in the US. The main finding is that while monetary policy reacts significantly to stock price drops, no significant reaction to stock price increases is found. This result is obtained by applying the method of identification through heteroskedasticity to a daily dataset covering the period 1998-2008. The result is confirmed in an estimated, augmented Taylor rule based on monthly data for the same period. The size of the estimated, asymmetric reaction is modest.

The study constitutes an empirical contribution to the debate about the role of asset prices in monetary policy, which has seen a revival in the aftermath of the crisis. In particular, the results lend empirical support to recent claims that the pre-crisis approach to monetary policy implied an asymmetric policy stance towards stock price movements.

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; see e.g. Kuttner (2011). 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; calling 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 such an asymmetry. We study the monetary policy reaction to stock price movements, but contrary to common practice, we allow for different monetary policy reactions to stock price increases and decreases, respectively. This allows us to investigate the claims that the US Federal Reserve (Fed) may have been reacting asymmetrically to stock prices in the years before the crisis. We 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 us to investigate whether this reaction is symmetric.

The results indicate that the Fed has in fact been pursuing an asymmetric policy over the period 1998-2008. We find that the reaction to stock price drops turns out to be significant, while no significant reaction to an increase in stock prices is found. While this result is obtained using daily data, the interpretation should not be that small, daily changes in stock prices lead to small, daily adjustments of monetary policy. Indeed, the Federal Open Market Committee (FOMC) meets only 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 in this way, the results indicate that a 5 % drop in the S&P 500 index increases the probability of a 25 basis point interest rate cut by about

[1] The term 'pre-crisis consensus' is coined by Bini Smaghi (2009). See also Issing (2011) and Mishkin (2010) for further discussion of this 'consensus'.

one third, while a rise in stock prices leads to no significant monetary policy reaction.

To evaluate the robustness of our results, we further use a monthly dataset spanning the same sample period to estimate a Taylor rule augmented with stock prices. This exercise confirms the finding of an asymmetric policy reaction to stock price movements. The estimated response to stock price drops is in the same region, though somewhat larger, than our estimate from the high-frequency study. The result is consistent with the findings in a recent study by Hall (2011), who uses quarterly data to estimate a Taylor rule augmented with stock price deflation for the US in the period 1987-2008. She finds that stock price deflation leads to a cut in the interest rate, and that including stock price deflation improves the fit of the estimated Taylor rule.

Importantly, detecting a response of monetary policy to stock prices does not necessarily imply that the Fed has been 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, we discuss how the asymmetric policy found in this paper could reflect a response to a 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 (2011) finds that the magnitude of the response of US monetary policy to stock prices has been declining over time. Our 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.

At the theoretical level, 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). 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) and Borio and White (2003). Despite some enduring disagreement, it has been argued that a certain degree of consensus seemed to have been reached before the crisis, according to which central banks should not try to lean against asset price movements.[2] The aftermath of the crisis, however, has witnessed a revival of the debate. In particular, a critique has emerged of an alleged, inherent asymmetry in the pre-crisis consensus view; see White (2009), Mishkin (2010), and Issing (2011), among others. In the words of Stark (2011), the pre-crisis consensus implied that '*monetary policy should react to asset price busts; not to asset price booms*'. Issing (2011) points out that an asymmetric policy might lead to moral hazard problems for investors, and advocates that monetary policy should be '*leaning against 'headwind'* [asset price declines] *as well as 'tail wind'* [increases]*'*. The results of the present paper provide empirical support to these claims. However, the magnitude of the estimated asymmetry is modest, and perhaps too small to have caused substantial moral hazard problems.

The rest of this paper proceeds as follows: Section 2 describes the methodology and the identification strategy used in the high-frequency study. These results are presented in section 3, while section 4 contains the results from the estimation of an augmented Taylor rule. Section 5 offers a discussion and some concluding remarks.

2 Methodology

Estimating the response of monetary policy to changes in stock prices involves a number of challenges. As interest rates and stock prices are determined

[2] As argued by Bini Smaghi (2009), part of the explanation behind this consensus is that before the crisis, the New-Keynesian model framework, which has become the dominant theoretical workhorse for monetary policy analysis over the last decade, failed to pay sufficient attention to financial markets. 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 frictions in financial markets have important macroeconomic implications. Notable contributions to this literature include Christiano *et al.* (2010), Gertler and Kiyotaki (2010), and Woodford (2010).

simultaneously, the *ceteris paribus*-interpretation of the estimated response breaks down. If this endogeneity problem is not properly taken into account, the results are therefore likely to be misleading, as illustrated by Rigobon and Sack (2003). In the present paper, we account for the endogeneity by following the identification method proposed by Rigobon and Sack. This involves working with daily data.[3] Hence, it is not meaningful to estimate a standard monetary policy rule augmented with a reaction to stock prices, as these rules involve variables such as output and inflation, for which no daily observations exist.[4] Instead, as in Rigobon and Sack (2003), we set up the following system of two equations describing the dynamics of, and the interaction between, the interest rate and the stock price on a daily basis:

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

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

where

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

This system closely resembles the setup in Rigobon and Sack (2003), except for the asymmetric part. 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. This reflects that if the actual value of a given release is in line with the market's expectation of this release, there should be no effect on stock prices or interest rates, as this expectation will already be reflected in the market prices before the announcement is made. Hence, only surprising announcements will have an effect on the variables on the left-hand side. The following six variables are included in x_t: Output growth (GDP), nonfarm payrolls (NFPAY), consumer price index (CPI), producer price index

[3] At 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.

[4] In section 4, we use monthly data to estimate a monetary policy reaction function augmented with lagged stock prices as a robustness check.

(PPI), retail sales (RETL), and the purchasing managers index (ISM). These variables all contain important information regarding the outlook for economic activity and inflation. We 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.[5] Note that while the system presented above does not include lags of the variables, we do include five lags of i_t and s_t in the regression.

Further, the system contains three unobserved shocks. Given that these are structural or fundamental shocks, as opposed to reduced-form innovations, we follow Rigobon and Sack (2003, 2004) and Furlanetto (2011) 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.[6] 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.[7] If the central bank reacts in an asymmetric way

[5]The reason for not using a longer sample is lack of data, as we did not have access to Bloomberg data on market expectations for all the macroeconomic variables further back than 1998. The end of the sample, December 2008, is chosen so as to correspond to the time when the Federal Funds Target rate reached its lower bound of zero.

[6]Christiano *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 variation in the policy process

[7]The threshold separating the monetary policy reactions (i.e., a zero change in stock prices) is arbitrarily imposed. Using a threshold VAR (TVAR) model, it would be possible

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 not directly testable in the present setup. As will become evident in section 2.2, what is actually assumed is that the three shocks are mutually uncorrelated *conditional on* each of the four variance-covariance regimes into which we 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.[8] 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

to estimate this threshold from the data. That, however, is beyond the scope of this paper.

[8]Recall 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.

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., Clarida *et al.*, 1998; Christiano *et al.*, 1999), and is therefore assumed to be orthogonal to z_t also in this setup.[9]

Furthermore, in the context of the present paper, we also need to assume that the shocks are mutually uncorrelated *conditional on* the sign of s_t as well as on the covariance regime. 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 lead to a non-zero correlation of the shocks. 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 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.

To confirm the validity of this assumption, we simulate 500 replications of the estimated VAR regression (see subsection 2.2). We include three i.i.d. shocks; one in each equation and a common shock, as 'proxies' for η_t, ε_t, and z_t.[10] As the actual shocks in the model are unobserved, their variance is unknown. Instead, we calibrate the variance of the shocks in the simulation by matching the variance of the simulated series for stock prices and interest rates to their empirical counterparts. For each replication, we split the observations according to their sign, and then divide them into four covariance regimes,

[9] To 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.

[10] By using three i.i.d. shocks, our simulation effectively takes as given that the three shocks are orthogonal in the unconditional case. This is much less restrictive, and seems like a natural starting point.

exactly as with the actual data, but keeping track of the shocks that generated each observation. For each regime, we can then compute the correlation between the shocks. We find no evidence of non-zero correlations between any of the shocks in any of the regimes. This is illustrated in the online appendix for the correlation between the common shock and the stock market shock (interpretable as z_t and η_t, respectively) in each of the regimes. The computed correlations are distributed around zero, and show no clear tendency of being either positive or negative. A similar pattern arises for the correlation between each of these shocks and the monetary policy shock (interpretable as ε_t). Based on these simulations, we find no reason to reject our assumption of mutually orthogonal shocks on each subsample.

We follow existing literature on the topic (Rigobon and Sack, 2003; Furlanetto, 2011) 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 only 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 (2011), 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, we calculate the correlation between daily observations of the Federal Funds rate and the T-Bill rate lagged by 3 months. This gives a correlation coefficient as high as 0.97.[11] In other words, the market does seem to forecast quite precisely the short-term policy rate. Moreover, using the 6-month T-Bill rate produces largely the same estimate of the policy reaction, as demonstrated

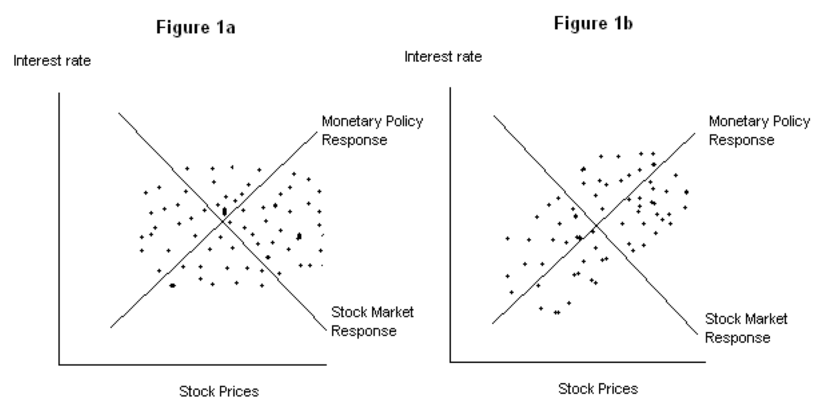
[11] Even after using a band-pass filter to filter out low-frequency movements (frequencies lower than six years), the correlation only drops to 0.96.

in section 3.1. This confirms the finding of Rigobon and Sack (2003) that the results are not very sensitive to the choice of interest rate variable.

Finally, we follow most of the literature (e.g. Rigobon and Sack, 2003, and Furlanetto, 2011) and use the interest rate series in levels. While an augmented Dickey-Fuller (1979) test fails to reject the null of a unit root in the interest rate series, this and other unit root tests are known to suffer from low power in short samples.[12] Moreover, they have a hard time distinguishing very persistent variables, such as the interest rate, from actual unit root variables. Instead, the stationarity test developed by Kwiatkowski *et al.* (1992) fails to reject the null hypothesis (at the 5 % level) that the interest rate is in fact stationary. The results of the stationarity tests are in the online appendix. In this light, we use the interest rate in levels, which ensures consistent parameter estimates (Hamilton, 1994). A specification with the interest rate entering in first-differences is estimated as a robustness check.

2.1 Identification through heteroskedasticity

To obtain identification, Rigobon and Sack (2003) apply the method of identification through heteroskedasticity described below. As it turns out, their method is also applicable in order to address the question of this paper, although they do not allow for any asymmetries in the monetary policy rule. The novelty of the present paper is to extend their method to allow for different policy reactions to positive or negative stock price changes.



[12]Note that while the number of observations in our sample is high, the sample spans a relatively short period, which matters for the power of unit root tests (Shiller and Perron, 1985).

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 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) curve will account for a larger part of the comovement between stock prices and interest rates than before. Correspondingly, the SMR curve 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. This slope is exactly the parameter of interest, as it measures the reaction of monetary policy to stock prices.[13]

In other words, the identification method exploits the fact that when the volatility of stock prices changes, so does the covariance between stock prices and interest rates. To confirm this empirically, we compute the 30-day rolling standard deviation of the daily stock price changes, as well as the 30-day rolling covariance between daily stock price changes and interest rate changes. For our sample period, the two series display a substantial, positive comovement, with a correlation coefficient of 0.60. The online appendix contains a plot of the two series in order to illustrate the comovement graphically.

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

[13]The illustrations in figure 1a and 1b are caricatures of the empirical scatterplots, which are shown in the online appendix to this paper. While the picture is much less obvious in these empirical scatterplots, the same pattern as in figure 1a and 1b emerges.

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 us to relax this assumption and investigate if there is any asymmetry in the reaction to stock market jumps and drops, respectively.

2.2 Obtaining Identification

We run the following VAR regression:

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

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 in (3) are given by:

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

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 the appearance of either β_1 or β_2. Therefore, in the following analysis we will work only with the system with β_1, as the analysis with β_2 is entirely analogous.

When running the regression in (3), we include five lags of each of i_t and s_t. We discuss this choice in subsection 3.1. 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:

$$\Omega = \frac{1}{(1-\alpha\beta_1)^2} \cdot \left[\begin{array}{cc} (\beta_1+\gamma)^2 \sigma_z^2 + \beta_1^2\sigma_\eta^2 + \sigma_\varepsilon^2 & (1+\alpha\gamma)(\beta_1+\gamma)\sigma_z^2 + \beta_1\sigma_\eta^2 + \alpha\sigma_\varepsilon^2 \\ (1+\alpha\gamma)(\beta_1+\gamma)\sigma_z^2 + \beta_1\sigma_\eta^2 + \alpha\sigma_\varepsilon^2 & (1+\alpha\gamma)^2\sigma_z^2 + \sigma_\eta^2 + \alpha^2\sigma_\varepsilon^2 \end{array} \right] \quad (5)$$

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. We 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.[14] 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

[14] An implicit assumption is that the parameters α, β and γ are also constant across regimes. Apart from being essential in obtaining identification, this allows us to avoid conducting a VAR with time-varying parameters, which is not the focus of this paper.

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 the mathematical appendix.

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 $zv = \{11, 12, 22\}$.

3 Results

The residuals are obtained by regressing (3). 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, we carry out an analysis of the optimal number of lags in the VAR-model. To this end, we perform a likelihood ratio test, and we calculate Schwarz's Bayesian Information Criterion for the model with p lags, where p = $\{1, 2, .., 10\}$. As it turns out, both of these methods lend support to the use of five lags. We alter this number as a robustness check 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. We 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 (2011) 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 3.1, the results are quite robust to alternative values for this threshold.

Four regimes result: One in which the variance of both v_t^i and v_t^s is high, a regime in which one variance is high and one is low, and vice versa, and one in which 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 %

For each regime, the first entry in the brackets refers to the variance of interest rate residuals, and the second entry to stock price residuals.

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, we apply bootstrap methods (see the online appendix 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. The estimate of β_1 is not included in the 95 % confidence interval for β_2. On the other hand, the estimate of β_2 is within the 95 % confidence interval for β_1, as the latter parameter is not very precisely estimated.

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.[15]

The results using regimes 2, 3 and 4 are not shown. Recall that around 85 % of all observations fell 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 grasp the economic significance of the estimated reaction to stock price

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

drops above, we need 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.[16] Strictly speaking, this should reflect a market expectation that the Federal Funds Target rate should be cut accordingly. However, the Federal Funds Target rate is usually changed only within certain time intervals (the FOMC meets every six weeks), and usually in units 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 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.[17] 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

[16] Using the alternative parameter estimate of ($\beta_2 = 0.0737$), the drop in the 3-month T-Bill rate equals 36.85 basis points.

[17] In 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.

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 stock price increases, one would expect that the asymmetric reaction in the present study should be numerically larger than the reaction found by Rigobon and Sack. However, Furlanetto (2011) finds that the Fed's response to stock prices has been sharply decreasing over time. Thus, as our 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.

3.1 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 changes are not likely to materialize within only 3 months.[18] 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.[19] The entire analysis is therefore conducted

[18] Rigobon & Sack (2003) use the 3-month T-Bill rate, but it can be argued that the transparency of US monetary policy is higher in our 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.

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

with the 6-month rate entering the VAR equation. The results (which are available in the online appendix) 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.

We further test the robustness of our results with respect to the number of lags in the VAR. 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, we run the system with seven lags. This does not change the results in any important way. The estimate for β_2 is now 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. The results (not reported) indicate that our findings are robust to this change. Specifically, the asymmetry in the policy reaction to stock prices is reproduced. Changing the threshold to 0.5 times the standard deviation leads to only minor changes in the parameter estimates, while 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 the regime 'low,low', leaving very few observations in the other regimes.

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 using an augmented Dickey-Fuller test. 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, following Rigobon and Sack (2003) and Furlanetto (2011). As already discussed, the stationarity tests for this variable were inconclusive. We therefore carry out the analysis with i_t measured in daily changes as a robustness check. Using regimes 1, 2 and 3, the estimate for β_1 is once again insignificant, while β_2 now becomes (borderline) insignificant. However, the estimates of β_1 and β_2 are not included in each other's 90 % confidence intervals, 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 could 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. A third possibility is to include quadratic terms in the monetary policy reaction function, thereby allowing large stock market fluctuations to cause a much larger monetary policy reaction than small fluctuations. I leave the investigation of alternative definitions of the asymmetric reaction function for future research.

4 Low-Frequency Evidence: Estimated Taylor Rules

While the empirical strategy chosen above involves the use of daily data, the bulk of the empirical literature on monetary policy takes a different approach by employing lower-frequency data. Typically, this approach involves estimating a reaction function of the type suggested by Taylor (1993). In this section, we investigate whether the results obtained above are confirmed when a Taylor rule is augmented with a potentially asymmetric reaction to stock prices and estimated using monthly data spanning the same sample as above.

The potential endogeneity of the right-hand side variables in the Taylor rule poses a serious challenge to the use of least squares estimation. For this reason, Clarida *et al.* (2000) estimate the policy reaction function using GMM; an approach that has since been followed by a number of authors. However, Boivin (2006) and Coibion and Gorodnichenko (2011) argue that least squares estimation is likely to produce consistent estimates in many cases. As they note, a robust finding from the VAR literature is that monetary policy shocks affect inflation and the output gap only with considerable lags.[20] Hence, at least when estimating contemporaneous Taylor rules, where the interest rate responds to current inflation and output, endogeneity of the right-hand side variables should not be a problem. The same is true for forward-looking Taylor rules, as long as the interest rate is set in response to expectations of inflation and output in a not-too-distant future. Moreover, Coibion and Gorodnichenko show that their least-squares estimates are very similar to the results from an instrumental variables (IV) regression using lagged values of inflation and the output gap as instruments, suggesting that the exogeneity assumption is in fact satisfied. We follow these authors and estimate the Taylor rule by least squares. The specification of the augmented Taylor rule is as follows:

$$i_t = c + \rho i_{t-1} + (1-\rho)\left(\phi_\pi E_t \pi_{t+k} + \phi_y E_t \widehat{y}_{t+k} + \phi_q^+ \Delta q_{t-1}^+ + \phi_q^- \Delta q_{t-1}^-\right) + \varepsilon_t, \quad (7)$$

where i_t is the nominal interest rate set by the central bank. The constant term c contains the steady-state or natural interest rate and the constant inflation target. The error term ε_t is a monetary policy shock as in Christiano *et al.* (1999). The specification allows for interest rate smoothing when $\rho > 0$ (following Clarida *et al.*, 1998), as well as a reaction to inflation π_{t+k}, the output gap $\widehat{y}_{t+k}$, and lagged stock price increases Δq_{t-1}^+ or decreases Δq_{t-1}^-. As stock prices react to monetary policy innovations within minutes of the announcement, the exogeneity assumption is surely not satisfied if current stock price changes are included in the regression. Instead, lagged stock price changes are included. This is consistent with our interpretation of the results from the previous section, according to which it is the accumulated change in stock prices during a specific period before each FOMC meeting that is relevant for the policy decision. The horizon k indicates whether we are estimating a contemporaneous ($k = 0$) or forward-looking ($k > 0$) Taylor rule. In the estimations presented below, the horizon for inflation and the output gap is

[20] In VAR studies, it is standard to *assume* that inflation and output gap are not affected by monetary policy shocks within the same quarter. Impulse responses tend to show that the effects of monetary policy shocks on these variables show up more than a single quarter after the shock has occurred. See e.g. Christiano *et al.* (1999).

always the same, but allowing for different horizons does not change the results.

We use monthly data series for the Federal Funds rate, CPI inflation and the industrial production index; which we employ to measure economic activity.[21] The industrial production gap is then computed using the Hodrick-Prescott filter with a smoothing parameter of 129,600, as suggested for monthly data by Ravn and Uhlig (2002). For stock prices, we use the logarithm of the change in the monthly average of the S&P 500 index. If the change is positive in a given month, the variable Δq_t^+ is set equal to this change, while the variable Δq_t^- equals zero for that month, and vice versa. All data is obtained from the FRED database maintained by the Federal Reserve Bank of St. Louis.[22]

Consider first the estimation of a contemporaneous Taylor rule ($k = 0$), displayed in Table 4. The first three columns show least squares estimation results for Taylor rules augmented with a reaction to, respectively, stock price increases, decreases, or both. The results from all three specifications indicate positive and highly significant reactions to the lagged interest rate and the industrial production gap. On the contrary, the reaction to inflation has the 'wrong' sign, but is never significant.[23] Finally, and of most interest for our purposes, the reaction to stock price drops is positive and significant at the 5 % level, regardless of whether stock price increases are included or not. The reaction to stock price increases, on the other hand, is always insignificant. Note also that the estimated reaction to stock price increases is outside the

[21] This follows the suggestion of Clarida *et al.* (1998). Our conclusions are the same if we instead use the unemployment gap as a measure of economic activity, although in that case, the size of the estimated interest rate reaction to stock price drops is slightly smaller. Following Boivin (2006), we use a historical average of the unemployment rate up to that point as our measure of the natural unemployment rate in each period.

[22] Orphanides (2001, 2004) suggests estimating Taylor rules using real-time data from the so-called Greenbook; a data collection prepared by the Federal Reserve staff before each FOMC meeting. However, Greenbook data is only made available to the public with a five-year lag, and thus does not cover the entire sample period studied in the previous section. Moreover, the monthly series for inflation and the industrial production index are subject only to small revisions during a few months after their release, making them very good proxies of real-time inflation and output gap (Hall, 2011).

[23] Clarida *et al.* (2000) suggest that a small (or, in our case, a 'missing') estimated reaction of monetary policy to inflation may result when the sample period is short and contains relatively little variation in observed inflation. As they argue, the central bank's reaction to inflation may be more aggressive when inflation is far away from its target level. In our sample, this is rarely the case, as the inflation rate is rarely below 1 % or above 4 %. Another potential explanation is suggested by Jensen (2011), according to whom an insignificant (or even negative) estimate of the interest rate reaction to inflation may result under commitment policies. Intuitively, if a central bank can credibly commit to keeping inflation at bay, a very small, actual increase in the interest rate in response to a rise in inflation will be sufficient.

confidence interval for the estimated reaction to stock price drops, and vice versa, indicating that the two reactions are significantly different from each other. In other words, these results corroborate the finding of an asymmetric stock price reaction discovered in the previous section. Column 4 shows the results from an IV estimation including both stock price increases and decreases, using lagged values of inflation and the industrial production gap as instruments for their current values. These results broadly confirm the least squares results from the corresponding regression in column 3, as all parameter estimates are quite similar. In particular, the asymmetric stock price reaction is reproduced. Very similar results are obtained from IV regressions of the specifications in columns 1 and 2. The Hausman test indicates that the least squares and IV estimates are not different; suggesting that the exogeneity assumption underlying the least squares regression is in fact satisfied.

Table 4: Contemporaneous Taylor rule

	OLS (1)	*OLS* (2)	*OLS* (3)	*IV* (4)
c	0.178683** (0.085753)	0.204997*** (0.077672)	0.238313*** (0.081966)	0.259187*** (0.092606)
ρ	0.962716*** (0.013260)	0.966071*** (0.012531)	0.966844*** (0.012519)	0.967439*** (0.013215)
ϕ_π	−0.922614 (0.621953)	−0.960367 (0.638204)	−1.129493 (0.693375)	−1.392807* (0.809988)
ϕ_y	1.378203*** (0.372555)	1.164632*** (0.333688)	1.151108*** (0.337591)	1.170485*** (0.351863)
ϕ_q^+	12.74651 (25.57968)		−36.72415 (33.13433)	−40.55011 (35.04386)
ϕ_q^-		69.08804** (31.74600)	80.84146** (37.47291)	83.69694** (41.35161)
R^2	0.987793	0.989142	0.989275	0.989260
Hausman p-value				0.4598

Sample: 1998:01 to 2008:12. Standard errors in brackets. *, **, and *** denote significance at the 10 %, 5 % and 1 % levels.

In order to compare the size of the estimated stock price reaction of the Federal Funds rate to that from the previous section, we need to multiply the estimate of ϕ_q^- by $(1-\rho)$. The estimates from the OLS and IV regressions in columns 3 and 4 in Table 4 then imply that a 5 % drop in the S&P 500 index leads to an interest rate cut of, respectively, 13.40 and 13.63 basis points. In other words, the asymmetric policy response is in the same region as the 8.20 basis points interest rate cut found in the previous section, though somewhat larger. According to our alternative interpretation, the results from this section indicate that a 5 % drop in the S&P 500 index increases the probability of a subsequent 25 basis point interest rate cut by about a half. These findings confirm that while the policy asymmetry is statistically significant, it is rather small.

Coibion and Gorodnichenko (2011) further suggest that adding an explicit measure of monetary policy shocks to the regression of (7) should eliminate any potential omitted variable bias; ensuring consistency of OLS. They use the shock variable constructed by Gürkaynak *et al.* (2005), which, however, ends in 2004. Instead, we use a similar (monthly) shock series constructed by Barakchian and Crowe (2010), which spans the entire period used in our analysis except the last 6 months. We estimate (7) with and without the Barakchian and Crowe shocks, with the last 6 months excluded from the sample. The inclusion of the shock does not alter the results in any substantial way, and in particular, does not overturn the finding of an asymmetric reaction to stock prices. The estimated reaction to stock price drops is slightly bigger, while the shock itself is significant only at the 10 % level.[24] These results are available in the online appendix.

Finally, we estimate a forward-looking Taylor rule ($k > 0$), in which the Federal Reserve is assumed to react to inflation and the industrial production gap $k = 1$, 2, or 6 months ahead. In this case, we follow Clarida *et al.* (1998) and assume perfect foresight, so that the expected values of future output and inflation in (7) are replaced with actual future values. These results are in the online appendix. At all three horizons, we compare least squares estimates to the results obtained from an IV regression using current inflation and industrial production gap as instruments for their future counterparts. At each horizon, the least squares and IV estimates are very similar, although the difference is slightly larger for $k = 6$, for which the exogeneity assumptions underlying the OLS estimates are perhaps challenged.[25] The forward-looking reaction functions confirm our findings from the contemporaneous policy rule above. In particular, the reactions to the lagged interest rate and the expected industrial production gap are always positive and highly significant, while the reaction to expected inflation is never significant. Moreover, the reaction to stock price drops is always significant at the 5 % level, except in the IV estimation for $k = 6$, where the p-value rises to 0.07. Generally, the estimates of the reaction to stock price drops are slightly lower than in the contemporaneous rules. The reaction to stock price increases is never significant. Also, the reactions to

[24] We also observe that the estimated reaction to stock price drops is slightly larger when the last 6 months of 2008 are excluded, dismissing any concerns that our results could be driven by the unusual events during those months.

[25] The Hausman tests indeed confirm the exogeneity assumption for $k = 1$ and $k = 2$, but not for $k = 6$.

stock price drops and increases are always significantly different from each other at the 5 % level. Hence, the policy asymmetry is confirmed also in forward-looking Taylor rules.

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 as 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 (2011).[26]

In line with this interpretation, 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 could reflect an attempt by the central bank 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 needs to determine whether this movement is due to non-fundamentals, or whether it

[26] In fact, when interpreted in this way, the results of Rigobon and Sack (2003) and Furlanetto (2011) are not necessarily in opposition to those of Fuhrer and Tootell (2008).

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 that this drop is 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.[27] 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, where also small changes in stock prices are allowed to affect monetary policy.[28]

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, we point out 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 increases of the same size, one might suspect that stock

[27] Exceptions 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.

[28] To confirm this, we 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 our 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.

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. An increase in asset prices raises 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 studied in some detail by Ravn (2012), who investigates under what circumstances an asymmetric financial accelerator can offset the effects of an asymmetric policy reaction of the size found in the present paper.

In general, though, central banks should be cautious in using the interest rate to 'correct for' inherent asymmetries in the economy. Much of the recent debate about potential asymmetries in monetary policy have focused on the risk of creating moral hazard problems. This is a very relevant concern, as stressed by Issing (2011) and White (2009). The problem 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 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 investing more in the stock market. In this way, the central bank induces more risky investments as compared to the case when monetary policy is fully symmetric. This discussion is closely related to an 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. While the results of this paper indicate an asymmetric policy, they also suggest that this asymmetry is likely to be rather small. Whether an asymmetry of this size can cause moral hazard problems remains an open question.

The present paper is thus mute about the desirability of an asymmetric monetary policy reaction. As discussed, an 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, a general evaluation of the 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 (2012).

Mathematical Appendix

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 2, we 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 our 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, we follow Rigobon and Sack (2003) in rewriting the covariance matrix in the following way:

Define:

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

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:

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

$$\Delta\Omega_{21,12} = \frac{1}{(1-\alpha\beta_1)^2}\left[\theta\varpi_{z,2} + \beta_1\Delta\sigma^2_{21,\eta}\right] \qquad (A5)$$
$$\Delta\Omega_{21,22} = \frac{1}{(1-\alpha\beta_1)^2}\left[\theta^2\varpi_{z,2} + \Delta\sigma^2_{21,\eta}\right] \qquad (A6)$$

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

$$\theta\left(1-\alpha\beta_1\right)^2\Delta\Omega_{21,11} - \theta\beta_1^2\Delta\sigma^2_{21,\eta} + \beta_1\Delta\sigma^2_{21,\eta} = \left(1-\alpha\beta_1\right)^2\Delta\Omega_{21,12} \Longleftrightarrow$$

$$\Delta\Omega_{21,12} - \theta\Delta\Omega_{21,11} = \frac{\beta_1(1-\theta\beta_1)}{(1-\alpha\beta_1)^2}\Delta\sigma^2_{21,\eta} \qquad (A7)$$

Similarly, insert $(A5)$ into $(A6)$:

$$\theta\left(1-\alpha\beta_1\right)^2\Delta\Omega_{21,12} - \theta\beta_1\Delta\sigma^2_{21,\eta} + \Delta\sigma^2_{21,\eta} = \left(1-\alpha\beta_1\right)^2\Delta\Omega_{21,22} \Longleftrightarrow$$

$$\Delta\Omega_{21,22} - \theta\Delta\Omega_{21,12} = \frac{(1-\theta\beta_1)}{(1-\alpha\beta_1)^2}\Delta\sigma^2_{21,\eta} \qquad (A8)$$

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

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

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

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:

$$\Delta\Omega_{21,12}\Delta\Omega_{31,11} - \beta_1\Delta\Omega_{21,12}\Delta\Omega_{31,12} - \beta_1\Delta\Omega_{21,22}\Delta\Omega_{31,11} + \beta_1^2\Delta\Omega_{21,22}\Delta\Omega_{31,12} =$$

$$\Delta\Omega_{31,12}\Delta\Omega_{21,11} - \beta_1\Delta\Omega_{31,12}\Delta\Omega_{21,12} - \beta_1\Delta\Omega_{31,22}\Delta\Omega_{21,11} + \beta_1^2\Delta\Omega_{31,22}\Delta\Omega_{21,12}$$

$$\Longleftrightarrow 0 = \beta_1^2\left[\Delta\Omega_{31,22}\Delta\Omega_{21,12} - \Delta\Omega_{21,22}\Delta\Omega_{31,12}\right]$$
$$-\beta_1\left[\Delta\Omega_{31,22}\Delta\Omega_{21,11} - \Delta\Omega_{21,22}\Delta\Omega_{31,11}\right] + \left[\Delta\Omega_{31,12}\Delta\Omega_{21,11} - \Delta\Omega_{21,12}\Delta\Omega_{31,11}\right]$$

$$\Longleftrightarrow 0 = a\beta_1^2 - b\beta_1 + c \qquad (A11)$$

- 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.

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