Can the Fed Talk the Hind Legs off the Stock Market? (replaces EBC DP 2011-017)

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Can the Fed talk the hind legs off the stock market?*

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Abstract: This paper analyzes the impact of US central bank communication on individual stock returns. We find a strong conditional effect of communication on stocks. The response of equities to central bank talk depends critically on the business cycle. In bad times, monetary policy communication inducing an upward revision of the path of future policy is good news for stocks. During an expansion the effect is weaker and on average negative. The impact of central bank communication on stock prices displays similar cross-sectional variation as central bank actions. Cyclical industries are found to be more sensitive to central bank communication. In our sample of S&P 500 companies we find that the stock prices of firms with low cash flows, low returns to assets or equity, very high or low debt levels, small size or using more trade credit to be affected more by central bank communication. Our evidence suggests that central bank communication by the FOMC has an impact on stocks and provides additional evidence for the demand and the credit channel.

Keywords: Monetary policy announcements; Federal Reserve communication; Credit channel; Business cycle; Stock market; Financial constraints;

JEL Classification Numbers: G14, E44, E52, E58

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What impact does central bank communication have on the stock market? Does the impact of central bank communication vary in the cross-section and over time? What are the determinants of such variation?

The impact of monetary policy on the stock market is a topic of wide interest. Policy makers, academics as well as market participants would like to know the consequences of particular interventions on stock prices. While the impact of *central bank actions* (e.g. lowering the interest rate) on stock returns has been extensively studied, the impact of *cental bank communication* on asset prices has received far less attention in the literature.

As discussed in detail by Woodford (2005), theory suggests that the *path* of expected short-term rates in the future is crucial for the economic decisions which a central bank may wish to influence. In this view, even in the absence of central bank communication, the fact that monetary policy actions (surprise moves in the policy rate) are able to move markets can be attributed to the implications for the forward path of interest rates. If the path of future short-term interest rates is so important, central banks may as well try to influence expectations by communicating to the markets and the general public. This is the idea of *forward guidance* i.e. the central bank communicates in order to *manage* expectations of future short-term interest rates. Over the decade this idea has become increasingly popular among policy makers.

In this paper, we study the impact of FOMC communication on stocks in the S&P 500. As such, this paper complements a string of papers which focused on the impact of central bank actions on the stock market. At the same time our results add to the body of research examining the potence of forward guidance; a topic for which there is renewed interest in the current debate on monetary policy at the zero-lower bound, see Woodford (2012).[1]

We contribute to the literature in several ways. First, we account for the state of

[1]The reader unfamiliar with the current state of the literature may wish to consult the excellent literature reviews by Blinder, Ehrmann, Fratzscher, de Haan, and Jansen (2008) and Blinder (2009). This body of research talks about the potential benefits (drawbacks) of central bank communication, the practical implementation and the effectiveness of central bank communication near the zero lower bound. A succinct article on forward guidance as a policy instrument is Bernanke and Reinhart (2004).

the economy by allowing for different effects of central bank communication depending on particular phases of the business cycle. The finance literature shows that there may be considerable state dependence in the response to *news* in the stock market. Boyd, Hu, and Jagannathan (2005) show that on average an announcement of rising unemployment is good news during expansions and bad news during economic contractions. We find that Federal Reserve communication implying an upward revision of the path of future policy is perceived as good news during recessions whereas the effect is negative (and much weaker) in an expansion. We interpret this as a response of the stock market to central bank communication signalling better times ahead. We expect stocks to respond in this way to monetary policy communication when two conditions are met. First, the monetary policy maker is deemed to be credible. Second, market participants attribute superior forecasting performance to the Federal Reserve.

If a central bank is perceived to be a better forecaster and has sufficient credibility, then market participants may update their views with the information provided by central banks. Communication suggesting a future policy tightening may then be positive news for the stock market if stock market participants interpret this as signalling a positive outlook. The intuition is that the Federal Reserve, with its dual mandate, would be very reluctant to raise the policy rate unless there are clear signs of economic recovery.[2]

Our second contribution is that we provide a detailed and systematic analysis of the response of the stock market to central bank communication. To that end we consider the response of individual stocks. This approach allows us to consider firm and industry effects. This is of interest because the literature on the credit channel of monetary policy transmission predicts asymmetric responses of firms to a tightening of monetary policy. A firm with severe credit constraints will find it harder to access credit when interest rates go up. This may constrain their operational activities, jeopardizing their profits and pushing stock prices downwards. However also the demand for a firm's goods may be affected. The interest rate channel suggests that firms facing a highly cyclical

[2] The credibility of the Federal Reserve as central bank is commonly accepted, see de Haan, Eijffinger, and Waller (2005) p.122-123. Evidence for the (attributed) superior forecasting performance of the Federal Reserve is given by Romer and Romer (2000).

or interest-sensitive demand should be more responsive to monetary policy, see Ehrmann and Fratzscher (2004). Therefore we also expect variation in responses to monetary policy across industry affiliations. In so far that financial markets are forward-looking, we expect the industry effects of central bank communication to be similar to the industry effects of central bank actions. If financial market participants are convinced by a monetary policy announcement and they revise their expectations accordingly, then the same channels should be active. Our results confirm that indeed the *cyclical* industries are more responsive to central bank communication.[3]

A few studies have considered the effect of central bank communication on the stock market. An influential study is the paper by Gürkaynak, Sack, and Swanson (2005). In this paper the authors introduced a methodology to consider the effects of central bank communication. The paper focused on the impact on interest rates and a composite stock market index. They found that central bank communication did not matter for the aggregate stock market whereas it may exert a large influence on interest rates. Wongswan (2009), Ammer, Vega, and Wongswan (2010) and Hausman and Wongswan (2011) investigated the link between U.S. monetary policy and foreign assets. In line with Gürkaynak, Sack, and Swanson (2005) their results indicate that central bank communication does not matter that much for equities while it does matter for interest rates and exchange rates. In contrast, surprise changes in the federal funds rate (central bank actions) matter a lot for foreign equities.

Besides the study of Federal Reserve communication authors have investigated the communication strategies of other central banks and their effects as well. Brand, Buncic, and Turunen (2010) consider the effects of ECB communication on interest rates, Karagedikli and Siklos (2008) study the effects of verbal statements by the central bank of New Zealand on exchange rates. The literature on the effects of central bank communication has predominantly focused on interest rates. Some authors have focused on the effects of central bank communication on other assets such as commodities, CDS

[3] In the case of monetary policy actions Ehrmann and Fratzscher (2004), Bernanke and Kuttner (2005), Basistha and Kurov (2008), Kurov (2010) and Laeven and Tong (2010) consider industry effects. Most of these studies only use a very crude break up of industries. Firm effects are considered by Ehrmann and Fratzscher (2004), Thorbecke (1997) and Perez-Quiros and Timmermann (2000).

spreads or on exchange rates.[4] As mentioned above, papers focusing on central bank communication and the stock market tend to find small or no responses in the stock market. In this paper we demonstrate that considering individual stocks instead of indices, and accounting for the business cycle does lead to substantial effects from central bank communication to individual stock prices. Moreover these responses are in line with theoretical predictions.

There are two empirical approaches to investigating the link between monetary policy and the stock market. Some studies investigate responses of stocks to shocks derived from an identified vector autoregression. Examples of this approach are Thorbecke (1997) and recently D'Amico and Farka (2011) which improved on earlier work by proposing a new identification strategy with the use of high-frequency data. The other approach, known as the event study approach is more popular and our paper fits into this strand of the literature. Notable early contributions in this literature are Bernanke and Kuttner (2005) and Ehrmann and Fratzscher (2004), and more recently Ammer, Vega, and Wongswan (2010), Hausman and Wongswan (2011) and Laeven and Tong (2012).

This paper proceeds as follows. In section 1 we present the event study approach. In section 2 we discuss the sample and data used in this paper. Thereafter we present our empirical results in three sections. In section 3 we present some benchmark results which we elaborate in a section on industry effects and a section on firm effects. After discussing the empirical evidence, we discuss the robustness of our results in section 6. In section 7 we conclude.

1 The event study approach

The event study approach to investigating the response of financial markets to monetary policy dates back to a study by Cook and Hahn (1989). In their study the authors regressed changes in market interest rates on changes in the Federal funds rate for a sample of 75 days on which the Federal Reserve changed the federal funds rate.

[4] Hayo, Kutan, and Neuenkirch (2011) considers the effects of central bank communication on commodity price volatility and Fender, Hayo, and Neuenkirch (2011) on CDS spreads. Two studies on central bank communication and exchange rates are Fratzscher (2008a,b).

But markets are forward looking. If a change in the federal funds rate is entirely anticipated, we expect this change to be incorporated in market interest rates already. If the policy action is correctly priced in advance, the action itself should have no effect on asset prices.[5]

Therefore we need a way to extract the unexpected part of the change. A way to do this, was put forward by Kuttner (2001) who showed how to extract monetary policy surprises from federal funds futures data. With these surprise measures or unexpected monetary policy interventions, many studies subsequently estimated regressions of the following form:[6]

$$\Delta y_t = \alpha + \beta \text{Surprise}_t + \epsilon_t, \tag{1}$$

where Δy_t is the change in an asset price, like a stock index, individual stocks, investment portfolios or market interest rates measured over an interval that includes the monetary policy announcement. Subsequently Gürkaynak, Sack, and Swanson (2005) extended this one factor approach by formally testing whether the variation in short term interest rates on FOMC dates is characterized by one or more factors. Their results provided strong evidence for a two factor approach. Two factors are able to capture movements in asset prices due to monetary policy whereas one factor misses a large part of the monetary policy induced variation. The *current federal funds rate target factor* is the monetary policy surprise above and reflects the surprise associated with a change in the federal funds rate target (or lack thereof). The *future path of policy factor* is closely associated with Federal Open Market Committee statements and reflects the influence the FOMC committee exerts on market expectations through its communication strategy. We are going to pursue the two factor approach in this paper. In the remainder of this study we refer to these factors as *target* (factor) and *path* (factor).[7]

[5] This intuitive prediction is confirmed in Bernanke and Kuttner (2005), p.1226.

[6] In this paper we use federal funds futures and eurodollar futures. Other financial contracts can be used too as in Cochrane and Piazzesi (2002) or Rigobon and Sack (2004). Our choice follows the recommendations by Gürkaynak, Sack, and Swanson (2007) and is the most common choice in the literature.

[7] Gürkaynak, Sack, and Swanson (2005) tested for the required number of factors using the matrix rank test of Cragg and Donald (1997). Subsequently they constructed the two factors from the first two principal components of a set of short term interest rates with a suitable scaling and rotation to allow for a structural interpretation.

1.1 Market-based surprise measures of monetary policy

Federal funds futures have a value at expiration of a hundred minus the average federal funds rate over the expiry month. Consider the value of such a contract on the day before a FOMC meeting taking place at time t. Denote with r_{-1} the federal funds rate before the meeting and with r_0 the federal funds rate prevailing after the meeting. The no-arbitrage condition demands that the implied spot rate ff^0 on such a futures contract before the meeting would be the following:

$$\mathrm{ff}^0_{t-\Delta t} = \frac{d_0}{D_0} r_{-1} + \frac{D_0 - d_0}{D_0} \mathbb{E}_{t-\Delta t}(r_0) + \mu^0_{t-\Delta t}. \tag{2}$$

Here D_0 indicates how many days the month we consider contains, and d_0 how many days have elapsed before the FOMC meeting takes place. This equation states that the implied spot rate on the contract $\mathrm{ff}^0_{t-\Delta t}$ (just before the meeting) equals a weighted average of the prevailing interest rate r_{-1} and the interest rate which is expected to prevail after the FOMC meeting $\mathbb{E}_{t-\Delta t}(r_0)$ plus a risk premium $\mu^0_{t-\Delta t}$. After the policy decision is known the implied rate is the following:

$$\mathrm{ff}^0_t = \frac{d_0}{D_0} r_{-1} + \frac{D_0 - d_0}{D_0} r_0 + \mu^0_t, \tag{3}$$

that is, the weighted average of both interest rates plus a risk premium. Using the two equations above we can construct the unanticipated component of the monetary policy action:

$$\begin{aligned}
\mathrm{Surprise}_t &\equiv r_0 - \mathbb{E}_{t-\Delta t}(r_0) \qquad (4)\\
&= \left[\mathrm{ff}^0_t - \frac{d_0}{D_0} r_{-1} - \mu^0_t\right] \frac{D_0}{D_0 - d_0} - \left[\mathrm{ff}^0_{t-\Delta t} - \frac{d_0}{D_0} r_{-1} - \mu^0_{t-\Delta t}\right] \frac{D_0}{D_0 - d_0}\\
&= \left[(\mathrm{ff}^0_t - \mathrm{ff}^0_{t-\Delta t}) + (\frac{d_0}{D_0} r_{-1} - \frac{d_0}{D_0} r_{-1}) - (\mu^0_t - \mu^0_{t-\Delta t})\right] \frac{D_0}{D_0 - d_0}\\
&\cong \left[\mathrm{ff}^0_t - \mathrm{ff}^0_{t-\Delta t}\right] \frac{D_0}{D_0 - d_0}.
\end{aligned}$$

We arrive at the final line by assuming that high frequency changes in the risk premium are negligible or $\mu_t^0 - \mu_{t-\Delta t}^0 \cong 0$. Evidence for this assumption was provided by Piazzesi and Swanson (2008). The scaling factor $\frac{D_0}{D_0 - d_0}$ blows up the change in the term premium at the end of the month, causing measurement error concerns. To alleviate this concern we switch to the contract that expires in the next month when the scaling factor is larger than four.

We define the path factor as the change in the four-quarters-ahead eurodollar interest rate futures orthogonal to the target surprise. So the path surprise equals the residual term ϵ_t in the following regression:

$$\Delta\text{Eurodollar future}_{4Q,t} = \alpha + \beta\text{Target Surprise}_t + \epsilon_t. \tag{5}$$

where the regressor Target Surprise$_t$ is the surprise measure we constructed in equation 4. The four-quarters ahead eurodollar futures is assumed to capture the markets expectations of the policy path for the coming year. The regression above allows for a simple decomposition in a target factor) and a residual path factor. This residual path factor corresponds to all news that moves futures rates for the upcoming year on FOMC meeting days without changing the current federal funds rate. This factor should be interpreted as the news that market participants have learned from the FOMC's statement about the expected future path of monetary policy besides what they have learned about the level of the target rate.[8]

2 Sample choice and data sources

In this paper we use a sample of events starting with the FOMC meeting of February 1994. From that meeting onwards the Federal Reserve started issuing a press release after

[8] The construction of factors above differs from Gürkaynak, Sack, and Swanson (2005) but is more straightforward and easier to understand. The approach outlined in the text was put forward in Wongswan (2009) and Hausman and Wongswan (2011). Unreported regressions using the (more complex but essentially equivalent) construction of factors from Gürkaynak, Sack, and Swanson (2005) confirmed that both approaches yield very similar results.

every FOMC meeting and change in policy.[9]

Since 1994, a number of changes in the communication practices of the FOMC took place.[10] Several authors argue that these have enhanced the transparency and credibility of the Fed, see Swanson (2006), Yellen (2006) and Kwan (2007).

We have investigated alternative sample periods motivated by changes in communication practices but the conclusions presented in this paper remain by and large the same. One innovation in communication practices seems especially influential, the inclusion of forward-looking language. Kwan (2007) stresses that these forward-looking statements have significantly improved market participants' understanding of near term monetary policy. For this reason, while we focus throughout the paper on a sample starting February 1994 and ending in 2009, we do report estimated coefficients for a sample starting after June 2003 to give a feel for the variation in estimated effects when considering a different data sample.

The events we consider in this paper are all FOMC meetings, both scheduled and unscheduled, starting in February 1994 and ending in December 2009. We have omitted the unscheduled FOMC meeting after the terroristic attacks of September 11 2001 as is custom in the literature. This results in 144 FOMC meetings for which the dates can be found on the web page of the Federal Reserve.[11]

For each meeting we use the companies which were in the S&P 500 at that time. Throughout this paper we focus on daily stock returns. Higher frequency data has the advantage of allowing for more precise estimates and a better model fit because less confounding news is captured. However, at a lower frequency we can focus on effects which are longer-run and we can assure ourselves that we are not capturing overshooting effects that quickly disappear, see Ehrmann and Fratzscher (2004). By comparing the results from different frequencies, authors have found that for daily intervals endogeneity

[9] For more details, see section 1.2 in Gürkaynak, Sack, and Swanson (2005).

[10] These changes are respectively: the inclusion of a balance of risks in the press release (in 2000), the addition of individual votes and preferred policy choices of FOMC members (in 2002), the introduction of forward-looking language (in 2003) and the release of the minutes of a meeting with three weeks delay (in 2004). Finally, in April 2011 the FOMC held a press conference after the FOMC meeting for the first time.

[11] http://www.federalreserve.gov/monetarypolicy/fomccalendars.htm

and simultaneity problems are not an issue. Studies investigating this in some detail are Gürkaynak, Sack, and Swanson (2005) and D'Amico and Farka (2011).

The stock data used in this paper is obtained from the CRSP database, and were combined with accounting data obtained from the Compustat database. Furthermore, we use macroeconomic data obtained from the Federal Reserve Board and NBER recession indicators. The data on federal funds futures and eurodollar futures were obtained from the CME group. The construction of the target and path surprises follows our description in Subsection 1.1. Exact item definitions and details on the construction of all variables used in this paper can be found in the appendix.

3 Event study analysis

In this section we undertake our benchmark event study. In the subsequent sections we extend this benchmark study to explore cross-sectional variation. As explained above, the analysis centers around two explanatory variables: the target and path factor. In Figure 1 we have plotted both variables.

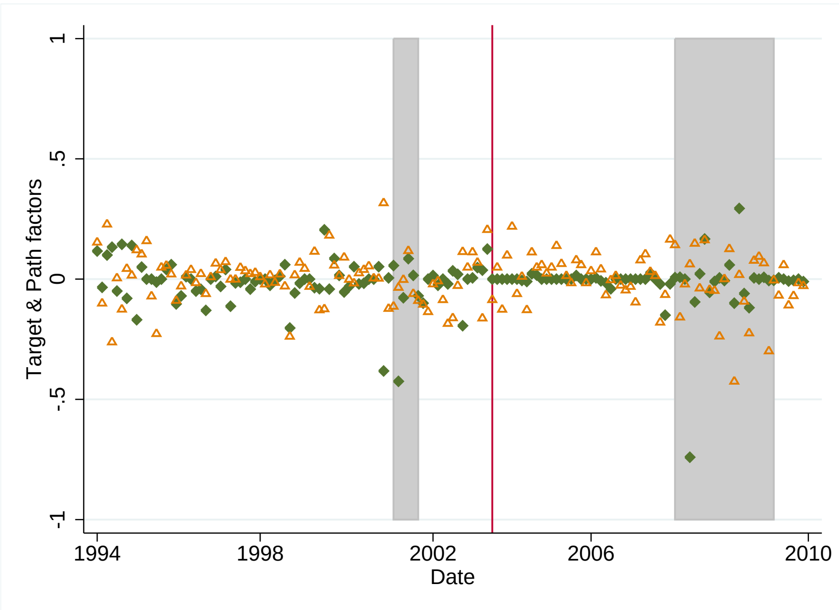

Figure 1: This graph shows a plot of the target surprises (solid diamond dots) and path surprises (hollow triangles). The shaded areas depict periods marked as a recession by the NBER turning points. That is from March until November in 2001 and from December 2007 until June 2009. The vertical line serves as a demarcation line to split the sample in two parts: before and after the introduction of forward-looking statements.

The figure shows that the path factor varies throughout the entire sample whereas the target factor shows much less variation after the introduction of forward looking statements. Target surprises became smaller because the forward-looking statements had the purpose of *guiding* market participants and the Federal Reserve seemed successful; at least during expansions. We also see that large values (in absolute value) of both factors tend to occur mainly during recessions (the shaded areas). These observations may be particularly influential and we pay attention to this in the empirical analysis.

Table 1: Descriptive statistics of the target and the path factor

	Target			Path		
	Unconditional	Expansion	Recession	Unconditional	Expansion	Recession
Mean	-0.01	0.00	-0.04	0.00	0.01	-0.03
Minimum	-0.74	-0.38	-0.74	-0.43	-0.26	-0.43
Maximum	0.29	0.20	0.29	0.32	0.32	0.16
10th percentile	-0.08	-0.06	-0.19	-0.13	-0.13	-0.24
90th Percentile	0.17	0.05	0.17	0.12	0.11	0.15
Standard Deviation	0.10	0.07	0.18	0.11	0.10	0.14

This table reports descriptive statistics for the target and path surprises we use throughout the paper. The sample statistics are rounded up to two decimals.

Table 1 presents some descriptive statistics for both factors during expansions and during recessions. These descriptives emphasize the fact that both the target factor and the path factor become more variable in downturns.

With the relative size of these variables in mind we turn to the event study. The basic linear model we estimate is the following:

$$\text{Return}_{it} = \alpha + \gamma \text{Rec}_t + \beta_1 \text{Target}_t + \beta_2 \text{Target}_t * \text{Rec}_t + \beta_3 \text{Path}_t + \beta_4 \text{Path}_t * \text{Rec}_t + \epsilon_{it}, \quad (6)$$

where the variables $Target_t$ and $Path_t$ are the variables discussed in Subsection 1.1. The regressand $Return_{it}$ is the return on stock i at time t and Rec_t is a dummy variable to account for the business cycle. In the context of monetary policy *actions*, several studies have found that stocks react more pronounced during recessions, see for example Basistha and Kurov (2008) or Kurov (2010). We estimate six varieties of this model and present the results in Table 2. All specifications presented here and in the remainder of the paper are estimated with firm fixed effects and heteroskedasticity consistent standard errors unless mentioned otherwise . For a discussion on the error construction and some robustness checks we refer to Section 6 and the online appendix. These additional tests confirm that the results presented here are robust.

First, we estimate the model as it is presented above, that is with individual stock returns over the whole sample. Second, we estimate the same model but we now use aggregate returns on the S&P 500 index as dependent variable. This serves as a robustness check for the model with individual returns on which we build in subsequent sections. Third, we estimate the model again with individual returns as the dependent variable, but now the sample is restricted to the period after the introduction of forward-looking statements in FOMC communication. Fourth, we estimate the model with individual returns as dependent variable and over the whole sample but now we drop outlier dates. As pointed out by Bernanke and Kuttner (2005), there is the concern that exceptional FOMC meetings may generate the results we present in the paper. In particular, our recession indicator captures the onset of the financial crisis in 2008-2009. By removing outlier dates we aim to show that our results are not driven by a few exceptional trading days. We identify outliers by estimating regression (6) with returns on the S&P 500 index as a dependent variable. Then we use the DFITS statistic of Welsh and Kuh (1977) to find influential dates. Using the cutoff value proposed by Belsley, Kuh, and Welsh (1980) we determine the dates that are marked as outliers. A brief overview of the dates marked as outliers as well as alternative procedures to determine outliers can be found in the online appendix to this paper. In that appendix we also discuss the robustness of our results with respect to the outlier choice. In the fifth and the sixth specification we re-estimate the second and the third specification while omitting outlier dates.

Inspection of the estimation results in Table 2 reveals that the estimated coefficients re quite similar over all specifications presented. We point to some results which are important for our further discussion. First, we find a negative coefficient on the target factor, a result in line with theory and earlier empirical work, see for example Ehrmann and Fratzscher (2004). Second, the coefficient on the path factor is also negative but smaller in absolute value. The negative sign suggests that in good times (i.e. the recession

Table 2: Benchmark event study

	(1)	(2)	(3)	(4)	(5)	(6)
Target	-6.992***	-7.041***	-14.365***	-3.893***	-2.992**	-14.250***
	(-23.62)	(-2.99)	(-25.71)	(-18.09)	(-1.99)	(-25.45)
Target*Rec	3.739***	4.770	12.889***	-13.102***	-11.053*	-3.785*
	(9.12)	(1.01)	(20.32)	(-14.74)	(-1.83)	(-1.91)
Path	-1.906***	-2.268*	-2.662***	-2.052***	-2.648***	-2.709***
	(-12.75)	(-1.89)	(-14.46)	(-16.14)	(-2.78)	(-14.84)
Path*Rec	10.838***	10.737*	11.826***	16.100***	14.674***	18.394***
	(22.32)	(1.86)	(22.88)	(37.79)	(7.71)	(36.20)
N	69608	144	30945	64277	133	27057
R^2	0.06	0.20	0.08	0.05	0.24	0.13
Sample	Whole	Whole	Late	Whole	Whole	Late
Return on	Stocks	S&P Index	Stocks	Stocks	S&P Index	Stocks
Outliers removed	No	No	No	Yes	Yes	Yes

Student t-statistics are mentioned in parentheses.

* p < 0.1, ** p<0.05, *** p<0.01

This table presents the results from estimating regression equation (6). The table only presents the estimated coefficients and t-statistics on the variables of interest and not on the constant and the recession indicator. We omitted the FOMC meeting on September 17 2001 because of the exceptional character of this meeting in the wake of 9/11. The reported t-statistics are based on heteroskedasticity robust standard errors. Firm fixed effects were included in all regression specifications.

dummy equals zero) an upward revision of the future path of monetary policy depresses stocks. Third, we notice that state dependence matters. Interacting both factors with a recession indicator improves the fit of the model greatly and allows for much more precise estimates of the target and the path factor. When we regressed S&P 500 index return on the target and the path factor without interaction terms and over the entire sample we found very large standard errors and an R^2 statistic less than 0.06 (compared with 0.2 or more when interactions were included).[12] The sign on the target-recession interaction term is ambiguous and depends on whether outlier dates are included. If we consider the whole sample the sign is positive; if we drop the outlier dates then the sign becomes negative. However, our main interest is in the path-recession interaction which is found to be positive across all specifications presented. The path-recession interaction coefficients imply that communication inducing an upward revision of the expected path of future policy during a recession has a positive effect for the average stock return.

[12]This corresponds to the regression we estimated in columns column 2 and 4 of Table 2 but with coefficients γ, β_2, β_4 restricted to be zero.

With the descriptive statistics from Table 1 in mind, we can get a feel for the economic significance of the results. For example, one in five FOMC meetings in a recession is associated with a path surprise of more than fifteen basis points in absolute value. The regression results in column four indicate that a path surprise of fifteen basis points has an impact of more than 2% on the average stock return with the sign depending on whether is was a positive or negative path surprise. The overall impact of a particular meeting depends on the target factor too. However, with the exception of a few remarkable meetings in which the FOMC meetings surprised the financial markets, the target factor has become less important. The calculation we did was based on regression results on a sample in which we excluded the most influential policy dates. This is comforting as it reinforces our main story. Central bank communication, captured here by the path factor, has a non-negligible influence on financial markets. Moreover, its effect in downturns is opposite to the effect in expansions. Our intuition behind this result is that financial market participants read FOMC communication to update their views on the state of the economy. A future tightening of the policy rate during a downturn suggests that the Federal Reserve, with its dual mandate and reluctance to raise the federal funds rate too soon, hints to better economic times ahead.

When comparing the results of regressions over the whole sample with regressions over the sample starting after the introduction of forward looking statements (columns 3 and 6 in Table 2), we notice that the results are in line with each other. The most noticeable difference is that the model fit improves when we restrict ourselves to the later sample. The sign of the variables in the regressions remain the same. For this reason we prefer to use the whole sample.[13]

We are hesitant to take a strong stance on whether we should base the analysis on the sample with or without outliers. Both choices have their merits. By excluding outliers we show that the results do not depend crucially on a few FOMC meetings. On the other

[13]In an earlier version of this paper, we emphasized the *regime change* due to the introduction of forward-looking statements. While the size of the estimated coefficients and the precision changes, the conclusions presented in this paper, carry over to the case where we use a smaller sample. To avoid burdening the reader with additional regression results we do not report additional regression results here. In the web appendix to this paper, we present some regression results with the late subsample as a robustness check.

hand, the outlier dates are likely to reflect important policy dates. Excluding them may give an imperfect picture of exceptional times. In the remainder of this study we present results excluding outliers.[14]

An important motivation for considering individual stock returns is that we expect a large heterogeneity in responses among stocks. In the following sections we investigate the responses of stocks in more detail by considering firm specific and industry specific effects.

4 Industry effects

In this section we relate the responses of stock prices to industry affiliation. Industry-specific effects may arise through the interest channel. Industries with a more interest sensitive demand are expected to be more responsive to Federal Reserve communication. The cross-sectional dimension of monetary policy has been studied by a few papers. Peersman and Smets (2005) study the effects of monetary policy on sectoral production indices across OECD and euro area countries. Hayo and Uhlenbrock (2000) study industry effects within Germany. Bernanke and Kuttner (2005) and Ehrmann and Fratzscher (2004) explore the cross-sectional effects of monetary policy *actions* on stock returns in the US. Our analysis differs from these studies in two ways. First, we allow for *state dependence*. Monetary policy may have different effects depending on the business cycle. Second we adhere the *two factor view* introduced earlier and we distinguish between a current federal funds rate target factor and future path of policy factor. Third we tie the industry effects we observe to the cyclicality of industries.

To gauge the industry specific effects we pool stocks according to the SIC classification system. We re-estimate regression (6) for each major group, for which we have at least seven companies in the sample to ensure that we have sufficient observations. The results of these regressions can be found in Table 3.

The results in the table are in line with the results from our benchmark event study. The estimated coefficients on the target factor, the path factor and the target-recession

[14] Further results including outliers are available upon request.

Table 3: Industry effects

Industry Division	Major Group	Target	Target*Rec	Path	Path*Rec
Mining	Metal Mining	-8.610***	-4.354	-2.879**	5.484
	Oil and Gas Extraction	-3.474***	-22.31***	0.712	6.288***
Construction	Building Construction	-6.568***	-51.32**	-10.06***	64.14***
Manufacturing	Food and Kindred products	-1.168*	-6.193***	-2.701***	9.539***
	Apparel, finished products	-4.320*	-18.91**	-1.922	15.93***
	Paper	-3.103***	5.735	-2.417***	12.82***
	printing and Publishing	-1.664	-0.167	0.214	9.577***
	Chemicals	-3.531***	-7.018***	-1.179***	7.549***
	Petroleum	-2.915***	-17.14***	-2.032***	13.10***
	Rubber	-6.097***	-5.217	-3.623***	16.03***
	Primary metal	-2.157*	-19.96***	-4.752***	25.12***
	Fabricated metal	-4.180***	-8.817	-3.821***	13.99***
	Industrial/commercial machinery	-5.010***	-11.37***	-3.500***	17.67***
	Electronic equipment	-6.111***	-18.45***	-1.700***	20.47***
	Transportation equipment	-3.469***	-27.02***	-0.617	17.09***
	Photo/Medical/Optical Goods	-2.287***	-18.21***	-1.511***	9.631***
Transport, gas, etc.	Railroad transport	-2.763*	-8.000	-3.082***	13.13***
	Communications	-2.311**	-14.55***	-1.150	11.53***
	Electricity, Gas, Sanitary	-2.894***	-2.387	0.239	3.541***
Wholesale	Wholesale durable	-2.174	-9.572*	-1.708**	10.70***
	Wholesale nondurable	-1.836	4.789	0.00685	2.144
Retail	General merchandise stores	-4.937***	-9.612*	-3.596***	11.06***
	Food stores	-3.101**	-2.868	-1.366	15.16***
	Apparel and accessory stores	-3.618*	-11.25	-2.097*	20.10***
	Eating and drinking places	-2.420	-13.96***	-3.227***	18.06***
	Miscellaneous Retail	-5.728***	-11.16	-2.742***	6.686*
Finance, real estate	Depository Institutions	-3.082***	-15.05***	-4.805***	30.54***
	Nondepository Credit Institutions	-4.681***	-37.09***	-4.856***	45.37***
	Security and commodity brokers	-8.061***	-22.50***	-3.735***	28.58***
	Insurance carriers	-4.934***	-15.65***	-1.222***	23.37***
	Investment offices	-13.07***	16.47	-1.694	39.89***
Services	Business Services	-6.642***	-5.469	-0.886	13.08***
	Health Services	-3.595*	-5.433	-1.113	9.385**

* $p<0.1$, ** $p<0.05$, *** $p<0.01$

This table presents the results from estimating regression equation (6). The table only presents the estimated coefficients on the variables of interest and not on the constant and the recession indicator. The table presents point estimates in order to improve readability. We omitted the FOMC meeting on September 17 2001 because of the exceptional character of this meeting in the wake of 9/11. We also omitted eleven dates marked as outliers as explained in the text. The p-values (indicated by stars) are based on heteroskedasticity robust standard errors. Firm fixed effects were included in all regression specifications.

interaction are in general negative. When we obtain a positive coefficient, the estimate is always indistinguishable from zero. What becomes apparent is that the estimated coefficients vary a lot in size. For example, compare the estimated coefficient on the path-recession interaction for the major group labeled *Chemicals* and the major group labeled *Electrical equipment*. For both groups we estimate a similar coefficient on the path factor but for the path-recession interaction we find a substantial difference. In their paper considering the effect of the target factor on stock prices, Ehrmann and Fratzscher (2004) suggest that industry differences in responsiveness are likely due to differences in cyclicality. They do not test for this and only provide a heuristic argument. We expect a similar mechanism to work here as well. When state dependence matters, we expect industries, that are more susceptible to the business cycle (cyclical industries), to show more pronounced responses.

In order to pin this down we need to determine which industries can be classified as cyclical. A way to classify industries in terms of cyclicality was put forward in Boudoukh, Richardson, and Whitelaw (1994) and we follow that approach. In this approach industries are ranked according to the *industrial production growth beta*. More specifically we construct sectoral growth rates of industrial production and the growth rate of the aggregate industrial production. The industrial production growth beta is then the estimated coefficient of a regression of the sectoral growth rate on the aggregate growth rate:

$$\mathrm{IPG}_t = \alpha + \beta \mathrm{Aggregate\ IPG}_t + \epsilon_t \tag{7}$$

where IPG stands for Industrial Production Growth rate. This model is estimated for each industrial sector covered by the G17 Federal Reserve data. The data is sampled quarterly from 1972 until 2009. The results are reported in Table 4.

The middle column of Table 4 reveals substantial variation in growth beta's across industries ranging from coefficients below 0.3 for food, beverages, tobacco and electric power generation to coefficients larger than 2 for primary metal and motor vehicles. The right column presents the standardized betas which we use in our analysis.

To see whether more cyclical industries are more responsive to monetary policy, we

Table 4: Cyclicality of industrial sectors

Industrial Sector (sorted on β)	β	Standardized β
Motor vehicles and parts	2.819***	2.679
Primary metal	2.378***	1.995
Plastics and rubber products	1.565***	0.732
Electronic equipment	1.483***	0.605
Furniture	1.483***	0.605
Machinery	1.377***	0.440
Wood production	1.305***	0.328
Fabricated metal products	1.288***	0.302
Computer and electronic products	1.265***	0.266
Nonmetallic mineral products	1.234***	0.218
Textile production	1.211***	0.182
Chemical	1.004***	-0.139
Paper	0.980***	-0.176
Apparel and leather goods	0.862***	-0.360
Miscellaneous	0.738***	-0.552
Printing	0.611***	-0.750
Petroleum and coal products	0.600***	-0.767
Mining	0.494***	-0.931
Aerospace and miscellaneous transportation	0.428**	-1.034
Natural gas distribution	0.407***	-1.066
Electric power generation	0.292***	-1.245
Food, beverage, tobacco	0.236***	-1.332

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The second column presents the industrial production growth beta's. These beta's are estimated using the following model for each separate sector: $\text{IPG}_t = \alpha + \beta\text{Aggregate IPG}_t + \epsilon_t$ where IPG stands for industrial production growth. We estimate this for each sector for which have data available (see data appendix). The reported p-values are based on Newey-West standard errors. In the third column we present the standardized beta's. We calculate these by taking the estimated beta's, subtracting the mean (1.093636) and dividing by the standard deviation (0.643924) and rounding up to three decimals.

estimate the following regression:

$$\begin{aligned}\text{Return}_{ikt} = \alpha + \gamma\text{Rec}_t + \beta_1\text{Target}_t + \beta_2\text{Path}_t + \beta_3\text{Target}_t * \text{Rec}_t + \beta_4\text{Path}_t * \text{Rec}_t \\ + \beta_5\text{Target}_t * \text{Cyclical}_k + \beta_6\text{Path}_t * \text{Cyclical}_k \\ + \beta_7\text{Target}_t * \text{Rec}_t * \text{Cyclical}_k + \beta_8\text{Path}_t * \text{Rec}_t * \text{Cyclical}_k + \epsilon_{ikt}\end{aligned} \tag{8}$$

where the subscripts i, k, t indicate firm i in industry k at time t and *Cyclical* is a cyclicality indicator. In Table 5 we present the results of this regression with two different cyclicality indicators. In the left column we present the regression result where the standardized production growth beta's are used as cyclicality indicators. In the right column we present the results when using a ternary indicator, taking the value of -0.5 when the stock belongs to the industries which are the least cyclical, 0.5 when the stock belongs to the most cyclical industries and 0 when it falls between these extremes. The most (least) cyclical are the industries containing the the upper (lower) quintile of observations when we rank the industrial sectors according to the industrial production growth betas as we did in Table 4. This corresponds to the top eight and bottom three industrial sectors respectively. Coding the upper and bottom group as +0.5 and -0.5 makes the interpretation of the estimated regression coefficients straightforward; a one unit increase in the explanatory variable now corresponds to a shift from the lower to the upper quintile as explained as the regression coefficient is now just the difference between the upper and the lower quintile.[15]

We estimate Equation (8) for all firms in industries which are covered by the Federal Reserve Statistical Release data on industrial production (all industries covered in Table 4), yielding 35513 observations. The results can be found in Table 5.

Inspection of Table 5 confirms that industry patterns in the response of stock returns to monetary policy can partially be traced back to the cyclicality of the industry. Both specifications indicate that the impact of monetary policy is more pronounced for companies operating in cyclical industries. In the left column we use the standardized production growth betas as interaction term. We see that for a company operating in the textile production industry, a manufacturing industry with a typical comovement with the business cycle, a positive path surprise of fifteen basis points has a negligible impact on the stock return. Contrast this with the impact on a stock of a company operating in a highly cyclical industry. For example, using the results in tables 4 and 5, we expect for a company operating in the primary metal producing industry an impact of $-1.511 \times 15 \times 1.995 \approx -45$ basis points whereas a similar calculation yields approximately -4 basis points for the textile industry. When we consider the impact on stock returns in a downturn, we get a larger and positive impact as we emphasized throughout this paper. For the textile industry the impact on the average stock return is estimated to

[15]This approach is discussed in Section 2.8 ofGelman and Park (2008).

Table 5: Responses of cyclical and non-cyclical industries

	Standardized β	Low vs High
Target	-2.850***	-3.614***
	(-5.94)	(-12.26)
Target*Rec	-5.875***	-12.170***
	(-3.01)	(-10.71)
Path	-0.257	-1.711***
	(-0.85)	(-10.52)
Path*Rec	3.637***	12.246***
	(4.25)	(25.13)
Target*Cycl	-0.813*	-2.114**
	(-1.86)	(-2.51)
Target*Rec*Cycl	-6.507***	-12.003***
	(-3.56)	(-3.65)
Path*Cycl	-1.511***	-2.728***
	(-5.72)	(-6.41)
Path*Rec*Cycl	9.031***	13.135***
	(10.18)	(9.82)

Student t-statistics in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

This table presents the results from estimating equation (8). In the middle column we present the results when using the standardized betas (see Table 4) as cyclicality indicator. In the right column we use a ternary indicator coded such that the coefficient on the cyclicality-interaction represents the difference between high cyclical and low cyclical firms. The table presents the estimated coefficients and t-statistics on the variables of interest only, and not on the constant. The reported t-statistics are based on heteroskedasticity robust standard errors. We omitted the FOMC meeting on September 17 2001 because of the exceptional character of this meeting in the wake of 9/11. We also omitted eleven dates marked as outliers as explained in the text. Firm fixed effects were included in all regression specifications.

be nearly +0.35%, while the impact on stocks from firms operating in a highly cyclical industry like primary metal is estimated to be about +2.8%.[16]

In the right column the coefficient on the interaction with the cyclicality indicator represents a shift from the lower quintile to the upper quintile as explained above. The results show that we expect the impact of central bank communication (i.e. the path factor) to be more than twice as large when comparing stocks in the bottom and upper cyclical industries.

The results shown in Table 5 confirm our priors. The effects of central bank communication are in line with central bank actions. For central bank actions i.e. surprise changes in the policy rate, Ehrmann and Fratzscher (2004) showed in a series of industry-by-industry regressions that industries which are more cyclical show a more pronounced response. As an example, they found that stocks belonging to the *electrical equipment* major group are twice as sensitive than stocks in the *chemicals* group. Our results can be seen as an extension. We show that the same pattern carries through for the two factors and the recession interactions. Furthermore, we aimed at explaining cross-sectional variation with a variable capturing cyclicality. Our results confirm the idea that cyclical industries tend to be more responsive to central bank actions and communication.

We now turn to firm-specific effects.

5 Firm-specific effects

There is a substantive literature on the credit channel of monetary policy transmission documenting asymmetric effects of monetary policy on firms. This literature emphasizes that firms facing financial constraints are more affected by changes in interest rates than firms that are less constrained. The literature on the credit channel of monetary policy transmission broadly suggests two reasons why some firms are affected more than others. Worsening credit markets affect the balance sheets of firms and thus affects the present value of collateral, see Bernanke and Gertler (1989). This is sometimes referred to as the

[16]In a recession we *add* $3.637 \times 15 + 9.031 \times 15 \times 0.182 \approx 80$ for the textile industry and $3.637 \times 15 + 9.031 \times 15 \times 1.995 \approx 325$ for the primary metal producing industry, yielding an impact of nearly +35 and about +280 basis points for these industries respectively.

balance sheet channel. In worsening credit market conditions, the firms for which there is the least information are also the first to get cut from credit lines. This is referred to as the bank lending channel.

The literature has spurred a variety of proxies for financial constraints. A popular proxy for credit constraints is firm size. Studies by Perez-Quiros and Timmermann (2000), Gertler and Gilchrist (1994) and Ehrmann and Fratzscher (2004) find that smaller firms are more affected by monetary policy tightening than larger firms. Other proxies for financial constraints rely on financial ratios. A variety of various capital and book ratios were tested in a study by Kaplan and Zingales (1997).

In this paper we investigate cross-sectional variation at the firm level and consider six proxies for financial constraints. Our notion of financial constrains follows Kaplan and Zingales (1997) and Ehrmann and Fratzscher (2004). Firms facing more financial constraints find it relatively more difficult to raise funds. The first two variables we consider are the *total amount of assets* of a firm and the *number of employees*. Both quantities capture the size of the firm. Next, following papers by Kaplan and Zingales (1997), Lamont, Polk, and Saa-Requejo (2001) and Ehrmann and Fratzscher (2004) we consider the *cash flow to income ratio* and the *debt to assets ratio*. The idea is that firms with relatively large cash flows or low debt face less financial constraints as they have less external financing needs. Finally we consider the *return on equity* (a measure of profitability) and *trade credit*. Trade credit is considered to be a particularly expensive form of finance and was also used in Basistha and Kurov (2008) to capture financial constraints. As argued in Nilsen (2002) financially constrained firms are more likely to resort to trade credit than less constrained firms.

To investigate the cross-sectional variation across firms we estimate the following regression:

$$
\begin{aligned}
\text{Return}_{it} = \alpha + \gamma \text{Rec}_t + \beta_1 \text{Target}_t + \beta_2 \text{Path}_t + \beta_3 \text{Target}_t * \text{Rec}_t + \beta_4 \text{Path}_t * \text{Rec}_t \\
+ \beta_5 \text{Target}_t * \text{Firm}_{it} + \beta_6 \text{Path}_t * \text{Firm}_{it} + \beta_7 \text{Target}_t * \text{Rec}_t * \text{Firm}_{it} \\
+ \beta_8 \text{Path}_t * \text{Rec}_t * \text{Firm}_{it} + \sum_{j=1}^{3} \delta_j \text{Control}_{j,it} + \epsilon_{it}
\end{aligned} \tag{9}
$$

where *Firm* is a firm specific variable capturing the financial constraint a firm faces. The $Control_j$'s are three firm level control variables. Following Laeven and Tong (2012) we include the three Fama and French (1992) factors as firm characteristics directly in our regression as control variables.

We estimate this model with the six different *Firm* variables explained above: the number of employees, the total amounts of assets, cash flow to net income, returns on assets, trade credit and debt to assets. We rank the firms for *each* FOMC meeting according to their position in the cross-sectional distribution of the variable under consideration. We then divide the firms in three groups: the lower quintile, the upper quintile and the middle group. This categorization on a daily basis allows for temporal changes in the financial constraints firms face. We then code the variable *Firm* as taking the value of -0.5 for the quintile we expect to be the least financially constrained, 0 for the middle group and +0.5 for the quintile we expect to be the most constrained. For the variables we consider, we expect the firms to be the least financially constrained to be those firms with the most employees, the largest amount of assets, the largest cash flow to income, the least trade credit and the lowest debt to assets ratio. The variable *Firm* is then interacted with the variables of interest to gauge the impact of moving from the least financially constrained group to the most financially constrained group.

Following Laeven and Tong (2012) we drop firms active in the utilities industry, the wholesale industry, the financial industry and public administration. These firms are subject to strict regulation or they have strongly differing financing needs, and keeping these in our sample would confound the results. In Table 6 we provide correlations between the *Firm* variables we consider. The table illustrates that the different *Firm* variables we consider have a very low correlations except for the two variables capturing firm size, the number of employees and the total amount of assets.

The results of estimating regression model (9) are provided in Table 7.

Table 6: Correlation between Firm Characteristics

	Employees	Total Assets	Cash flow to net income	Return on equity	Trade Credit	Debt to Assets
Employees	1					
Total Assets	0.655	1				
Cash flow to net income	0.027	0.017	1			
Return on Equity	-0.028	-0.030	0.015	1		
Trade Credit	-0.100	-0.038	0.020	0.026	1	
Debt to assets ratio	0.119	0.102	-0.005	-0.043	-0.37	1

In the first two columns, *Firm* is an indicator variable capturing the size of the firms in terms of employees and total assets respectively. Firms are ranked such that the large firms are in the bottom quintile and the small firms in the top quintile. The results for both specifications are very and show that smaller firms tend to be more responsive central bank communication in downturns. When considering a path surprise in a downturn of 15 basis points, we expect an additional impact of over 85 (40) basis points on the stock return when comparing the 20% smallest companies with the 20 % largest companies as measured by the number of employees (total assets). When proxying financial constraints by a low cash flow to income ratio, a low return on equity or a high trade credit we find similar results. What is noticeable is that we only find weak evidence of firm effects in the target factor. In only one of the first five specifications we find that the target factor is more negative for firms facing financial constraints. We notice that in general all the estimated coefficients on the *Firm*-interactions have the sign we would expect. However only the coefficient on the Path-Recession-Firm interaction is statistically distinguishable from zero in all of the first five specifications. In the last specification we present, we do not find a difference between firms carrying a low and high amount of debt. This does not contradict previous findings as Ehrmann and Fratzscher (2004) found that the effect of debt is nonlinear: *"firms with either high or low values of these ratios* [debt to capital

Table 7: Firm effects

	Employees	Total Assets	Cash flow to net income	Returns on equity	Trade Credit	Debt to Assets
Target	-3.663***	-3.671***	-3.640***	-3.670***	-3.657***	-3.667***
	(-12.16)	(-12.29)	(-12.07)	(-12.31)	(-12.25)	(-12.27)
Target*Rec	-12.892***	-12.857***	-12.749***	-12.865***	-12.853***	-12.873***
	(-11.36)	(-11.38)	(-11.29)	(-11.45)	(-11.39)	(-11.40)
Path	-1.895***	-1.900***	-1.882***	-1.896***	-1.903***	-1.898***
	(-11.15)	(-11.25)	(-11.04)	(-11.24)	(-11.28)	(-11.23)
Path*Rec	14.232***	14.214***	14.181***	14.223***	14.162***	14.208***
	(28.13)	(28.12)	(28.26)	(28.41)	(28.00)	(28.10)
Target*Firm	-1.408*	-1.400	-0.392	-0.870	-0.026	0.461
	(-1.79)	(-1.61)	(-0.44)	(-0.86)	(-0.03)	(0.51)
Path*Firm	-0.049	-0.162	-0.084	0.899	-0.810	0.490
	(-0.09)	(-0.31)	(-0.14)	(1.47)	(-1.59)	(0.83)
Target*Rec*Firm	-6.334*	1.903	-5.863	-2.874	-4.844	-4.767
	(-1.66)	(0.55)	(-1.64)	(-0.77)	(-1.28)	(-1.22)
Path*Rec*Firm	5.561***	2.829*	8.965***	8.452***	5.121***	0.546
	(2.95)	(1.79)	(5.44)	(4.61)	(3.02)	(0.28)

Student t-statistics in parentheses
* p<0.1, ** p<0.05, *** p<0.01

This table presents the results from estimating regression equation (9) with six different *Firm* variables capturing financial constraints as explained in the text. We omitted ten dates marked as outliers as explained in section 3. The table only presents the estimated coefficients and t-statistics on the variables of interest and not on the constant, the recession indicator and the control variables. We omitted the FOMC meeting on September 17 2001 because of the exceptional character of this meeting in the wake of 9/11. We also omitted eleven dates marked as outliers as explained in the text. The reported t-statistics are based on heteroskedasticity robust standard errors. Firm fixed effects were included in all regression specifications.

ratio] *respond more than firms with intermediate levels"*, see Ehrmann and Fratzscher (2004) p.731. Our specification is restrictive as it only allows for a monotonous effect. When we estimate a specification which allows for this nonlinearity, we find that this applies here for path-recession interaction as well. We do not report these results here but these can be found in the online appendix to this paper. As a robustness check we estimated this specification for the other proxies for financial constraints too. The results are in line with what we presented above and do not reveal similar nonlinearities as in case of the debt to assets ratio.

Taken together, the results in Table 7 show that the asymmetric response of stocks to the *path* factor in a downturn can be explained by the degree to which they are financially constrained.

6 Further robustness checks

We have performed additional checks to assure that the findings are robust. Tables with results from some of these checks can be found in the online appendix to this paper.

Alternative approaches to outlier detection

In the online appendix to this paper we consider alternative ways to detect outliers. Alternative ways include the use of a different outlier statistic, relying on a subsample instead of the entire sample to detect outliers or using a baseline regression without recession dummy to pick up outliers. All procedures pick up by and large the same outlier dates. Since the regression results without outliers are in line with the regression results with outliers, we are convinced of the robustness of our results. As mentioned earlier, we chose to base our analysis on a sample from which we have omitted outliers. The reason is that some meetings are exceptional and commenters have expressed a concern that these special meetings might confound our results. Building our event study on a sample without outlier dates and checking our regression results on subsamples (as mentioned above) alleviates these concerns.

Standard errors

The appropriate choice of standard errors in studies with finance panel data sets is rarely clear cut. Petersen (2009) provides a detailed study on the different ways of calculating standard errors in the finance literature. In this paper we have chosen to present results with heteroskedasticity robust errors and firm fixed effects. As a robustness check we have constructed errors in different ways. In the online appendix we report the results from our baseline regression in six variations: heteroskedasticity consistent errors with firm fixed effects, errors clustered at the industry group level with firm fixed effects, clustered at the date level (with and without firm fixed effects), bootstrapped and clustered at two levels (time and industry). While the size of the standard errors changes a bit, the coefficients on both the target factor and the path*rec interaction (the coefficients of interest) remained significant in every approach.

Investigating subsamples

The introduction of forward-looking statements by the FOMC was a major step in the evolution of communication practices by the FOMC. In Table 2 we presented the results of our baseline regression for a sample starting after the introduction of these statements. We have done our analysis also for this subsample and the results are very much in line with what we presented in this paper. In the online appendix to this paper we present some key regressions of this paper for this restricted sample and for the subsample *ending* at the introduction of forward-looking statements.

Alternative recession indicators

All results presented in this paper rely on the NBER recession indicator for determining downturns. As an alternative to such a recession indicator we can use recession probabilities. Recession probabilities have the advantage of providing a finer measure of the state of the economy as opposed to the crude 0-1 measure provide by a recession dummy. Using recession probabilities instead of the NBER recession indicator does not alter the results of this paper. We refer the interested reader to the our online appendix containing the results of our baseline regression with recession probabilities (as in Chauvet and Piger (2008)) instead of the NBER recession indicator.

Alternative proxies for financial constraints

In the section on firm-specific effects we have presented results with a variety of proxies for financial constraints. Some of the proxies can be constructed in a different way or close substitutes are available. We have constructed an an alternative for the cash flow to net income ratio, an alternative for the debt to assets ratio and we used return on assets instead of return on equity. These alternative variables have a high correlation with their counterparts used in this paper and their use does not alter the results presented above in a meaningful way.

7 Concluding remarks

In this paper we analyzed the reaction of S&P 500 stocks to FOMC actions and communication over the period 1994-2009. We extended the methodology proposed by Gürkaynak, Sack, and Swanson (2005) to allow for temporal and cross-sectional variation in stock responses. The results in this paper are then a natural extension to the work by Ehrmann and Fratzscher (2004) and Bernanke and Kuttner (2005). Our analysis indicates that the impact of central bank communication is very heterogenous. Cyclical industries are much more sensitive as well as individual firms facing financial constraints. At the same time we have stressed that the impact on stocks varies over the business cycle. This finding is in line with what the finance literature has found with respect to other news such as the impact of unemployment news, see Boyd, Hu, and Jagannathan (2005).

Over the whole sample we find that a hypothetical unanticipated cut of 25 basis points in the federal funds rate is associated with about a 1% increase in the average return of S&P 500 stocks. This finding mimics the finding of Bernanke and Kuttner (2005, p.1221).

Our results on the impact of central bank communication imply that during a recession, statements inducing an upward revision of the policy path of 15 points may have a large impact on asset returns, with daily return effects of over 3.5% for the most cyclical stocks. By construction both our factors where orthogonal to each other but this does not mean that these policy levers are entirely independent. Moreover, monetary policy communication is constrained by the credibility of the policy maker.

Our results add to the topical debate on the use of forward guidance by the FOMC and central banks in general. The methodology we have built on is currently the most influential approach. But, as stressed in Woodford (2012), the approach has its limits. We cannot disentangle *why* market participants expect a different path for interest rates after the release of the statement. This implies that we do not know what part of FOMC communication matters. Do stock market participants change their forecast of future economic conditions? Do stock market participants infer a change in the reaction function of the FOMC? For a given FOMC meeting, our methodology does not allow for discriminating between different scenarios. For this reason we thought of communication in terms of its immediate effects on market expectations: "Does the statement induces an upward (downward) revision of future policy?" and not so much in terms of what the policy maker explicitly communicated.

The key result of this empirical exercise is that changes in the revision of the path future policy had strong conditional effects in the sample we analyzed. A variety of checks confirmed that this finding is robust. From a policy point of view a key question is how these results carry over to forward guidance at the zero lower bound, see Woodford (2012). We feel that the approach used here is difficult to transfer to the current events in US monetary policy. In 2011 and 2012 chairman Bernanke has used forward guidance repeatedly and to a much larger extent than in our sample. With FOMC commitments further into the future we may wonder whether using an approach which is limited to handling expectations one year out in the future is warranted. A related concern may be that monetary policy near the zero lower bound constitutes another *regime* for which one needs to control. Analyzing this promises to be an interesting venue for further research and become feasible as time progresses and more data becomes available.

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A Data appendix

In this appendix we provide details for all variables used in this paper. We present these variables in the order of appearance in the text. The sample consists of all FOMC meetings from the beginning of 1994 until the end of 2009, 144 in total. The meeting after the terrorist attacks of 9/11 is dropped. The dates of the FOMC meetings can be found at the website of the Federal Reserve: www.federalreserve.gov/monetarypolicy/fomc.htm.

Baseline event study analysis

- Surprises: The construction is explained in the text. The data on federal funds futures and Eurodollar futures were acquired from the CME group.
- Recession indicators: These indicators are based on NBER recession turning points, see www.nber.org.
- Return: Stock return are calculated as $100 * \log(\text{price}_t) - \log(\text{price}_{t-1})$. Daily stock prices were retrieved from CRSP.

Industry Effects

- Industry classification: This classification is based on the SIC codes as found in COMPUSTAT.
- Industrial production growth rates: Quarterly data on industrial production were obtained from the Federal Reserve Board, data release G.17, see www.federalreserve.gov/releases/g17/

Firm effects

All COMPUSTAT data are retrieved from the CRSP/COMPUSTAT merged annual fundamentals file.

- Employees: Employees corresponds to the COMPUSTAT item EMP
- Total Assets: Total assets correspond to COMPUSTAT item AT.
- Cash Flow to Net Income: This is constructed as (income before extraordinary items + depreciation and Amortization) / net income, expressed in COMPUSTAT items: IB+DPC/NI.
- Return on Equity: This is constructed as (net income / book value on equity), expressed in COMPUSTAT items: NI/(CSHO *PRCC-F).
- Trade Credit: This is constructed as (accounts payable / total liabilities), expressed in COMPUSTAT items: AP/LT
- Debt to Assets: (Long Term Debt Total + Debt in current liabilities) / Assets Total, Liabilities and Stockholder's equity, expressed in COMPUSTAT items: (DLC+DLTT)/LSE
- Market-to-Book: Following Compustat North American User's Guide, this is constructed as PRCC-F / (CEQ/CSHO)
- Size: This is constructed as the natural logarithm of total assets (see above).
- Beta*Index return: This is constructed as the product of Beta and the return on the index, that is CRSP item SPRTRN. Beta itself is constructed as the correlation between the monthly index return and the monthly individual stock returns for all firms in our sample over the period 1994-2009.

Further robustness checks

As an alternative to the NBER recession indicator we have used real time recession probabilities. The results are mentioned below. The data on these recession probabilities were downloaded from http://pages.uoregon.edu/jpiger/us_recession_probs.htm.

B Online Appendix - not for publication

Discussion of the outlier dates

As explained in the text we have chosen the outlier dates as follows. First we estimate

$$\text{Return}_{\text{S\&P500},t} = \alpha + \gamma \text{Rec}_t + \beta_1 \text{Target}_t + \beta_2 \text{Path}_t + \beta_3 \text{Target}_t * \text{Rec}_t + \beta_4 \text{Path}_t * \text{Rec}_t + \epsilon_{\text{S\&P500},t}$$

Then we calculate the DFITS statistic for each observation, see Welsh and Kuh (1977). This statistic is defined as the change in the predicted value when one observation is left out the regression. This change is subsequently scaled by the estimated standard deviation at that point.

We drop observations above the cutoff value suggested by Belsley, Kuh, and Welsh (1980). Eliminating observations on the basis of statistics and subsequently using standard inference should be done cautiously. We do not necessarily want to drop observations with large residuals for example. Since the results with and without these outliers are in line with each other we are confident that we do not loose too much important information. In the next subsection we investigate alternative approaches to detect outliers.

The above procedure resulted in the following outlier dates: 1998: October 15; 2001: January 3 and April 18; 2008: January 22, 30, March 18, September 29, October 7, December 16; 2009: Januari 28, March 18. It should be noted that except the first two outlier dates, all outlier dates fall in a recession.

It may be of interest to the reader why these dates were outliers. The table below provides some details on the meeting which may shed some light on this. Further analysis of these specific meetings lies outside the scope of this study.

Table 8: Background info on the outlier meetings

Date	Details
October 15, 1998	First intermeeting move since 1994 and statement pointing to "unsettled conditions in financial markets... restraining aggregate demand" increases expectations of further easings.
Januray 3, 2001	Large surprise intermeeting ease reportedly causes financial markets to mark down probability of a recession; Fed is perceived as being "ahead of the curve" and as needing to ease less down the road as a result.
April 18, 2001	FOMC decides to lower federal funds target rate with 50 basis points. The FOMC FOMC is worried about economic slowdown and states: "As a consequence, the Committee agreed that an adjustment in the stance of policy is warranted during this extended intermeeting period."
January 22, 2008	Unplanned FOMC meeting by conference call. "To further its long-run objectives, the Committee in the immediate future seeks conditions in reserve markets consistent with reducing the federal funds rate to an average of around 3.5 percent." This was a 75 basis point cut.
January 30, 2008	This was a planned meeting only one week after an unplanned conference call. The FOMC decided to lower the target federal funds rate by an additional 50 basis points to 3 percent.
March 18, 2008	The combination of a slowing growth, inflationary pressures, and financial market disruptions encouraged the FOMC members to approve another 75 basis point cut in the federal funds rate.
September 29, 2008	This was an unplanned meeting by conference call. "In light of severe pressures in dollar funding markets abroad, the Committee unanimously approved both extending the liquidity-related swap arrangements with foreign central banks an additional three months, through April 30, 2009, and increasing substantially the sizes of those existing arrangements.
October 7, 2008	An unplanned meeting in which the FOMC decided to cut the target federal funds rate with 50 basis points.
December 16, 2008	The FOMC installs a *target range* for the federal funds rate between 0 and 25 basis points. The federal funds rate is effectively at the zero lower bound, instead of specific target the FOMC uses now a range
January 28, 2009	From the FOMC statement: " The Committee continues to anticipate that economic conditions are likely to warrant exceptionally low levels of the federal funds rate for some time." and further: "The Committee anticipates that a gradual recovery in economic activity will begin later this year, but the downside risks to that outlook are significant."
March 18, 2009	From the FOMC statement: "In these circumstances, the Federal Reserve will employ all available tools to promote economic recovery and to preserve price stability." The chairman of the Federal Reserve announced that the Fed would increase its balance sheet further by buying mortgage-backed securities and that it would purchase long-term treasury securities in the next six months.

Note: The details for the first two dates were literally taken from a discussion in Gürkaynak, Sack, and Swanson (2005). The details for the other dates come from the statements after the FOMC meetings along with readings from the financial press.

Alternative choices of outlier dates

As explained in the previous section we have determined the outlier dates by estimating a regression over the entire sample and then using the DFITS statistic. Alternative approaches could use a regression with recession dummies, estimate a regression over subsamples or use an other diagnostic statistic. We determine in this subsection outliers along these lines. The following table provides an overview:

Table 9: Overview

Sample	Recession dummy	Outlier statistic	Dates
Whole	No	DFITS	05/17/94, 10/15/98, 01/03/01, 04/18/01, 01/22/08 03/18/08, 07/24/08, 09/29/08, 10/07/08, 12/16/08, 03/18/09
Late	No	DFITS	01/22/08, 03/18/08, 09/29/08, 10/07/08, 12/16/08, 03/18/09
Late	Yes	DFITS	09/18/07, 01/22/08, 03/18/08, 09/29/08, 10/07/08, 12/16/08, 03/18/09
Whole	Yes	Cook's distance	01/22/08, 09/29/08

The resulting dates show considerable overlap, which strengthens our belief that we have taken a reasonable approach to select outlier dates. Specifically if we test for outliers using the whole sample and we do not allow for state dependence then we get somewhat more outliers not in a recession. The use of Cook's distance (a similar outlier statistic, see Cook (1979)) also leads to only two outlier dates at the end of our sample. Our choice for determining outlier dates yields dates which are mostly picked up by other procedures too. This gives us confidence that our selection of outlier dates is reasonable. In the table below, we repeat our baseline regressions with some alternative choices of outlier dates. The results are satisfying in the sense that the signs are the same for all three estimation results. In the second specification we find that the target-recession interaction term is not significant at the 10% confidence level but that does not hamper the findings in the paper.

Alternative choices of recession indicator

In the paper we have relied on the NBER recession indicator to capture changes in the business cycle. We have argued that one could also rely on a recession probability instead of a recession dummy. To do this, we estimate the following regression:

$$\begin{aligned} \text{Return} = \alpha &+ \beta_1 \text{Target}_t * (1 - \text{Rec}_t) + \beta_2 \text{Path}_t * (1 - \text{Rec}_t) \\ &+ \beta_3 \text{Target}_t * \text{Rec}_t + \beta_4 \text{Path}_t * \text{Rec}_t + \epsilon_t \end{aligned} \tag{10}$$

Table 10: Results with alternative procedures for determining outliers

	(1)	(2)	(3)
Target	-3.890***	-4.133***	-6.999***
	(-18.07)	(-18.36)	(-23.61)
Target*Rec	-14.278***	-1.033	-4.559***
	(-15.86)	(-1.28)	(-8.74)
Path	-2.052***	-1.853***	-1.901***
	(-16.14)	(-13.61)	(-12.71)
Path*Rec	17.823***	11.838***	6.150***
	(41.22)	(27.02)	(14.50) (
Influence Statistic	DFITS	DFITS	Cook
Sample	Whole	Whole	Whole
Recession dummy	Yes	No	Yes

Student t-statistics are mentioned between parentheses
* p<0.1, ** p<0.05, *** p<0.01

The table only presents the estimated coefficients and t-statistics on the variables of interest and not on the constant and the recession indicator. We omitted the FOMC meeting on September 17 2001 because of the exceptional character of this meeting in the wake of 9/11. We also omitted eleven dates marked as outliers as explained in the text.

with Rec_t the recession probability at time t. In Table 11 we show the results of estimating the above regression with real time recession probabilities obtained from a dynamic-factor markov-switching model developed in Chauvet and Piger (2008). It is clear that the results are in line with the results we presented in the paper.

Robust errors

Another concern may arise because of our choice of specification. We chose to present regression results in which we included firm fixed effects and heteroskedasticity robust standard errors. In the table below we present the results of estimating our baseline regression with alternative error constructions. For ease of reference we repeat this regression here:

$$\text{Return}_{it} = \alpha + \gamma \text{Rec}_t + \beta_1 \text{Target}_t + \beta_2 \text{Target}_t * \text{Rec}_t + \beta_3 \text{Path}_t + \beta_4 \text{Path}_t * \text{Rec}_t + \epsilon_{it}. \quad (11)$$

We estimate this regression over the entire sample and with outliers dropped. This corresponds to column 4 of Table 2 in the paper.

The table shows that the main findings of our paper are fairly robust. To ease com-

Table 11: Recession probabilities

	(1) b/t	(2) b/t	(3) b/t
Target	-3.468***	-14.079***	-2.604
	(-15.71)	(-22.93)	(-1.63)
Path	-2.271***	-2.264***	-2.898***
	(-17.26)	(-11.68)	(-2.96)
Target*Rec	-23.009***	-22.225***	-20.120***
	(-21.89)	(-10.37)	(-3.18)
Path*Rec	16.852***	18.094***	15.097***
	(31.40)	(27.19)	(5.45)
Sample	Whole	Late	Whole
Returns on	Stocks	Stocks	S&P Index

Student t-statistics are mentioned in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

This Table presents the results from estimating regression equation (10). The table only presents the estimated coefficients and t-statistics on the variables of interest and not on the constant. We omitted the FOMC meeting on September 17 2001 because of the exceptional character of this meeting in the wake of 9/11. We also omitted eleven dates marked as outliers as explained in the text. The reported t-statistics are based on heteroskedasticity robust standard errors. Firm fixed effects were included in all regression specifications.

Table 12: Alternative error construction

	(1) return b/t	(2) return b/t	(3) return b/t	(4) return b/t	(5) return b/t	(6) return b/t
Target	-3.893***	-3.893***	-3.893**	-3.961**	-3.893***	-3.961**
	(-18.09)	(-13.41)	(-2.50)	(-2.50)	(-17.23)	(-2.52)
Target*Rec	-13.102***	-13.102***	-13.102**	-13.123**	-13.102***	-13.123**
	(-14.74)	(-10.88)	(-2.24)	(-2.23)	(-15.53)	(-2.28)
Path	-2.052***	-2.052***	-2.052**	-2.055**	-2.052***	-2.055**
	(-16.14)	(-7.76)	(-2.02)	(-2.03)	(-14.94)	(-2.01)
Path*Rec	16.100***	16.100***	16.100***	16.150***	16.100***	16.150***
	(37.79)	(11.08)	(7.75)	(7.85)	(27.60)	(6.82)
Firm Fixed Effects	Yes	Yes	Yes	No	Yes	No
Cluster Level		Group	Date	Date		Group + Date
Standard Errors	Robust				Bootstrapped	

* p<0.1, ** p<0.05, *** p<0.01

This Table presents the results from estimating regression equation (11). The table only presents the estimated coefficients and t-statistics on the variables of interest and not on the constant and the recession indicator. We omitted the FOMC meeting on September 17 2001 because of the exceptional character of this meeting in the wake of 9/11. We also omitted eleven dates marked as outliers as explained in the text. The error construction is explained in the text and the bottom of the table.

parison we repeat the result from the paper in the first column (column 4 of Table 2 in the paper). In the second column we cluster the standard errors at the level of the industry group. In the third column we cluster the standard errors at the date level. In the fourth column we do the same but now we drop the firm fixed effects. In the fifth column we present bootstrapped errors with firm fixed effects. In the last column we present two way clustered errors.

Subsamples

Here we re-estimate some regressions we presented in the paper but we change the sample. We distinguish two subsamples. The *early* subsample ends at the introduction of forward-looking statements and contains all observations from the original sample up to and including July 2003. The *late* subsample starts in August 2003. In Table 13, the baseline regression are re-estimated over both subsamples. For both subsamples we present the baseline regression with three different error specifications in the spirit of what we have done above. In Table 14 we estimate for both samples the regression on the industry effects and one of our firm effects regressions. The results suggest that the patterns we showed in the data are valid in both subsamples but more so on the late subsample. The demand channel effects as found in the paper are not as clear for the early sample and we find a low t-statistic for the *Path-Rec-Cycl* interaction.

Table 13: Subsample regressions

Target	-2.934***	-2.969**	-2.934***	-14.250***	-14.232***	-14.250***
	(-13.00)	(-2.10)	(-16.34)	(-25.45)	(-3.06)	(-28.79)
Target*Rec	-11.355***	-11.369**	-11.355***	-3.785*	-3.802	-3.785**
	(-12.16)	(-2.28)	(-11.87)	(-1.91)	(-0.36)	(-1.99)
Path	-1.452***	-1.424	-1.452***	-2.709***	-2.698	-2.709***
	(-8.76)	(-1.19)	(-7.68)	(-14.84)	(-1.45)	(-13.07)
Path*Rec	8.299***	8.278***	8.299***	18.394***	18.405***	18.394***
	(10.65)	(2.82)	(10.75)	(36.20)	(5.81)	(22.63)
Subsample	Early	Early	Early	Late	Late	Late
Errors	Robust	Group + Date	Bootstrap	Robust	Group + Date	Bootstrap
Firm fixed effects	Yes	No	Yes	Yes	No	Yes

Student t-statistics in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

The table only presents the estimated coefficients and t-statistics on the variables of interest and not on the constant and the recession indicator. We omitted the FOMC meeting on September 17 2001 because of the exceptional character of this meeting in the wake of 9/11. We also omitted eleven dates marked as outliers as explained in the text.

Nonlinearities

Here we show another specification then we have used in the paper. The regression we estimate is the following:

$$\begin{aligned}\text{Return}_{it} = {} & \alpha + \gamma \text{Rec}_t + \beta_1 \text{Target}_t + \beta_2 \text{Path}_t + \beta_3 \text{Target}_t * \text{Rec}_t + \beta_4 \text{Path}_t * \text{Rec}_t \\ & + \beta_5 \text{Target}_t * \text{High}_{it} + \beta_6 \text{Path}_t * \text{High}_{it} + \beta_7 \text{Target}_t * \text{Rec}_t * \text{High}_{it} \\ & + \beta_8 \text{Path}_t * \text{Rec}_t * \text{High}_{it} + \beta_9 \text{Target}_t * \text{Low}_{it} \\ & + \beta_{10} \text{Path}_t * \text{Low}_{it} + \beta_{11} \text{Target}_t * \text{Rec}_t * \text{Low}_{it} \\ & + \beta_{12} \text{Path}_t * \text{Rec}_t * \text{Low}_{it} + \sum_{j=1}^{3} \delta_j \text{Control}_{j,it} + \epsilon_{it}. \end{aligned} \tag{12}$$

In this model *High* means that the firm belongs to the top quintile in the cross-section of the firm characteristic (see also the paper), *low* means that the firm belongs to the bottom quintile. Note that in the paper we construct our ternary indicator such that the coefficient could be interpreted as the jump from non-constrained to constrained. Here

Table 14: Subsample regressions

Target	-6.603***	-2.947***	-11.520***	-11.990***
	(-16.00)	(-8.75)	(-15.85)	(-17.21)
Target*Rec	-4.195***	-12.237***	-7.898***	-5.073**
	(-5.29)	(-8.19)	(-3.51)	(-2.20)
Path	-1.054***	-1.616***	-2.146***	-1.824***
	(-4.12)	(-6.76)	(-8.54)	(-6.76)
Path*Rec	7.872***	8.779***	15.802***	13.530***
	(7.55)	(6.77)	(26.24)	(22.79)
Target*Firm	-5.516***		0.033	
	(-4.12)		(0.02)	
Path*Firm	2.311***		-1.219	
	(2.80)		(-1.46)	
Target*Rec*Firm	-0.387		-10.755	
	(-0.14)		(-1.45)	
Path*Rec*Firm	9.971***		5.242**	
	(2.62)		(2.32)	
size	0.155**		-0.103	
	(2.05)		(-1.14)	
marketbook	-0.001		-0.001	
	(-0.28)		(-1.03)	
betasprtrn	5.829***		7.403***	
	(5.31)		(4.54)	
targetcycl		-1.948*		-13.248***
		(-1.85)		(-4.51)
targetnbercycl		-1.941		-6.419
		(-0.49)		(-0.68)
pathcycl		-2.337***		-0.907
		(-3.65)		(-0.92)
pathnbercycl		3.272		12.643***
		(1.03)		(6.14)
Subsample	Early	Early	Late	Late

Student t-statistics in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

The table only presents the estimated coefficients and t-statistics on the variables of interest and not on the constant and the recession indicator. We omitted the FOMC meeting on September 17 2001 because of the exceptional character of this meeting in the wake of 9/11. We also omitted eleven dates marked as outliers as explained in the text.

High and *Low* are just dummy variables indicating that a firm belongs to the top or bottom of the cross-sectional distribution (on an event date by event date basis as in the paper). Careful inspection shows that the results of this model, presented in Table 15, are in lign with what we presented in the paper. Moreover we can see which part of the distribution is meaningful. Noteworthy for the paper is the result when we use the *debt-to-assets* ratio and look at the interaction with *Path*Rec*. As Ehrmann and Fratzscher (2004) we find that it are the extremes i.e. companies with high or low debt, that are more responsive to monetary policy.

Table 15: Flexible specification

	Debt to Assets	Employees	Total Assets	Cash flow to net income	Return on Equity	Trade Credit
Target	-3.903***	-3.824***	-3.727***	-3.582***	-3.135***	-3.763***
	(-10.06)	(-9.02)	(-9.27)	(-9.03)	(-8.63)	(-8.90)
Target*Rec	-11.250***	-11.700***	-14.451***	-11.154***	-11.593***	-12.115***
	(-8.43)	(-8.46)	(-9.71)	(-7.79)	(-8.40)	(-8.74)
Path	-1.648***	-1.869***	-1.992***	-1.705***	-2.101***	-1.885***
	(-8.09)	(-8.49)	(-9.12)	(-8.34)	(-10.88)	(-8.39)
Path*Rec	12.674***	13.106***	14.906***	12.799***	12.618***	12.953***
	(23.02)	(22.87)	(22.55)	(20.17)	(21.98)	(20.29)
Target*High	0.356	1.103	0.838	0.053	-0.894	0.253
	(0.55)	(1.62)	(1.31)	(0.08)	(-1.08)	(0.37)
Target*Rec*High	-1.652	0.203	3.006	-1.037	-1.736	-4.255
	(-0.58)	(0.08)	(1.18)	(-0.39)	(-0.66)	(-1.43)
Path*High	-0.864**	-0.039	0.309	-0.398	0.056	-0.450
	(-2.34)	(-0.10)	(0.81)	(-1.10)	(0.12)	(-1.01)
Path*Rec*High	3.538**	0.022	-3.133***	-1.038	-0.227	5.562***
	(2.51)	(0.02)	(-2.80)	(-0.96)	(-0.19)	(4.01)
Target*Low	0.826	-0.297	-0.559	-0.341	-1.781**	0.281
	(1.03)	(-0.42)	(-0.68)	(-0.41)	(-2.35)	(0.39)
Target*Rec*Low	-6.471**	-6.186*	4.957	-6.942**	-4.639	0.570
	(-1.98)	(-1.75)	(1.59)	(-2.21)	(-1.40)	(0.19)
Path*Low	-0.383	-0.087	0.151	-0.486	0.967*	0.359
	(-0.70)	(-0.19)	(0.32)	(-0.86)	(1.94)	(0.88)
Path*Rec*Low	4.135***	5.629***	-0.327	7.960***	8.255***	0.484
	(2.70)	(3.29)	(-0.22)	(5.23)	(5.18)	(0.37)

Student t-statistics in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

The table only presents the estimated coefficients and t-statistics on the variables of interest and not on the constant, the recession indicator and the control variables. We omitted the FOMC meeting on September 17 2001 because of the exceptional character of this meeting in the wake of 9/11. We also omitted eleven dates marked as outliers as explained in the text.

References

AMMER, J., C. VEGA, AND J. WONGSWAN (2010): "International Transmission of U.S. Monetary Policy Shocks: Evidence from Stock Prices," *Journal of Money, Credit and Banking*, 42(s1), 179–198.

BASISTHA, A., AND A. KUROV (2008): "Macroeconomic cycles and the stock market's reaction to monetary policy," *Journal of Banking & Finance*, 32(12), 2606–2616.

BELSLEY, D., E. KUH, AND R. WELSH (1980): *Regression Diagnostics: Identifying Influential Data and Sources of Collinearity.* Wiley, New York.

BERNANKE, B., AND M. GERTLER (1989): "Agency Costs, Net Worth, and Business Fluctuations," *American Economic Review*, 79(1), 14–31.

BERNANKE, B. S., AND K. N. KUTTNER (2005): "What Explains the Stock Market's Reaction to Federal Reserve Policy?," *Journal of Finance*, 60(3), 1221–1257.

BERNANKE, B. S., AND V. R. REINHART (2004): "Conducting Monetary Policy at Very Low Short-Term Interest Rates," *American Economic Review*, 94(2), 85–90.

BLINDER, A. (2009): "Talking about monetary policy: the virtues (and vice?) of central bank communication," BIS Working Papers 274, Bank for International Settlements.

BLINDER, A. S., M. EHRMANN, M. FRATZSCHER, J. DE HAAN, AND D.-J. JANSEN (2008): "Central Bank Communication and Monetary Policy: A Survey of Theory and Evidence," *Journal of Economic Literature*, 46(4), 910–45.

BOUDOUKH, J., M. RICHARDSON, AND R. F. WHITELAW (1994): "Industry Returns and the Fisher Effect," *Journal of Finance*, 49(5), 1595–1615.

BOYD, J. H., J. HU, AND R. JAGANNATHAN (2005): "The Stock Market's Reaction to Unemployment News: Why Bad News Is Usually Good for Stocks," *Journal of Finance*, 60(2), 649–672.

Brand, C., D. Buncic, and J. Turunen (2010): "The Impact of ECB Monetary Policy Decisions and Communication on the Yield Curve," *Journal of the European Economic Association*, 8(6), 1266–1298.

Chauvet, M., and J. Piger (2008): "A Comparison of the Real-Time Performance of Business Cycle Dating Methods," *Journal of Business & Economic Statistics*, 26, 42–49.

Cochrane, J., and M. Piazzesi (2002): "The Fed and Interest Rates - A High-Frequency Identification," *American Economic Review*, 92(2), 90–95.

Cook, D. (1979): "Influential observations in linear regression," *Journal of the American Statistical Association*, 74, 169–174.

Cook, T., and T. Hahn (1989): "The effect of changes in the federal funds rate target on market interest rates in the 1970s," *Journal of Monetary Economics*, 24(3), 331–351.

Cragg, J. G., and S. G. Donald (1997): "Inferring the rank of a matrix.," *Journal of Econometrics*, 76, 223–250.

D'Amico, S., and M. Farka (2011): "The Fed and the Stock Market: An Identification Based on Intraday Futures Data," *Journal of Business & Economic Statistics*, 29(1), 126–137.

de Haan, J., S. Eijffinger, and S. Waller (2005): *The European Central Bank: Credibility, Transparency and Centralization*, CESifo Book Series. The MIT Press.

Ehrmann, M., and M. Fratzscher (2004): "Taking stock: monetary policy transmission to equity markets," *Journal of Money, Credit and Banking*, 36(4).

Fama, E. F., and K. R. French (1992): "The Cross-Section of Expected Stock Returns," *Journal of Finance*, 47(2), 427–65.

Fender, I., B. Hayo, and M. Neuenkirch (2011): "Monetary policy spillovers and emerging market credit: The impact of Federal Reserve communications on sovereign CDS spreads," Discussion paper.

Fratzscher, M. (2008a): "Communication and exchange rate policy," *Journal of Macroeconomics*, 30(4), 1651–1672.

——— (2008b): "Oral Interventions Versus Actual Interventions in Fx Markets - An Event-Study Approach," *Economic Journal*, 118(530), 1079–1106.

Gelman, A., and D. K. Park (2008): "Splitting a Predictor at the Upper Quarter or Third and the Lower Quarter or Third," *The American Statistician*, 62.

Gertler, M., and S. Gilchrist (1994): "Monetary Policy, Business Cycles, and the Behavior of Small Manufacturing Firms," *The Quarterly Journal of Economics*, 109(2), 309–40.

Gürkaynak, R. S., B. Sack, and E. Swanson (2005): "Do Actions Speak Louder Than Words? The Response of Asset Prices to Monetary Policy Actions and Statements," *International Journal of Central Banking*, 1(1).

Gürkaynak, R. S., B. T. Sack, and E. P. Swanson (2007): "Market-Based Measures of Monetary Policy Expectations," *Journal of Business & Economic Statistics*, 25, 201–212.

Hausman, J., and J. Wongswan (2011): "Global asset prices and FOMC announcements," *Journal of International Money and Finance*, 30(3), 547–571.

Hayo, B., A. M. Kutan, and M. Neuenkirch (2011): "Communication Matters: U.S. Monetary Policy and Commodity Price Volatility," Discussion paper.

Hayo, B., and B. Uhlenbrock (2000): "Industry Effects of Monetary Policy in Germany," *Regional Aspects of Monetary Policy in Europe, Boston: Kluwer,J. von Hagen and C.J. Waller (eds.)*, (127-158).

Kaplan, S. N., and L. Zingales (1997): "Do Investment-Cash Flow Sensitivities Provide Useful Measures of Financing Constraints," *The Quarterly Journal of Economics*, 112(1), 169–215.

Karagedikli, O., and P. L. Siklos (2008): "Explaining Movements in the NZ Dollar - Central Bank Communication and the Surprise Element in Monetary Policy?," Reserve Bank of New Zealand Discussion Paper Series DP2008/02, Reserve Bank of New Zealand.

Kurov, A. (2010): "Investor sentiment and the stock market's reaction to monetary policy," *Journal of Banking and Finance*, 34, 139–149.

Kuttner, K. N. (2001): "Monetary policy surprises and interest rates: Evidence from the Fed funds futures market," *Journal of Monetary Economics*, 47(3), 523–544.

Kwan, S. (2007): "On forecasting future monetary policy: has forward-looking language mattered?," *FRBSF Economic Letter*, (Jun 15), 2007–15.

Laeven, L., and H. Tong (2010): "U.S. Monetary Shocks and Global Stock Prices," IMF Working Papers 10/278, International Monetary Fund.

——— (2012): "US monetary shocks and global stock prices," *Journal of Financial Intermediation*, 21(3), 530 – 547.

Lamont, O., C. Polk, and J. Saa-Requejo (2001): "Financial Constraints and Stock Returns," *Review of Financial Studies*, 14(2), 529–54.

Nilsen, J. H. (2002): "Trade Credit and the Bank Lending Channel," *Journal of Money, Credit and Banking*, 34(1), 226–53.

Peersman, G., and F. Smets (2005): "The Industry Effects of Monetary Policy in the Euro Area," *Economic Journal*, 115(503), 319–342.

Perez-Quiros, G., and A. Timmermann (2000): "Firm Size and Cyclical Variations in Stock Returns," *Journal of Finance*, 55(3), 1229–1262.

Petersen, M. A. (2009): "Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches," *Review of Financial Studies*, 22(1), 435–480.

Piazzesi, M., and E. T. Swanson (2008): "Futures prices as risk-adjusted forecasts of monetary policy," *Journal of Monetary Economics*, 55(4), 677–691.

Rigobon, R., and B. Sack (2004): "The impact of monetary policy on asset prices," *Journal of Monetary Economics*, 51(8), 1553–1575.

Romer, C. D., and D. H. Romer (2000): "Federal Reserve Information and the Behavior of Interest Rates," *American Economic Review*, 90(3), 429–457.

Swanson, E. T. (2006): "Have Increases in Federal Reserve Transparency Improved Private Sector Interest Rate Forecasts?," *Journal of Money, Credit and Banking*, 38(3), 791–819.

Thorbecke, W. (1997): "On Stock Market Returns and Monetary Policy," *Journal of Finance*, 52(2), 635–54.

Welsh, R., and E. Kuh (1977): "Linear regression diagnostics.," Discussion paper.

Wongswan, J. (2009): "The response of global equity indexes to U.S. monetary policy announcements," *Journal of International Money and Finance*, 28(2), 344–365.

Woodford, M. (2005): "Central bank communication and policy effectiveness," *The Greenspan era: Lessons for the future - the Jackson Hole Symposium, 2005.*

——— (2012): "Methods of policy accomodation at the Interest-Rate Lower Bound," *The changing policy landscape - the Jackson Hole Symposium, 2012.*

Yellen, J. L. (2006): "Enhancing Fed credibility," *FRBSF Economic Letter*, (Mar 17), 2006–05.