Stockholm School of Economics

Master of Science in Finance

The effect of monetary policy on stock price prediction

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Abstract

This paper examines the effects of U.S. monetary policy announcements in the aftermath of the subprime crisis on financial analysts' ability to predict stock prices. We study such effects, if any, using Bloomberg data on equity analyst 12-month target prices and subsequent realized stock prices. We perform event studies to test whether predictability changed as a result of policy announcements. The monetary policy event dates are chosen based on the surprise effect they had on the markets. Our results show a lower stock predictability than normal during policy announcements. However, when taking into account the general volatility of analyst's predictability this abnormal effect is quite small. Hence, we cannot conclude anything precise as to whether central bankers' pervasive presence in financial markets has an unprecedented impact on equity analysts' ability to predict stock prices.

1. Introduction

Financial research analysts have an important role in financial markets. They guide investors by giving recommendations on what securities to invest in and what to avoid. For equities these recommendations are usually labeled as *Buy, Sell* or *Hold.* In combination with the recommendation, most analyst reports also include a specific *price objective* or *price target*. The *price target* indicates the potential upside or downside potential if an investor would follow the analyst's advice. When a recommendation is issued it tends to attract attention in the markets and impact the price of financial assets as market participants factor in the newly released information and analysis into their assessment of the fair price. (see, e.g. Womack, 1996; Brav and Lehavy, 2003; Lin et al., 2016). This despite that the accuracy of most analysts' recommendations have shown to be far from perfect (see, e.g., Asquith et al., 2005; Bonini et. al, 2010). In addition to assisting the investment community, analyst coverage of equity securities helps companies to raise money by reducing the knowledge gap between investors and issuers. Studies have also shown that analyst coverage improves informational efficiency and thus makes a stock more liquid, and as a consequence *required return* may fall (Amihud and Mendelson, 1986).

What grabbed our interest were comments from various managers on the difficulty of making strategic investment decisions in markets that to a large extent recently have been driven by the monetary policy decisions of central banks.[1] As it has been shown in previous research that fund managers tend to listen to financial analyst recommendations and forecasts (see, e.g., Brav and Lehavy, 2003; Lin et al., 2016) we wanted to investigate if analysts' ability to correctly recommend stocks changes as a result of central bank intervention. Bear in mind that after the subprime crisis, central banks around the world have very actively supported the economy through low interest rates and various quantitative easing efforts (see, e.g., Blinder, 2010; Reis, 2010; Krishnamurthy and Vissing-Jorgensen, 2011; Joyce, Lasaosa, Stevens, and Tong, 2011). These policy decisions have been the focus of market participants and their outcomes have had a key impact on the pricing of financial assets. The effect of monetary policy decisions on financial markets has already been discussed, for example, by Bernanke and Kuttner (2005) and Basistha and Kurov (2008). Our

[1] Dan Loeb, Jay Polesky. www.politco.eu. Patrik Brummer www.brummer.se. New York Times (May 5, 2015). "Hedge Fund Investing: A practical approach to understanding Investor Motivation, Maneger Profits, and Fund Performance.

goal is to contribute to this literature by analyzing the implications of central bankers' interventionism in financial markets on equity analyst's prediction accuracy, defined as *predictability*. The key question is: has central bank intervention in financial markets made it more difficult, or easier for financial analysts to forecast stock prices.

To investigate this question, we perform event studies during eight unexcepted monetary policy announcements by the U.S. Federal Reserve (henceforth, Fed) between the years 2008 and 2016. In our view, a better understanding of the effects of monetary policy decisions on analyst *predictability* should help investors to evaluate how much confidence they should have in analyst recommendations during periods which are highly influenced by monetary policy decisions and central bank interventions. We would expect monetary policy announcements to result in lower prediction accuracy, as it has been documented that unexpected monetary policy decisions have strong and consistent effects on the stock markets and volatility (see, e.g., Bernanke and Kuttner, 2005). Equity analysts tend to focus on the fundamentals of the company they are analyzing. Hence, we would not expect them to properly incorporate unexpected, macro-driving, monetary policy announcements in their price target forecast.

Our results show that on average abnormal, event-driven *predictability* is 0.0943, indicating lower stock predictability than normal. Of the eight monetary policy events we investigate, five show positive values while three show negative ones. However, two of the three negative ones are close to zero, implying no change in predictability. The exception is the 9th of August 2011, when the Federal Open Market Committee (FOMC) guided for exceptionally low rates at least through mid-2013. Although our results would support the argument that unexpected central bank intervention makes it more difficult to predict stock, when looking at the scale of the change in *predictability* it is quite small. The *abnormal predictability* value 0.0943 is small and should be compared with the normal standard deviation of our *predictability* variable of 0.2285. This indicates that although there appears to be some effect from monetary policy announcements on analyst's predictability there seems to be several other factors that alter this ability through our sample period. Hence, we cannot conclude that central bankers' high interventionism in financial markets during and in the aftermath of the Great Financial Crisis had an unprecedented effect on equity analysts' ability to predict stocks prices.

2. Literature Review

This section reviews the literature related to factors determining stock price prediction accuracy and the effect of monetary policy on financial markets. Because the literature explicitly discussing the impact of monetary policy announcements on stock price predictability is very limited, we choose to divide the literature review into two parts. The first one presents the literature on equity financial analysts' ability to predict stock prices, where much of the research has focused on the impact of financial analysts on stock prices but also the accuracy of their predictions. The second part of the literature review covers the effects of monetary policy on financial markets. Here we emphasize studies of how changes in monetary policy transmit to the pricing of equities.

2.1 Equity analyst predictability

As stock prices are a function of supply and demand for specific equities, and sell-side[2] financial analysts don't tent to trade securities themselves, a necessity is that investors listen to their recommendations. There have been several studies on this topic. Womack (1996) looks at the impact of financial analyst's recommendations (i.e *Buy, Sell* and *Hold*) and shows that shares tend to rise following analyst upgrades and to drop when analysts lower their ratings. Our study does not look at recommendation ratings but rather analysts' 12-month *price targets,* as we believe it allows for a more precise way to measure analyst accuracy. Here Lin et al. (2016) have found that institutions trade in the same direction as *price target* changes based on 6,415 U.S. firms from 1999 to 2011, even after controlling changes in stock recommendations and earnings forecasts. Further, using a large database of analysts' target prices issued over the period 1997–1999, Brav and Lehavy (2003) examined short-term market reactions to target price revisions and long-term co-movement of target and stock prices. They find a significant market reaction to the information contained in analysts' target prices. Also, using a cointegration approach, Brav and Lehavy analyze the long-term behavior of the market and target prices. They find that, on average, the one-year-ahead target price is 28 percent higher than the current market price.

When it comes to the forecasting accuracy of financial analysts, Bonini et. Al (2010) argue that it is very limited: prediction errors are consistent, auto-correlated, non-mean reverting and large (up to 36.6 percent). Also, they find that the size of forecasting errors increases

[2] Sell side refers to a Research firm. Often part of a large brockerage frim or investment bank. They provide financial reccomendation to institutional investor referred to the "Buy side".

with the predicted growth in the stock price, the size of the company, and for loss making firms. Additionally, the intensity of research and the market momentum negatively affect accuracy. There have also been studies on analyst predictability specifically during financial crisis'. Loh and Mian (2003) document that the quality of earnings estimates for analysts in Singapore was worst for the time around the Asian crisis in the years 1997 and 1998. Further, Sidhu and Tan (2011) demonstrate that analysts' ability to forecast developments of U.S. and Australian stocks worsened during the most recent financial crisis in 2008. Similar results were reported by Arand and Kerl (2012), who documented a decline in analysts' accuracy during the crisis.

2.2 Monetary policy's effect on financial markets

Bernanke and Kuttner (2005) document that unexpected monetary policy decisions have strong and consistent effects on the stock market. That is that stock markets tend to increase/decrease as a results Fed announcement and this is a pattern that recurs with different policy announcements. They find that the cause of the effect is not the impact of monetary policy on real interest rates but rather its impact on expected future excess returns or expected future dividends. Basistha and Kurov (2008) study stock market reactions to monetary policy announcement during different macroeconomic cycles. They find a stronger stock market response to unexpected changes in the Federal funds target rate during recessions and in tight credit market conditions. These findings support the notion that unexpected policy announcements should affect the worsen the *predictability* for stocks. Kuttner (2001) examines the effect of changes in Fed policy on market interest rates and finds a strong relationship for unexpected policy actions but that there is little response by markets to anticipated actions. Edelberg and Marshall (1996) use a vector autoregression (VAR) model to estimate the effects of monetary policy shocks on bond yields. They find that there is a substantial impact on one-month bond yields while the response of longer-term bonds is much weaker. In addition, the study finds no deviations from this general pattern during the Asian financial crisis of 1994.

Other studies have researched the effects that monetary policy has on market volatility. An example is Chen and Clements (2007) who find that the VIX index, which is computed based on implied volatility in the market, falls significantly on the day of Federal Open Market Committee (FOMC) meetings. Bomfim (2003), on the other hand discusses how U.S. equity volatility responds to surprises in monetary policy decisions and shows that they tend to boost equity volatility significantly in the short term. In addition, the paper presents that positive surprises, which is defined as a higher federal funds rate than expected, tend to increase volatility more than negative ones. In our study we would expect higher systematic volatility, to have a negative effect on *predictability.* Hence, not volatility that is firm-specific.

3. Method

This section gives a detailed description of the methods we use to examine the impact of monetary policy announcements on equity analysts' ability to predict future stock prices. We begin by estimating the accuracy of prediction through time and presenting the monetary policy announcement dates we choose to investigate. Then, we perform an event study to assess whether there is a change in predictability as a result of policy announcements.

3.1 Estimating analyst predictability

Analyst accuracy or *predictability* is defined as the risk adjusted difference between the forecasted and realized price for each SP500 stock *i*:

$$z_{i,t} = \frac{E(price_{i,t-12}) - price_{i,t}}{s_i}, \qquad (1)$$

where $z_{i,t}$ denotes the risk-adjusted deviation for each stock *i* at month *t* and $E(price_{i,t-12})$ is the average analyst *price target* 12 months prior. $price_{i,t}$ represents the actual realized price and s_i is the sample standard deviation of the stock, based on the last twelve months. The rationale for adjusting for risk is that it tends to be more difficult to forecast the exact price for riskier, more volatile stocks. We then proceed by averaging the absolute values of $z_{i,t}$ as we are interested in the variation of *predictability* and not the specific sign of the deviation:

$$\hat{z}_t = \frac{\sum | z_{i,t} |}{n}, \qquad (2)$$

where $\hat{z}_t$ denotes the average *predictability* at time *t.* A low value indicates *high* predictability while a high value means *low* predictability*.* It is this time-series of $\hat{z}_t$ that we analyze to try to determine if there is indeed an impact from monetary policy announcements on price *predictability*.

3.2 Monetary policy announcement dates selection

The specific policy announcement dates we choose to examine are those which had a high surprise effect on the markets. The rationale being that unexpected policy decisions are more likely to move markets and hence impact the accuracy of predictions than anticipated ones (Kuttner, 2001). This selection is based on an analysis on the surprise effect of Fed policy decisions on the markets prepared by Goldman Sachs Global Investment Research (2016). In total we select eight Fed announcement dates from the start of the Great Financial Crisis in 2007 until 2016, all with a big surprise effect on the markets. The first date we choose to analyze is the 24th of November 2008, when the Fed unveiled its $800 billion plan to encourage lending and housing. This is commonly referred to as quantitative easing one or "QE 1". The second date is the 18th of March 2009, when the Fed announced it would buy $300 billion in long-term Treasury bonds to help to halt the negative move in the U.S. economy. This led to a sharp increase in U.S. stock indices and gold prices. In addition, U.S. Treasury yields decreased by amounts not seen in decades. The third date is the 3rd of November 2010, when they said that they would buy an additional $600 billion long-term Treasury bonds. This was called "QE 2" and the effect was once again a sharp increase in stock markets. The fourth date of investigation is the 9th of August 2011, when the Federal Open Market Committee (FOMC) announced that it "currently anticipates that economic conditions—including low rates of resource utilization and a subdued outlook for inflation over the medium run—are likely to warrant exceptionally low levels for the federal funds rate at least through mid-2013." This was the first time the FOMC gave forward guidance of the future policy rate path including a specific date (Raskin, 2013). The fifth announcement is the 19th of June 2013. On this date Fed Chairman Ben Bernanke said that the Fed might reduce its bond purchase program later in the year, contingent on the economic outlook. The news led to a decrease in stock prices and a jump in the U.S. 10-year Treasury yield. The sixth date is just three months later, on September 18th, when Bernanke announced that the Fed has decided not to taper and instead to keep the bond buying program at current levels. The decision surprised markets and sent both the S&P500 and Dow Jones indices to record highs. The seventh date is the 15th of March 2015, when the Fed released a lower so-called "dot plot" which presents each FOMC member's expectations of the future Fed key rate. The effect of the lower "dots" was a sharp decrease in the U.S. dollar as markets adjusted themselves to a lower rate outlook. The eighth and final date in our analysis is the 16th of March 2016, when the FOMC members once again surprised markets by lowering their predictions of the future Fed key rate path.

3.3 Event study

To analyze the impact of monetary policy announcements on stock price predictability we perform event studies for our time-series of *predictability*. For each policy announcement the event window is set to include the month prior to the announcement, the month of the announcement, as well as the month after. By doing this we can capture both anticipatory and lagged effects that the monetary policy decisions may have on stock prices and as a result *predictability*. The estimation window is defined as the *predictability* 12 months before the event window, excluding any preceding event months in the time series. Abnormal, event-driven, *predictability* is calculated as:

$$\hat{z}_{abnormal} = \hat{z}_{event} - \hat{z}_{estimation}, \tag{3}$$

where $\hat{z}_{event}$ is the average *predictability* in the event window and $\hat{z}_{estimation}$ is the average *predictability* in the estimation window. As a reminder, the actual forecast that is assessed is always done 12 months before the realized price at each time *t,* both for the observations in the estimation and event widows. The logic is that *abnormal predictability* should be the residual value after adjusting for *normal predictability*. An issue with this method is that we assume that the monetary policy effect only last for three months when it might be the case that the impact has a prolonged effect on stock prices and hence forecast accuracy.

4. Data

This section describes and motivates the variables used in our analysis and the databases they were retrieved from. Our dataset consists of monthly Bloomberg prices and analyst *price targets*. It stretches from March 2005 until December 2016, with 142 months is total. In addition, to determine which specific monetary policy announcements to analyze we use a study by Goldman Sachs Global Investment Research[3] (2016) on the surprise effect of Federal Reserve announcements.

[3] http://www.bloomberg.com/news/articles/2016-03-18/goldman-sachs-this-was-one-of-the-most-dovish-fed-decisions-of-the-21st-century

4.1 Bloomberg analyst price targets and stock prices

We collect monthly stock prices from Bloomberg for all stocks included in the SP500 equity index. We also gather Bloomberg data on 12-month equity analyst *price targets* for each members of the index. These *price targets* are based on what sell-side analysts have submitted to the Bloomberg database. Hence, the number of observations vary depending on the specific stock, where higher market cap stocks tend to have more observations as more financial analysts cover them. These *price targets* are collected on a rolling basis, hence for each month *t* we retrieve the current 12-month average *price target* for the specific stocks.

4.2 Goldman Sachs study on surprise effect of Federal Reserve announcements

The monetary policy announcements we select in our study are U.S. Federal Reserve announcements from the start of the Great Financial Crisis to the end of our data set, December 2016. Within the time range, the specific announcements examined are chosen based on their surprise effect on the markets. To identify which announcement where truly unexpected we use an analysis on the surprise factor of different Fed announcements provided by Goldman Sachs Global Investment Research (2016). The study examines the correlation of 18 different market variables and the change in those variables on days of Fed policy announcements. Large moves in the variables indicate a high surprise factor.

5. Results

This section presents and discusses our results from our study. Sample statistics are presented in Table 1. Here we find that the mean *predictability* is 1.8250 indicating that realized stock prices on average are 1.8250 standard deviations from the consensus forecasted *price target* 12 month earlier. To investigate if the *predictability* is affected by monetary policy announcements we perform event studies to see if there is any deviation from the *normal predictability* level during these dates.

Table 2 presents our results from the event studies where we test for *abnormal*, event-driven, *predictability* coinciding with monetary policy announcements. As each of the eight event dates consist of three monthly observations we end up with 24 *abnormal predictability* observations in total. Specifically, the table shows the mean *abnormal predictability* for each event as well the mean of all the 24 event months.

The first event is QE 1, the 24th of November 2008, when the Fed unveiled its $800 billion plan to encourage lending and housing. Here the mean *abnormal predictability* is 0.2986, above one standard deviation from the average *predictability*. The second date is the 18th of March 2009, when the Fed announced it would buy $300 billion in long-term Treasury bonds to help to halt the negative move in the U.S. economy. Here the mean *abnormal predictability* is less, 0.1375. The third date is the 3rd of November 2010, when the Fed said that it would buy an additional $600 billion long-term Treasury bonds. This time *abnormal predictability* was 0.1763. The fourth date of investigation is the 9th of August 2011, when the Federal Open Market Committee (FOMC) guided for exceptionally low rates at least through mid-2013. Here *abnormal predictability* is negative -0.2225, indicating that predictability increased during this event. The fifth announcement is the 19th of June 2013 when Fed Chairman Ben Bernanke said that the Fed might reduce its bond purchase program later in the year, contingent on the economic outlook. Here *abnormal predictability* was slightly positive, 0.1092. The sixth date is just three months later, on September 18th, when Bernanke announced that the Fed has decided not to taper and instead to keep the bond buying program at current levels. Once again *abnormal predictability* was positive, 0.3499, indicating that it was more difficult to predict stock prices. The seventh date is the 15th of March 2015, when the Fed released a lower so-called “dot plot” which presents each FOMC member’s expectations of the future Fed key rate. This time *predictability* was basically unaffected with an *abnormal predictability* value of -0.1020. We noticed the same for the eighth and final date in our analysis, the 16th of March 2016, with a value of -0.1025. This was the date when the FOMC members once again surprised markets by lowering their predictions of the future Fed key rate path. Although five of the eight events indicate lower accuracy the economic scale of the effect is quite small. The mean *abnormal predictability* 0.0943 should be compared with the normal standard deviation of our *predictability* variable of 0.2285. In addition, statistical significance is also not high with a z-stat of 0.36.

6. Conclusions

In this paper we analyze the effect of unexpected monetary policy announcements on financial analysts’ predictability. The *predictability* variable is defined as the absolute deviation between financial analysts’ 12-month *price targets* for different stocks versus realized prices, controlling for the volatility of each individual stock. This data is provided by

Bloomberg. We find that the mean *predictability* is 1.8250, indicating that realized stock prices on average are 1.8250 standard deviations from the analyst consensus *price target* 12 months earlier. To investigate the potential effect of monetary policy on stock predictability we perform an event study on the change in *predictability* within a three-month event window around eight monetary police announcements. These announcements are chosen based on the surprise effect they had on the markets. The change in *predictability* is defined as *abnormal predictability*. Here our results show that on average *abnormal predictability* is 0.0943, indicating lower stock predictability than normal. Of the eight events, five show positive values while three show negative ones. However, two of the three negative ones are close to zero, implying no change in predictability. The exception was the 9th of August 2011, when the Federal Open Market Committee (FOMC) guided for exceptionally low rates at least through mid-2013. However, when looking at the scale of the change in predictability it is quite small. 0.0943 to be compared with the normal standard deviation of our *predictability* variable of 0.2285. This indicates that although there seems to be some effect from monetary policy announcements on analyst's predictability there appears to be several other factors that alter this ability through our sample period. Hence, we cannot conclude that central bankers' high interventionism in financial markets during and in the aftermath of the Great Financial Crisis had an unprecedented effect on equity analysts' ability to predict stocks.

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Figure 1
Monthly predictability vs. monetary policy announcements

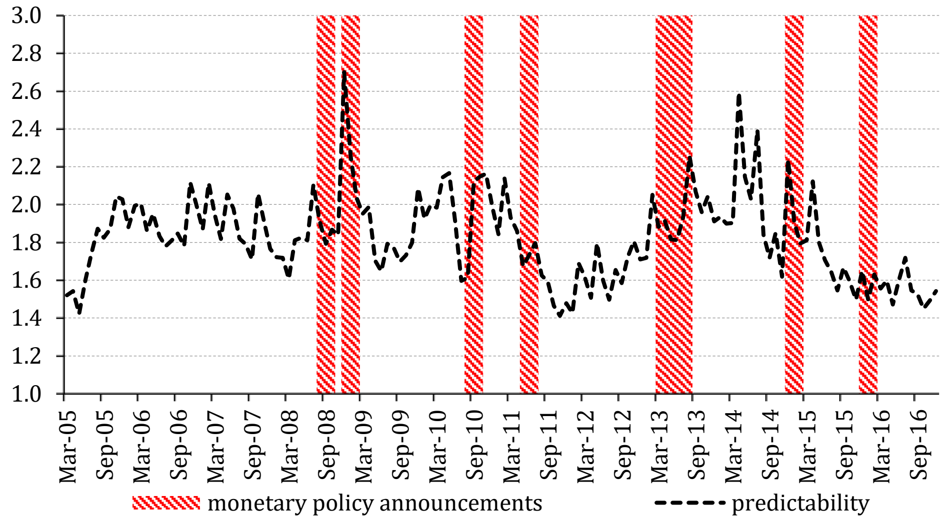

Table 1
Sample statistics predictability variable

Sample months:	2005-03 – 2016-12
Observations	142
Mean	1.8250
Median	1.8114
Standard Deviation	0.2285

Table 2
Event study results: Abnormal predictability

Sample months:	2005-03 – 2016-12
Event dates:	2008-11, 2009-03, 2010-11, 2011-08, 2013-06, 2013-09, 2015-03, and 2016-03
Event date	**Abnormal predictability**
2008-11	0.2986
2009-03	0.1375
2010-11	0.1763
2011-08	-0.2225
2013-06	0.1092
2013-09	0.3499
2015-03	-0.1020
2016-03	-0.1025
Total	0.0943

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The effect of monetary policy on hedge funds' alpha

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Index

Abstract

This paper examines the effects of U.S. monetary policy announcements during the subprime crisis on the excess returns, or "alpha" abnormal performance measures, of the hedge fund industry. We study such effects, if any, both on the industry as a whole as well as for different sub-hedge strategies using data from the Credit Suisse Hedge Fund Index. We apply different econometric techniques of increasing sophistication to test whether alphas changed as a result of policy announcements. The first technique consists of event studies, followed by Chow tests for breaks at known dates, Bai-Perron's tests for multiple global breaks, and finally Markov regime switching models. We find that long-short equity and emerging market hedge fund strategies were recurrently affected by unexpected monetary policy announcements while other strategies appeared to be impacted only occasionally. However, when analyzing regime-specific estimates for the more strongly affected strategies we do not find that policy announcements systematically increased or decreased alphas. Hence, we cannot conclude anything precise as to whether central bankers' pervasive presence in financial markets has made it easier or more difficult for funds to generate alpha. Our results simply indicate that unexpected monetary policy announcements cause variability in the alpha of a subset of commonly employed hedge fund strategies.

1. Introduction

A hedge fund is a lightly regulated alternative investment vehicle that is generally aiming at generating absolute returns for its shareholders. This is of course a broad definition, as there exists several different kinds of hedge funds with different investment strategies and risk profiles. However, a general concept is that hedge fund managers are evaluated based on their ability to generate high risk-adjusted returns. Ideally, this means returns in excess of the risk the fund is exposed to. In the industry, this excess return is commonly referred to as "alpha". The idea is that a skillful manager should be able to perform well irrespective of the general performance of the market and that returns should be less volatile than the market.[4] In practice, the performance of the hedge fund industry varies over time. The industry has been struggling to outperform the market during last ten to fifteen years and several commentators have alleged that an overall decline in fund performance may be taking place.[5] Some commentators say that more readily available information has made it difficult to have an informational edge in the markets.[6] Researchers in the field like Berk and Green (2004) and Fung, Hsieh, Ramadorai and, Naik (2008) have argued that the industry is getting too crowded with too much capital chasing too few opportunities. Similar views have been reiterated more recently in the financial press.[7]

What grabbed our interest were comments from various managers on the difficulty of making strategic investment decisions in a market that to a large extent has been recently driven by the monetary policy decisions of central banks.[8] Subsequent to the subprime crisis, central banks around the world have very actively supported the economy through low interest rates and various quantitative easing efforts (see, e.g., Blinder, 2010; Reis, 2010; Krishnamurthy and Vissing-Jorgensen, 2011; Joyce, Lasaosa, Stevens, and Tong, 2011). These policy decisions have been the focus of market participants and their outcomes have had a key impact on the pricing of financial assets. The effect of monetary policy decisions on

[4] Blackstone. https://www.blackstone.com/docs/default-source/black-papers/taking-stock.pdf?sfvrsn=0.
[5] Credit Suisse Hedge Fund Index (CSHFI) historic returns versus MSCI world index. "Hedge funds: Overpriced, Underperforming". Financial Times (May 24, 2016). "It was another great year for investors who avoid hedge funds". Financial Times (January 5, 2017). "Family Offices Back Away From Hedge Funds After Returns Decline". Bloomberg (September 8, 2016).
[6] "Hedge funds are for suckers" Bloomberg (July 12, 2013).
[7] "Hedge funds with crowded positions feel the pressure". Financial Times (May 8, 2016). "Barclays: The hedge fund industry is overcrowded". Business Insider (9 August, 2016).
[8] Dan Loeb, Jay Polesky. www.politco.eu. Patrik Brummer www.brummer.se. New York Times (May 5, 2015). "Hedge Fund Investing: A practical approach to understanding Investor Motivation, Maneger Profits, and Fund Performance.

financial markets has already been discussed, for example, by Bernanke and Kuttner (2005) and Basistha and Kurov (2008). Our goal is to contribute to this literature by analyzing the implications of central bankers' interventionism in financial markets on hedge fund performance. We do this by analyzing the impact of monetary policy decisions on fund managers' ability to outperform the market on a risk-adjusted basis. Hence, we are interested in the effect that monetary policy may have had on hedge funds' alpha, independently of whether policy decisions moved asset prices up or down, in general. For example a manager can generate positive alpha even when prices go down as long as the performance is less negative than what is expected given the manager's risk exposures.

Another issue of interest is whether monetary policy decisions may produced heterogeneous—in terms of both size and sign—effects on different hedge fund strategies. Therefore, in addition to analyzing the hedge fund industry as a whole, in this thesis we also investigate the specific effect on eight of the most common sub-strategies.[9] The first type of strategy is the *long-short equity,* where fund managers aim to invest in stocks they expect to appreciate while selling short stocks they expect to depreciate. By taking relative bets on different stocks, long-short funds are able to minimize their market exposure and generate returns based on firm-specific factors. The second fund strategy is the *event-driven* one. The group of funds that based their operations on this strategy generate returns by trying to exploit pricing inefficiencies that occur around corporate events like mergers, earnings, and bankruptcy-related situations. The third strategy is the *market neutral* one, where managers aim to generate performance while constantly having zero or close to zero correlation with the market. While *long-short equity* and *event-driven* funds can tactically change market exposure to time the market, *market neutral* funds rebalance their portfolios usually on a daily basis to avoid any correlation to the market. The fourth strategy is the so-called *dedicated short bias* one: this strategy maintains a net short exposure to aggregate market and strives to profit when the market declines by holding positions that are overall biased to the short side. The fifth strategy is the *emerging market* one. Funds in this category specialize in investing in financial instruments issued in emerging countries. At the moment, this generally refers to countries in Eastern Europe, Middle East, Africa, Latin America, and Asia. The sixth strategy is *fixed-income arbitrage*: funds adopting this strategy tries to exploit small

[9] Based on assets under management (AUM) in the Credit Suisse Hedge Fund Index (CSHFI). https://www.hedgeindex.com/.

price misalignments across bonds. The seventh strategy is *global macro*, which focuses on investing across asset classes making predictions of large-scale events on a country-wide, continental, and global scale. The aim it to capitalize on macroeconomic and geopolitical trends.[10] The eight and final strategy is the *multi-strategy* one, which is a combination of several, ideally uncorrelated, hedge fund strategies, such as those described above.

In our study, we investigate whether it is possible to estimate any differences in the effects of monetary policy on the different strategies listed above. Specifically, we would like to test whether some strategies may have been more affected than others by policy decisions and whether there are any indications of over- or under-performance for particular strategies. In order to pursue this goal, we apply a range of statistical methodologies describing an increasing degree of sophistication to assess whether there is a change in alpha as a result of policy announcements. The first technique consists of simple event studies, followed by Chow tests for breaks at known dates, Bai-Perron's tests for multiple global breaks, and finally Markov regime switching models. In our view, a better understanding of the effects of monetary policy decisions on different hedge fund strategies should help investors in their portfolio allocation process during periods that are highly influenced by monetary policy decisions and central bank interventions. We would like to determine if these interventions actually do make it more challenging for the funds to generate alpha or if they instead create market distortions which funds can take advantage of, increasing alpha. We would expect monetary policy announcements to cause an increase in alpha for strategies that make tactical bets on the outcome of macro events like *global macro* and *fixed income* funds. The rationale being that a skillful manager should be able to profit from the market distortions created by these announcements. On the other hand, we would expect to see a negative effect on funds that do not focus on predicting monetary policy decisions, but nonetheless invest in securities that are strongly influenced by them. The primary example would be *long-short equity* funds, as it has been documented that unexpected monetary policy decisions have strong and consistent effects on the stock markets (see, e.g., Bernanke and Kuttner, 2005). Further, we would expect to find little impact on alpha for *market neutral* funds, given their strict emphasis on continuously having zero or close to zero correlation to the market. The same is expected for *event-driven* funds, as they strive to solely be exposed to idiosyncratic, firm-specific, factors. However, a limitation of our study is that our data consist of the average

[10] Investopedia. http://www.investopedia.com/terms/g/globalmacro.asp

alpha for each strategy, hence we cannot segment between high and low performing fund managers. This is especially an issue when evaluating the *global macro* and *fixed-income* funds that aim to generate alpha from tactical bets on macro events like monetary policy announcements. It might be the case that skilled managers take advantage of the trading opportunities that unexpected monetary policy announcements create, increasing their alpha, but that this result is not properly captured by only studying the average performance of these strategies.

The results from our event studies indicate that hedge funds on average report a monthly *abnormal* alpha of -2.76 percent during periods dominated by monetary policy announcements. When we adjust for standard deviation and examine the coefficient of variation, results show that the most positively impacted funds by policy announcements are *emerging market* funds while *dedicated short bias*- and *fixed-income arbitrage* funds are the most negatively affected.[11] A key limitation of the event studies performed in this thesis, is the assumption that policy announcements do not trigger changes in risk exposures.[12] Therefore, we proceed next by applying Chow and Bai-Perron break tests, which also tests for breaks in risk exposures. Here our empirical results indicate that *long-short equity* and *emerging market* strategies are affected by unexpected monetary policy announcements while other strategies only appear to be impacted occasionally. An explanation for the impact on the *long-short equity* funds could be that our data consists largely of U.S. funds which are highly exposed to movements in U.S. equity markets caused by unexpected monetary policy changes by the Fed. Regarding the effect on *emerging market* funds, a potential reason could be that a many emerging market countries have U.S. dollar denominated debt. The value of this debt and the potential fiscal stability of these countries can be martially impacted by currency appreciation and deprecation triggered by monetary policy announcements (see, e.g., Arora and Cerisol, 2001; Rowland and Torres, 2004). In addition, changes in fund flows in and out of emerging markets can significantly affect liquidity in these markets and hence the ability to generate alpha in them.[13] However, when analyzing regime-specific estimates for the most affected strategies, we fail to find that policy announcements systematically

[11] Average *abnormal* alpha divided by standard deviation of *abnormal* alpha.
[12] In this study we perform a simple event study that does not account for changes in risk exposures. We do however note that there are ways to adjust for this in event (see, e.g., MacKinley, 1997). In addition, nonparametric test can also be applied to event studies.
[13] Edurman and Kaya (2016), "Liquidity fears loom over fund industry" Financial Times (1 February, 2015).

increase/decrease alpha. Our results from the Markov switching model show a similar picture as we cannot find evidence of a single *monetary policy* regime, with regime specific risk exposures and alpha. Hence, we cannot conclude that central bankers' high interventionism in financial markets during and in the aftermath of the Great Financial Crisis has made it easier or more difficult for funds to generate alpha; we only report that unexpected monetary policy announcements cause variability in alpha for some strategies.

2. Literature Review

This section reviews the literature related to hedge fund performance and the effect of monetary policy on financial markets. Because the literature explicitly discussing the impact of monetary policy announcements on hedge funds' alpha is very sparse, we choose to divide the literature review into two parts. The first one presents the literature on hedge fund performance, where much of the research has focused on the factors that distinguish successful funds from unsuccessful ones. In addition, we also survey a number of studies that investigate the difficulties with estimating hedge funds' alpha. The second part of the literature review covers the effects of monetary policy on financial markets. Here we emphasize studies of how changes in monetary policy transmit to the pricing of various asset classes.

2.1 Hedge fund performance and the estimation of alpha

As previously discussed, the hedge fund industry has been struggling to outperform the market during last ten to fifteen years. Academic researchers like Fung, Hsieh, Ramadorai, and Naik (2008) argue that high alpha-funds tend to attract more capital inflows; however, funds with high capital inflows tend to have lower probabilities of generating alpha in the future. The rationale is that larger funds need to invest in more liquid securities which tend be covered by more investors and analysts. As consequence, trading in these securities is more competitive and they are less likely to be mispriced. Based on this finding, Fung et al. (2008) suggest that the hedge fund industry may be headed towards a state where there is zero alpha available to investors. This statement is in line with the assumptions of the rational model of active portfolio management proposed by Berk and Green (2004), which predicts that hedge funds will face diminishing returns to scale in deploying their alpha generating ability.

Researchers have found that a key source of a hedge fund's success is its ability to deploy dynamic trading strategies to time the market. For example, Ackermann, McEnally and Ravenscraft (1999) find that hedge funds tend to outperform mutual funds but underperform market indices. They argue that one reason for superior performance versus mutual funds is the flexibility that hedge funds have while investing, like being able to use short selling and leverage. Further, Fung and Hsieh (1997) show that a difference between mutual and hedge funds' returns is the latter's use of dynamic trading strategies. Hedge funds can quickly trade in and out of their positions. Fung and Hsieh (1997) note that these dynamic strategies can achieve option-like returns, indicating a timing ability. Chen and Liang (2007) expand on this by presenting economically and statistically significant findings of a market timing ability for market timing funds, using a sample from January 1994 until June 2005. In addition, their paper suggests, that such timing skill is especially strong in bear and volatile markets. For our study, we would expect these flexibilities in investing to translate into changes in alpha during market influencing events, like monetary policy announcements. Skillful managers should be able to profit from these events, increasing alpha, while less skillful ones may loose and decrease their alpha.

A limitation in our study is that our data consists of the average alpha for each strategy, and hence we cannot segment between high and low performing fund managers. Fung, Hsieh, Ramadorai, and Naik (2008) show that during the period 1995 – 2004, the average fund-of-fund did not generate alpha, after controlling for risk factors.[14] The only exception is the months between October 1998 and March 2000. Further, Titman, and Tiu (2008) suggest that better-informed hedge funds carry lower risk factor exposures. They find that these funds exhibit both higher Sharpe and information ratios[15,16]. Kazemi and Islamaj (2014) study the relationship between hedge fund managers' trading activity and performance. They find that the more active managers achieve higher raw returns compared to their less active peers. However, the opposite result is found when examining risk-adjusted returns: the less active managers outperform the more active ones. Further, Kazemi, and Islamaj (2014) note that a small number of very active managers outperform the moderately active ones. They

[14] A fund-of-fund is an investment strategy of holding a portfolio of other investment funds rather than investing directly in financial securities.

[15] The Sharpe ratio is a measure of risk-adjusted returns and is defined as the average returns in excess of the risk free rate divided by the standard deviation of returns.

[16] The information ratio is a volatility-adjusted measurement of fund manager skill: it is defined as a portfolio alpha divided by the standard deviation of alpha.

therefore argue that the most active managers use their skills to manage portfolio risk and are hence able to achieve higher risk-adjusted returns. These papers' findings highlight the limitation of not being able to differentiate between high and low performing funds in our study. This is especially an issue when evaluating the *global macro* and *fixed-income* strategies, which aim to generate alpha from tactical bets on macro events like monetary policy announcements. It might be the case that skilled managers take advantage of the trading opportunities that unexpected monetary policy announcements create, increasing their alpha, but that this result is not properly captured by only studying the average performance of these strategies.

To be able to accurately evaluate the impact monetary policy has on fund mangers ability to generate alpha, we need make sure that we are actually measuring this skill correctly. The research on the methods to assess and estimate alpha in portfolio management is usually thought to have started with Jensen (1968). Jensen defines alpha as the excess return over the market using Sharpe's (1964) capital asset pricing model (CAPM). The methodology was later expanded with the Fama-French (1993) three-factor model and Carhart's (1997) four-factor model. Fung and Hsieh (2001) construct specific, hedge fund-tailored style factors which have option-like payoffs similar to the returns generated through the dynamic trading of hedge funds. Subsequently, Fung and Hsieh (2004) present a seven-factor model, which in addition to three style factors includes the market factor, size factor, and two fixed-income factors. It our study we incorporate Carhart's (1997) four-factor model as well as the two fixed-income factors proposed by Fung and Hsieh (2001). Further, Bollen and Whaley (2009) argue that because hedge fund strategies are dynamic and managers are able to change asset classes as well as leverage, assuming constant risk exposures will result in misleading measures of alpha. Similar issues related to mutual fund evaluation have also previously been underlined by Christopherson, Ferson, and Glassman (1998). To address this issue and incorporate for changes in risk exposure, we perform Chow and Bai-Perron's tests allowing for breaks in all parameters not just alpha.

2.2 Monetary policy's effect on financial markets

Bernanke and Kuttner (2005) document that unexpected monetary policy decisions have strong and consistent effects on the stock market. That is that stock markets tend to increase/decrease as a results of a Federal Reserve (henceforth, Fed) announcement and this is a pattern that recurs with different policy announcements. They find that the cause of the effect is not the impact of monetary policy on real interest rates but rather its impact on expected future excess returns or expected future dividends. Basistha and Kurov (2008) study stock market reactions to monetary policy announcement during different macroeconomic cycles. They find a stronger stock market response to unexpected changes in the Federal funds target rate during recessions and in tight credit market conditions. These findings support the notion that unexpected policy announcements should affect the alpha of hedge funds which invest heavily in stocks, like *long-short equity* funds. Kuttner (2001) examines the effect of changes in Fed policy on market interest rates and finds a strong relationship for unexpected policy actions but that there is little response by markets to anticipated actions. Edelberg and Marshall (1996) use a vector autoregression (VAR) model to estimate the effects of monetary policy shocks on bond yields. They find that there is a substantial impact on one-month bond yields while the response of longer-term bonds is much weaker. In addition, the study finds no deviations from this general pattern during the Asian financial crisis of 1994. This supports the idea that unexpected policy announcements should impact the alpha of strategies with large fixed income exposure, like *fixed-income arbitrage* and *global macro* funds*.*

Other studies have researched the effects that monetary policy has on market volatility. An example is Chen and Clements (2007) who find that the VIX index, which is computed based on implied volatility in the market, falls significantly on the day of Federal Open Market Committee (FOMC) meetings. Bomfim (2003), on the other hand discusses how U.S. equity volatility responds to surprises in monetary policy decisions and shows that they tend to boost equity volatility significantly in the short term. In addition the paper presents that positive surprises, which is defined as a higher federal funds rate than expected, tend to increase volatility more than a negative ones. In our study, we would expect skillful fund managers to be able to profit from a short-term change in volatility, hence increasing alpha post an announcement.

3. Method

This section gives a detailed description of the methods we use to examine the impact of monetary policy announcements on hedge funds' alpha. We begin by estimating the alpha for each strategy and presenting the monetary policy announcement dates we choose to investigate. Then, we apply a range of statistical methodologies describing an increasing degree of sophistication to assess whether there is a change in alpha as a result of policy announcements. The first technique is an event study, followed by Chow tests for breaks at known dates, Bai-Perron's tests for multiple global breaks and finally the Markov regime switching model.

3.1 Estimating alpha

The alpha of each hedge fund strategy is estimated using OLS:

$$R_t^i = \alpha_i + \beta_{i,MKT}(R_{MKT,t} - rf_t) + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t + \beta_{i,MOM}MOM_t + \beta_{i,\Delta 10y}\Delta 10y_t + \beta_{i,\Delta spread}\Delta spread_t + \varepsilon_i, \tag{2}$$

where R_t^i is the monthly return of each hedge fund strategy in excess of the risk free rate and $R_{MKT,t} - rf_t$, SMB_t, HML_t, and MOM_t are the risk factors proposed by Fama-French (1993) and Carhart (1997). $\Delta 10y_t$ and $\Delta spread_t$ are the fixed-income factors presented by Fung and Hsieh (2004). The construction of risk factors and factor portfolios is described in detail in the data section. Further, the $\beta_{i,MKT}$, $\beta_{i,SMB}$, $\beta_{i,HML}$, $\beta_{i,MOM}$, $\beta_{i,\Delta spread}$, and $\beta_{i,\Delta 10y}$ parameters represent each hedge fund strategy's exposure to each of the risk factors. Finally, ε_i stands for the error term and α_i for alpha.

3.2 Monetary policy announcement dates selection

The specific policy announcement dates we choose to examine are those that had a high surprise effect on the markets. The rationale being that unexpected policy decisions are more likely to move markets and impact hedge funds' alpha than anticipated ones (Kuttner, 2001). This selection is based on an analysis on the surprise effect of Federal Reserve (henceforth, Fed) policy decisions on the markets prepared by Goldman Sachs Global Investment Research (2016). In total we select eight Fed announcement dates from the start of the Great Financial Crisis in 2007 until 2016, all with a big surprise effect on the markets. The first date we choose to analyze is the 24th of November 2008, when the Fed unveiled its $800 billion plan to encourage lending and housing. This is commonly referred to as quantitative easing one or "QE 1". The second date is the 18th of March 2009, when the Fed announced it would buy $300 billion in long-term Treasury bonds to help to halt the negative move in the U.S. economy. This led to a sharp increase in U.S. stock indices and gold prices. In addition, U.S. Treasury yields decreased by amounts not seen in decades. The third date is the 3rd of November 2010, when they said that they would buy an additional $600 billion long-term

Treasury bonds. This was called "QE 2" and the effect was once again a sharp increase in stock markets. The fourth date of investigation is the 9th of August 2011, when the Federal Open Market Committee (FOMC) announced that it "currently anticipates that economic conditions—including low rates of resource utilization and a subdued outlook for inflation over the medium run—are likely to warrant exceptionally low levels for the federal funds rate at least through mid-2013." This was the first time the FOMC gave forward guidance of the future policy rate path including a specific date (Raskin, 2013). The fifth announcement is the 19th of June 2013. On this date Fed Chairman Ben Bernanke said that the Fed might reduce its bond purchase program later in the year, contingent on the economic outlook. The news led to a decrease in stock prices and a jump in the U.S. 10-year Treasury yield. The sixth date is just three months later, on September 18th, when Bernanke announced that the Fed has decided not to taper and instead to keep the bond buying program at current levels. The decision surprised markets and sent both the S&P500 and Dow Jones indices to record highs. The seventh date is the 15th of March 2015, when the Fed released a lower so-called "dot plot" which presents each FOMC member's expectations of the future Fed key rate. The effect of the lower "dots" was a sharp decrease in the U.S. dollar as markets adjusted themselves to a lower rate outlook. The eighth and final date in our analysis is the 16th of March 2016, when the FOMC members once again surprised markets by lowering their predictions of the future Fed key rate path.

3.3 Event study

We start our analysis of the impact of monetary policy announcements on hedge funds' alpha by performing a simple event study for the main hedge fund index and the strategy sub-indices. For each policy announcement the event window is set to include the month prior to the announcement, the month of the announcement, as well as the month after. By doing this we are able to capture both anticipatory and lagged effects that the monetary policy decisions may have on alpha. The estimation window is defined as the 12 months before the event window, excluding any preceding event months in the time series. Abnormal, event-driven, alpha is calculated as:

$$\alpha_{abnormal} = R_{event} - \hat{\beta} F_{return} - \hat{\alpha}, \qquad (3)$$

where R_{event} is the return of each fund index in the event window. $\hat{\beta}$ is a row vector containing estimated risk factor exposures calculated from the estimation window

$(\hat{\beta}_{MKT}, \dots, \hat{\beta}_{\Delta spread})$. F_{return} is the monthly returns of the risk factors during the event window $(MKT_t, \dots, \Delta spread_t)$ and $\hat{\alpha}$ is the alpha estimated from the estimation window. The logic is that *abnormal* alpha should be the residual event window fund return after adjusting for risk exposures and *normal* alpha. However, a limitation of the event studies performed in this thesis is the assumption that the risk exposures for the hedge fund strategies are identical during the event and estimation windows. This creates issues as it is quite likely that risk exposures also change when there is an unexpected monetary policy announcement.

3.4 Chow test

We continue our study by performing Chow tests introduced by Chow (1960) to investigate the presence of structural breaks in our model parameters at the specific monetary policy announcements dates. In contrast to the event study we test for breaks in all our parameters, both alpha and risk exposures. The Chow test splits the data based on the defined dates of interest. In our case the model:

$$R_t^i = \alpha_i + \beta_{i,MKT}(R_{MKT,t} - rf_t) + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t + \beta_{i,MOM}MOM_t + \beta_{i,\Delta 10y}\Delta 10y_t + \beta_{i,\Delta spread}\Delta spread_t + \varepsilon_i, \tag{4}$$

is split *m* times into *m*+1 different groups or regimes:

$$R_t^i = \alpha_j^i + \beta_{MKT_j}^i(R_{MKT,t} - rf_t) + \beta_{SMB_j}^i SMB_t + \beta_{HML_j}^i HML_t + \beta_{MOM_j}^i MOM_t + \beta_{\Delta 10y_j}^i \Delta 10y_t + \beta_{\Delta spread_j}^i \Delta spread_t + \varepsilon_i, \tag{5}$$

where $j = 1, \dots, m + 1$ indicates the specific regime. The null hypothesis of Chow's test for each strategy is that the parameters do not change before and after the specified break dates:

$$H_O: \alpha_j = \alpha, \ \beta_{MKT_j} = \beta_{MKT}, \ \beta_{SMB_j} = \beta_{SMB}, \beta_{HML_j} = \beta_{HML}, \ \beta_{MOM_j} = \beta_{MOM}, \ \beta_{\Delta 10y_j} = \beta_{\Delta 10y}, \ \beta_{\Delta spread_j} = \beta_{\Delta spread}. \tag{6}$$

The error term ε_i is assumed to be independent and identically distributed from a normal distribution. A limitation of monthly data is that we cannot include all eight dates of interest in the tests due to a lack of observations between adjacent announcements. Therefore, when two announcements are too close to each other we exclude the one with the lowest surprise factor. As a consequence, we end up testing the following five dates for breaks: March 2009, November 2010, August 2011, June 2013, and March 2015. The Chow test statistic is given by the formula:

$$F = \frac{(SSR_C - \sum_{j=1}^{m+1}(SSR_j))/(R)}{\sum_{j=1}^{m+1}(SSR_j)/(N-(m+1)k)}, \tag{7}$$

where SSR_j is the sum of squares residuals for each individual group and SSR_C the sum of squares residuals for the combined data. *N* stands for the number of observations, *m* number of breaks, and *k* the number of parameters. *R* is the amount of restrictions. This is the quantity of intercepts and slopes that are assumed to be equal to each other in the null hypothesis. It can be calculated as number of breaks m multiplied by number of parameters k. The test statistic follows an F-distribution with $(m+1)k$ and $N-(m+1)k$ degrees of freedom.

3.5 Bai-Perron's test

In addition to the Chow tests, we also perform Bai-Perron's tests for multiple global breaks. Unlike Chow's test, Bai-Perron's does not require us to specify the break dates. This is an advantage as we are not certain exactly when a monetary policy decision could start affecting alpha. The effect might start some time before the actual announcement due to anticipations in the market or be a lagged effect. Furthermore, the exact timing of the effect on alpha may vary for different announcements. The null hypothesis of the test is no structural breaks versus the alternative of *l* globally optimized breaks. Bai and Perron (2003) consider the following multiple regression with *m* breaks (*m* + 1 regimes):

$$y_t = x_t'\beta + z_t'\delta_j + u_t, \qquad t = T_{j-1}+1, \dots, T_j, \tag{8}$$

for *j* = 1, … , *m* + 1. Where y_t is the dependent variable at time *t*, x_t' (p x 1) and z_t' (q x 1) are vectors of explanatory variables while β and δ_j both represent coefficients. The difference between the two groups of coefficients is that δ_j changes between regimes while β is fixed. This gives the flexibility to choose which parameters one wants to test for change. As with the Chow test, we performed tests allowing for changes in all parameters. The breakpoints $T_1, \dots, T_m$ are unknown and as a convention $T_0 = 0$ and $T_{m+1} = T$. u_t stands for the error term at time *t.* We proceed by representing the multiple regression in matrix form:

$$Y = X\beta + \overline{Z}\delta + U, \tag{9}$$

where $Y = (y_1, \dots, y_T)'$, $X = (x_1, \dots, x_T)'$, $U = (u_1, \dots, u_T)'$, and $\delta = (\delta_1, \dots, \delta_{m+1})'$. The matrix $\overline{Z}$ diagonally partitions Z at $(T_1, \dots, T_m)$ with $Z_i = (z_{T_{i-1}+1}, \dots, z_{T_i})'$. Bai and Perron (2003) denote the true value of the parameters and the breakpoints with a 0 subscript. Therefore the data generating process is assumed to be:

$$Y = X\beta^0 + \overline{Z}^0 \delta^0 + U. \tag{10}$$

The estimation is based on least squares where the estimates of the parameters are retrieved by minimizing the sum of squared residuals for each m-partition $(T_1, \dots, T_m)$:

$$\left(Y - X\beta - \overline{Z}\delta\right)'\left(Y - X\beta - \overline{Z}\delta\right) = \sum_{i=1}^{m+1} \sum_{t=T_{i-1}+1}^{T_i} [y_t - x_t'\beta - z_t'\delta_j]^2. \tag{11}$$

The estimates $\hat{\beta}(\{T_j\})$ and $\hat{\delta}(\{T_j\})$ for each m-partition are substituted in the objective function to get the sum of squared residuals, denoted $S_T(T_1, \dots, T_m)$. Then the break points are estimated such that $(\hat{T}_1, \dots, \hat{T}_m) = \operatorname{argmin}_{T_1, \dots, T_m} S_T(T_1, \dots, T_m)$ where the minimization is taken over all partitions $(T_1, \dots, T_m)$ so $T_i - T_{i-1} \geq q^2$. Thus, the estimators of the break points are global minimizers of the objective function and since they are discrete parameters they can be estimated by a grid search.

The Bai-Perron's tests produce four results from different approaches of determining the number of breaks. The "Sequential" result is obtained by performing tests from one to the maximum number of breaks until we cannot reject the null while the "Significant" approach chooses the largest statistically significant breakpoint. Further, the UD_{max} and WD_{max} results show the number of breakpoints, determined by application of un-weighted and weighted maximized statistics.[17]

3.6 Markov regime switching model

It has been well documented that financial markets are unstable and that they tend to alter between different regimes. For example in the stock market Pagan and Sossounov (2003) observe "bull and bear" regimes where the "bull regime" is characterized by high returns and low volatility while the opposite is found for "bear regimes". Guidolin and Timmermann (2006) show similar results for fixed-income markets, which tend to alternate between

[17] See Bai and Perron (2003).

economic booms with rising rates and recessions with falling rates. Ang. and G. Bekaert (2002b) show that regime switching models forecast interest rates better than single regime models. Further, Guidolin and Timmermann (2006) find that while simple two- or three-state models capture the univariate dynamics in bond and stock return, a more complicated four-state model is required to capture their joint distribution. There are also studies indicating the presence of different regimes for monetary policy (see, e.g., Sims and Zha, 2006; Bikbov and Chernov, 2013). The general concept is that by allowing for regime switches we are able to more properly capture the dynamic nature of the statistical relationships between variables (Guidolin, 2012).

Even though we test for breaks in all parameters with the Chow's and Bai-Perron's tests, they do not account for the potential existence of a specific *monetary policy* regime with its own risk exposures and alpha, which is short-lived and triggered by policy announcements. To address this issue we implement the Markov regime switching model, with regime specific risk factor exposures, as well as alpha. The Markov model introduces an unobservable, discrete state variable S_t, and allows for the parameters in our original model to change contingent on the state or regime.

$$R_t^i = \alpha_{S_t}^i + \beta_{MKT,S_t}^i (R_{MKT,t} - rf_t) + \beta_{SMB,S_t}^i SMB_t + \beta_{HML,S_t}^i HML_t + \beta_{MOM,S_t}^i MOM_t + \beta_{\Delta 10y,S_t}^i \Delta 10y_t + \beta_{\Delta spread,S_t}^i \Delta spread_t + \varepsilon_i. \tag{12}$$

The switching mechanism is constructed on the time-invariant probability of moving from regime *i* to regime *j* and these probabilities are collected in the *k* x *k* transition matrix **P** where *k* is the number of regimes. In our analysis we test for two and three regimes but are only able to produce results for two due to a lack of observations.

$$P(S_t = j | S_{t-1} = i) = p_{i,j}. \tag{13}$$

The estimation process is performed recursively using filtered probabilities. These probabilities represent the best assessment of the regime at time *t*, given past information. They have to be initiated at time 0 where it is common to set the probabilities to the steady state values implied by the Markov transition matrix. We start by calculating the one-step ahead forecast of the regime probabilities given the filtered probabilities of the previous period $P(S_{t-1} = k | I_{t-1}, \theta)$ where θ is a vector containing the model parameters $\alpha_1^i, \ldots, \alpha_k^i, \beta_{1,MKT}^i, \ldots, \beta_{k,factor}^i, p_{11}, \ldots, p_{kk}, \sigma_1^i, \ldots, \sigma_k^i$. We perform tests both holding the standard deviation of the error term constant across regimes as well as ones where we allow it to change.

$$P(S_t = k|I_{t-1}, \theta) = \sum_{j=1}^{K} p_{j,k} \cdot P(S_{t-1} = j|I_{t-1}, \theta). \tag{14}$$

These filtered probabilities are then used to find the one step ahead joint density of data and regimes assuming that error term ε_i is normally distributed ϕ:

$$f(R_t^i, S_t = k\,|I_{t-1}, \theta) = P(S_t = k|I_{t-1}, \theta) \cdot \phi\left(\frac{R_t^i - \mu_{S_t}^i}{\sigma_{S_t}^i}\right). \tag{15}$$

By summing the joint probabilities for all regimes we get the conditional density of the return at time t:

$$f(R_t^i|I_{t-1}, \theta) = \sum_{k=1}^{K} f(R_t^i, S_{t-1} = k|I_{t-1}, \theta). \tag{16}$$

Then, by applying Bayes' rule we can calculate the filtered probabilities for the current period:

$$P(S_t = k|I_t, \theta) = \frac{f(R_t^i, S_t = k|I_{t-1}, \theta)}{f(R_t^i|I_{t-1}, \theta)}. \tag{17}$$

Finally, after continued recursive calculation of the filtered probabilities we estimate the parameters θ by maximizing the log likelihood:

$$L(\theta) = \sum_{t=1}^{T} \ln f(R_t^i, S_t = k|I_{t-1}, \theta). \tag{18}$$

4. Data

This section describes and motivates the variables used in our analysis and the databases they were retrieved from. Our dataset is based on 139 months, from November 2004 until May 2016. It consists of a combination of monthly hedge fund returns from the Credit Suisse

Hedge Fund Index[18] and monthly returns on the Fama-French (1993) and Carhart (1997) factor portfolios, downloaded from the Kenneth R. French data library[19]. The dataset also includes monthly returns on Fung and Hsieh's (2004) fixed-income factor portfolios, retrieved from the authors' website[20]. Finally, to determine which specific monetary policy announcements to analyze we use a study by Goldman Sachs Global Investment Research[21] (2016) on the surprise effect of Federal Reserve announcements.

4.1 Credit Suisse Hedge Fund Index

The Credit Suisse Hedge Fund Index (henceforth, CSHFI) is one of the leading asset-weighted hedge fund indices and includes, in addition to the flagship index, several sub-indices for individual strategies. This information allows us not only to analyze the overall effect from monetary policy announcements on hedge funds' alpha but also the potential difference in the effect on various strategies. To reduce subjectivity in the fund selection process, CSHFI applies a rules-based construction methodology. To be an eligible member of the index a fund has to satisfy the following criteria: Have a minimum of $50 million assets under management, a minimum one-year track record, and current audited financial statements. Each individual strategy index is constructed based on assets invested in that specific hedge fund strategy and each index represents at least 85 percent of the assets under management for that category. The objective of CSHFI is to attain maximum representation of the index universe. All indices are calculated net of fees and rebalanced on a monthly basis. In addition, funds are reselected as necessary every quarter. Funds are not removed from the index until they go bankrupt or fail to fulfill the financial reporting requirements, decreasing survivorship bias. Further, a maximum index weight of 15 percent is applied for any single fund to avoid concentration risk. However, since hedge fund managers can elect weather to report or not and also decide to stop reporting, the index naturally suffers from some selection bias. This, as better performing funds tend to be more motivated to report than poorly performing ones. In addition, fund managers sometimes launch several different funds and then only disclose the performance of the successful ones while hiding those of the ones that failed. This occurrence leads to what is commonly referred to as an incubation bias.

[18] https://secure.hedgeindex.com/hedgeindex/en/indexoverview.aspx?cy=USD&indexname=HEDG
[19] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[20] http://faculty.fuqua.duke.edu/~dah7/DataLibrary/TF-FAC.xls
[21] http://www.bloomberg.com/news/articles/2016-03-18/goldman-sachs-this-was-one-of-the-most-dovish-fed-decisions-of-the-21st-century

Finally there exists some backfill bias, as managers often wait with reporting performance until they have established a successful track record.

4.2 Factor Portfolios

The second part of our data consists of monthly returns on the Fama-French (1993) and Carhart (1997) factor portfolios. Fama and French (1993) observe that small cap stocks and stocks with high book-to-market ratios tend to achieve greater returns than the market. Based on this they introduced the three-factor model to explain asset returns, which in addition to the excess return of the market *(MKT)* includes the return of the small minus big *(SMB)* and high minus low *(HML)* factors. The *MKT* factor is calculated as the value-weighted monthly return of all CRSP[22] U.S. firms listed on the NYSE, AMEX, or NASDAQ exchanges minus the risk free rate, represented by the one-month Treasury bill rate. The *SMB* and *HML* factors are constructed with six value-weighted portfolios based on a combination of book-to-market ratio and size. Low market cap stocks are called *small* while large market cap stocks are referred to as *big*. Further, the high book-to-market firms are called *value* stocks, medium book-to-market *neutral* stocks, and low book-to-market *growth* stocks. The small minus big factor is constructed by taking the difference between the average return of the three *small* portfolios minus the average return of the three *big* portfolios:

$$SMB = \frac{1}{3} \cdot (Small\ Value + Small\ Neutral + Small\ Growth) - \frac{1}{3} \cdot (Big\ Value + Big\ Neutral + Big\ Growth). \tag{19}$$

Similarly, the high minus low factor is constructed by taking the difference between the average return of the two *value* portfolios and the average return of the two *growth* portfolios.

$$HML = \frac{1}{2} \cdot (Small\ Value + Big\ Value) - \frac{1}{2} \cdot (Small\ Growth + Big\ Growth). \tag{20}$$

Carhart (1997) added a fourth factor to the Fama-French model, called the monthly momentum factor *(MOM)*. The factor captures the tendency for a stock to continue to perform well when it has recently performed well and to continue to perform poorly when it has recently performed poorly. On the Kenneth R. French data library, the *MOM* factor is

[22] CRSP stands for The Center for Research in Security Prices. www.crsp.com/

constructed using a combination of size and one-month prior return. The one-month prior return is categorized into *low* and *high*, where return breakpoints are the 30th and 70th performance percentiles on the NYSE. The *MOM* factor is constructed by taking the difference between the average of the two prior high performing portfolios and the average of the two prior low performing portfolios:

$$MOM = \frac{1}{2} \cdot (Small\ High + Big\ High) - \frac{1}{2} \cdot (Small\ Low + Big\ Low). \qquad (21)$$

Finally, our dataset also includes monthly returns on Fung and Hsieh's (2004) two fixed-income factor portfolios. The first one is the *bond market* factor, which we represent as $\Delta 10y$. The factor return is calculated as the monthly change in the 10-year Treasury constant maturity yield. The second factor is called the *credit-spread* factor, denoted $\Delta spread$. Here the factor return is calculated as the monthly change in the Moody's Baa yield less 10-year Treasury constant maturity yield.

4.3 Goldman Sachs study on surprise effect of Federal Reserve announcements

The specific monetary policy announcements we select in our analysis are U.S. Federal Reserve (Fed) announcements from the start of the Great Financial Crisis to the end of our data set, May 2016. Within the time range, the specific announcements examined are chosen based on their surprise factor on the markets. To identify which announcement where truly unexpected we use an analysis on the surprise factor of different Fed announcements provided by Goldman Sachs Global Investment Research (2016). The study examines the correlation of 18 different market variables and the change in those variables on days of Fed policy announcements. Large moves in the variables indicate a high surprise factor.

5. Results

This section presents and discusses our results from the event studies, Chow tests, Bai-Perron's tests, and the Markov regime switching model. In addition, we highlight the limitations of the tests and models and how they affect our interpretations of the results.

5.1 Results from event studies

Table 1 presents results from the event studies where we test for *abnormal*, event-driven, alpha coinciding with monetary policy announcements. As each hedge fund strategy is tested using eight events where the event widow consists of three monthly *abnormal* alphas we end up with 24 *abnormal* alpha observations per strategy in total. The table shows the mean and standard deviation of the abnormal alphas for each fund strategy. We also calculate and present the coefficient of variation for each strategy.[23] Results show that the main hedge fund index has a mean *abnormal* alpha of -2.76 percent while the strategy indices have mean *abnormal* alphas stretching from -3.51 percent to 2.64 percent. *Emerging market* funds show the highest positive *abnormal* alpha while market neutral and fixed-income arbitrage strategies show the highest negative ones. However, *abnormal* alphas for most strategies are quite volatile and tend to switch from positive to negative in between events. When adjusting for standard deviation and studying the coefficient of variation, results indicate that *emerging market* funds are the most positively impacted by monetary policy announcements while *dedicated short bias* and *fixed-income arbitrage* funds are the most negatively affected. The least impacted strategies are *event-driven* and *global macro* funds. However, we note that a major limitation of the event studies we perform is the assumption that policy announcement do not trigger changes in risk exposures. Instead, the event studies assume that the parameters estimated during the estimation window also apply in the event window. This creates issues as it is quite likely that risk exposure also change when there is an unexpected monetary policy announcement. To incorporate this possibility in our analysis we proceed by applying Chow and Bai-Perron's tests.

5.2 Results from Chow tests

In Table 2 we present the Chow test results for each hedge fund strategy index, testing for breaks in all parameters, both risk exposures and alpha. The following five monetary policy announcement dates are simultaneously tested for breaks: March 2009, November 2010, August 2011, June 2013, and March 2015. As explained in the method section, we are reserved from including all of our eight dates of interest in the tests due to of a lack of observations between adjacent announcements. Therefore, when two announcements are too close to each other we exclude the announcement that is less unexpected. The test results show that there are breaks in parameters at our pre-specified dates for the *long short equity* and *fixed-income arbitrage* strategies at the five percent significance level. The other six strategies show no significant signs of breaks. A limitation of the Chow test is; however, that

[23] Average *abnormal* alpha divided by standard deviation of *abnormal* alpha.

we need to specify the exact dates while the effect of monetary policy on hedge funds' alpha could differ in timing both between strategies and specific announcements. Therefore, it could be the case that there exists monetary policy triggered breaks in the parameters for the other strategies as well but that the breaks lag the actual announcement. It might even be case that a parameter break precedes an announcement as the market anticipates a specific policy decision. This scenario should; however, be less likely in our case as the monetary policy announcements analyzed are chosen based on the surprise impact they had on the markets.

5.3 Results from Bai-Perron's tests

Table 3 to 20 present the findings from our Bai-Perron's tests of up to five globally determined breaks and hence up to six regimes. We compare the break dates determined by each test with our original eight unexpected monetary policy announcements. When testing the main hedge fund index we see five F-statistic determined breaks: March 2007, May 2009, October 2011, February 2013, and June 2015. The first break, March 2007, does not match with any of our monetary policy dates while three of the succeeding four break dates show signs of being lagged effects from announcements. The second break, May 2009, lags the March 2009 Fed announcement that it would buy $300 billion in long-term Treasury bonds by two months. The third break, October 2011, also lags a Fed announcement by two months. This time it is the August 2011 FOMC guidance on the future policy rate path. However, it is highly questionable whether the fourth break, February 2013, really is triggered by a monetary policy announcement given that the closest announcement is four months later in June 2013. The fifth and final break, June 2015, lags the March 2015 Fed announcement of a lower "dot plot", indicating lower expectations of the future Fed key rate. Table 4 shows the regime specific estimates for the hedge fund index, based on the breaks determined by the Bai-Perron's tests. We do not show any estimates for first regime as there are too few observations prior to the first break, but the following regimes indicate quite large changes in risk factor exposure after breaks as well as some changes in alpha. Alpha increases for the first three breaks and decreases for the final two breaks, becoming negative after the fifth break in June 2015. Overall, we see some effect from unexpected monetary policy announcements on the main hedge fund index. However, results suggest that other factors also exist that cause breaks in risk exposures and alpha.

When testing the *long short equity* strategy sub-index we also find five F-statistic determined breaks, presented in Table 5. The specific break dates found are: March 2008, May 2009, October 2011, August 2013, and February 2015. The first one, March 2008, does not align with any monetary policy but rather with the Bear Stearns collapse and fire sale to JPMorgan Chase. This is not surprising as Bear Stearns' downfall created a lot of turmoil in financial markets, which may have triggered changes in *long-short equity* funds risk exposures and alpha.[24] However, the following four break dates all align quite well with unexpected monetary policy announcements. May 2009, October 2011, and August 2013 all lag a specific announcement by two months while the final break date, February 2015, precedes a policy decision by one month. These findings for *long-short equity* resonate with the Chow's test results as Bai-Perron's globally determined break dates are very close to the pre-specified significant Chow's test breaks. When examining the regime specific estimates for the *long-short equity* sub-index in Table 6 we see changes in both risk exposures and alpha in between break dates. Alpha is positive before the Bear Stearns collapse and then turns negative. It increases after the March 2009 Fed decision on buying long-term Treasury bonds and once again after the Fed guided for continued low policy rates going forward in August 2011. Following the June 2013 policy announcement that the Fed was considering to lower their bond-buying program by the end of the year, alpha started to decrease again. This trend continued with alpha decreasing to even lower levels in the final regime, just prior to the March 2015 Fed release of a lower "dot plot". An explanation for the recurring impact on the *long-short equity* funds could be that our data consists largely of U.S. funds which are highly exposed to movements in U.S. equity markets caused by unexpected monetary policy changes by the Fed (see, e.g., Bernanke and Kuttner, 2005).

The Bai-Perron's test results for the *event-driven* sub-index is not as clear as the previous two strategy indices as the sequential F-statistic determined breaks is zero while the significant F-statistic largest breaks test indicates five breaks: March 2008, May 2009, February 2011, February 2012, and July 2015. The first break date occurs once again during the time of Bear Stearns' collapse but unlike the *long-short equity* index only one of the following four determined breaks align with our monetary policy announcement dates. This is the second break date, May 2009, which lags the March 2009 Fed decision to purchase long-term Treasury bonds. The three remaining break dates are all four or more months

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[24] Bloomberg data.

away from any of our monetary policy dates. Although we see some changes in risk exposures and alpha between the globally determined breaks they seem to be triggered by something else than monetary policy announcements. In our view, this makes sense as the events that *event-driven* funds tend to try to generate alpha from are corporate events rather than Fed policy ones and should hence be less influenced by monetary policy decisions.

Results from the *market neutral* sub-index, presented in Table 9, show five breaks both when observing the sequential F-statistic determined breaks and significant F-statistic largest breaks. However, when examining the specific break dates only two of the five appear to match our monetary policy announcements. The second break date, December 2008, follows the November 2008 QE 1 announcement and the fourth break date, January 2011, takes place two months after the QE 2 announcement in November 2010. The other three break dates, January 2008, November 2011, and January 2014, are not close to any of our monetary policy dates. Similar to the *event-driven* hedge fund results, changes in alpha for *market neutral* hedge funds do not seem to be consistently impacted by unexpected monetary policy announcements.

The Bai-Perron's test results for the *dedicated short bias* index, presented in Table 11, show five globally determined breaks from both F-tests; however, only two of the five break dates match with the monetary policy announcements. The first break date is March 2009, which occurs in the same month as the Fed revealed it would buy $300 billion in long-term Treasury bonds. The second break date that aligns with a monetary policy announcement is May 2013, which is one month prior to Chairman Bernanke's message that the Fed may reduce its bond purchase program later that year. As the majority of *dedicated short bias* breaks do not occur close to any monetary policy announcement this suggests that the hedge fund strategy is not affected in a consistent way by unexpected policy announcements.

When reviewing the results for the *emerging market* strategy sub-index, presented in Table 13, we see a different picture. Once again the F-tests determine five breaks: March 2008, February 2009, October 2011, August 2013, and April 2015. However, unlike the previous three sub-strategies the globally determined break dates for the *emerging market* index align well with our monetary policy announcement dates. In fact four out of five breaks are within a one or two month range of an announcement. The only break that is not close to one of our unexpected monetary policy dates is the first break, which as with the *long-short* *equity* and *event-driven* strategies coincides with the Bear Stearns collapse in March 2008. By going over at the regimes specific estimates, presented in Table 14, we note that alpha changes from being positive in the regime prior to the collapse of the investment bank to being negative. Post the second break in February 2009, one month prior to the March 2009 Fed announcement of long-term Treasury bond purchases, alpha shifts to become less negative. The trend of improving alpha continues after the third break in October 2011, two months after the FOMC indicated a longer low rate policy. After the fourth break in August 2013, two months after Bernanke indicated a possible rate rise before year-end, alpha turns negative again. It then stays negative following the fifth break, one month after the Fed released a lower "dot plot". These findings indicate that monetary policy announcement tend to have an impact on changes in alpha for hedge funds with a focus on emerging markets. A reason for this could be that many emerging market countries have U.S. dollar denominated debt. The value of this debt and the potential fiscal stability of these countries can be martially impacted by currency appreciation and deprecation triggered by monetary policy announcements (see, e.g., Arora and Cerisol, 2001; Rowland and Torres, 2004). In addition, changes in fund flows in and out of emerging markets can significantly affect liquidity in these markets and hence the ability to generate alpha.[25]

The sequential and significant F-statistic test results from the fixed-income arbitrage sub-index, displayed in Table 15, determines the following five break dates: March 2008, February 2009, May 2010, October 2011, and April 2013. Once again, the first break occurs at the time of Bear Stearns' collapse while the second, third, and fifth breaks all coincide with monetary policy announcements within a two-month range. The third break, May 2010, does not match any of our selected announcement dates. When examining at the regime specific estimates, presented in Table 16, we find that alpha jumps up and down between the different regimes. Overall our findings from the test suggest that unexpected monetary policy announcement have some impact on fixed-income arbitrage hedge funds but the effect does not seem to be as extensive as for *long-short equity* or *emerging market* strategies.

In addition, the Bai-Perron's results for the *global macro* sub-index, seen in Table 17, shows a similar picture as for fixed-income arbitrage. Both the sequential and significant F-statistic approaches determine five break dates for the *global macro* strategy: March 2008,

[25] Edurman and Kaya (2016), "Liquidity fears loom over fund industry" Financial Times (1 February, 2015).

February 2009, March 2010, August 2011, and February 2015. As with fixed-income arbitrage the first date coincides with Bear Stearns' collapse and three out of the other four break dates occur within a one-month range of an unexpected monetary policy announcement. Once again, it is the third break date, in the first half of 2010, which does not match with any unexpected announcement. These findings, in combination with changes in estimates from Table 18, suggest that unexpected monetary policy announcements have some effect on the alpha for *global macro* funds. In addition, there appears to be some other event in the first half of 2010 that triggers a break in risk exposures and alphas for both *global macro* and *fixed-income arbitrage* funds. The potential trigger event could either be the downgrade of Greek government bonds to junk by the credit agencies in April 2010 or the 110 billion euro bailout announcement by the International Monetary Fund that followed in May 2010. As both fixed-income arbitrage and *global macro* funds tend to have an international reach it makes sense that these strategies would be more impacted by the Greek sovereign debt crisis, compared to for example *long-short equity* which for our data sample consist mostly of U.S. focused funds.

Finally, the Bai-Perron's results for the *multi-strategy* sub-index, presented in Table 19, determine the following five break dates: January 2009, May 2010, November 2011, June 2013, and February 2015. Here, only the first and final breaks are within a two-month range of one of our unexpected monetary policy dates. The third and fourth break dates both occur three months after a policy event, and therefore it is difficult to determine if this is actually a prolonged lagged effect from an announcement or if the parameter break for the *multi-strategy* sub-index is reacting to something else. Finally, as with fixed-income arbitrage and *global macro*, the Bai-Perron's test determines a break at the time of the Greek debt crisis. When examining the changes of estimates in Table 20 we see that although we see breaks in the parameters the actual changes in alpha between the different regimes are minor. These findings highlight the point that *multi-strategy* funds are the most diversified ones, as they by construction are a collection of different strategies. Therefore it is expected that the strategy should experience less variation in alpha.

Overall the break date results from Bai-Perron's tests display both similarities and difference between the respective hedge fund strategies. The principal common theme is the reaction to the Bear Stearns collapse in March 2008, where all sub-indices except *multi-strategy* show a break date within a one-month range of the event. This result makes sense as the investment bank's failure sparked the financial crisis and caused major volatility in financial markets.[26] When it comes to the effect of unexpected monetary policy announcements on alpha, we group the funds strategies into three groups based on the Bai-Perron's results. The first group, which designates the strategies that appear to be affected the most, includes *long-short equity* and *emerging market* funds. For both fund strategies four out of five break dates coincide with an unexpected policy announcements within a two-month range. The second group comprises of the main hedge fund index as well as the f*ixed-income arbitrage*, and *global macro* sub-indices. This group also shows signs of being affected by monetary policy announcement; however, to a lesser extent than the members of the first group. For the second group, three out of four break dates match with a policy announcement within a two-month range. The third and final group is made up by *event driven*, m*arket neutral*, and *multi-strategy* funds. Here our results suggest that the alphas of these fund strategies are only slightly affected by policy announcements. The alphas of *event-driven* funds specifically, seem to be very little impacted by policy announcements.

Focusing on the more affected strategies, i.e., *long-short equity* and *emerging market*, we note that although the announcements tend to cause changes in alpha we do not observe any trends on the direction of these changes. Regime specific estimates show that some policy announcements increase alpha while others tend to decrease it. Hence, we cannot draw any conclusions on the directional effect on alpha from policy announcements. We can only say that they seem to cause variation in alpha for some strategies. In addition, the Bai-Perron results suggest that the more globally exposed strategies like *fixed-income arbitrage*, *global macro*, and *multi-strategy* were impacted by the Greek sovereign debt crisis, causing a break in risk exposures and alpha. Finally, the most stable alpha over regimes can be found for *multi-strategy* funds as they are diversified between different strategies.

A limitation of both Chow's and Bai-Perron's tests in our study is that because we use monthly observations the actual time between breaks in our results are quite long. As discussed previously this causes issues when we have two unexpected monetary policy events occurring close to each other. This also causes the regimes to be quite lengthy. However, it may be the case that there exists a specific *monetary policy* regime with its own

[26] Bloomberg data.

risk exposures and alpha, which is short-lived and triggered by a policy announcement. To account for this possibility we proceed by applying the Markov regime switching model.

5.4 Results from Markov regime switching model

Figure 1 to 9 show the filtered regime probabilities, y-axis, versus time, x-axis, for the hedge fund index and all the sub-indices. We test for both two and three regimes but are not able to produce any results for three regimes as our analysis is based on monthly data with limited observations. In addition, we test both assuming constant standard deviation of the error term across regimes and allowing it to change. However, the choice does not change the interpretation of the results. Therefore, all results presented in Table 1 to 9 are estimated assuming fixed standard deviation of the error term across regimes. The blue line in each figure shows the probability of being in what we define as the *monetary policy* regime. This is a regime triggered by a monetary policy announcement with regime specific risk exposures and alpha. A high value on the y-axis represents a high probability of being in the *monetary policy* regime. The dotted red lines show the dates of our eight unexpected monetary policy announcements. If there actually exists a *monetary policy* regime for a specific strategy, ideally we expect to see high probabilities at the time of our monetary policy dates and low probabilities during the rest of the time series. Visually this means temporary spikes of the blue line at the time of the red dotted lines in the respective figures. In addition, Tables 21 to 29 show the regime specific estimates for the *normal* regime and the potential *monetary policy* regime.

By analyzing our results we do not find any clear indication of a *monetary policy* regime. For all strategies except *market neutral*, we see high probabilities of a regime switches at several periods when there are no monetary policy announcements. This indicates that there are other events in the markets that trigger regime switches. For the *market neutral* strategy on the other hand we see some alignment of monetary announcements and high regime switching probabilities. However, this is only the case for four out of our eight unexpected policy announcements. Hence, the Markov regime switching results do not give us any conviction in the presence a *monetary policy* regime with regime specific risk exposures and alpha. In other words, we cannot conclude that there is a single monetary policy specific effect on alpha. This finding is inline with our results from the Bai-Perron's tests where we presented that even though monetary policy announcements seem to affect alpha for some strategies, most visibly *long-short equity* and *emerging market* funds, we do not find any consistency in which direction they impact alpha. This would mean that there does not exist a single *monetary policy* regime for these strategies. However, it may still be the case there are different *monetary policy* regimes depending on the specific policy announcement event, with different effects on alphas. Unfortunately, as mentioned previously testing for more than two regimes is beyond the scope of our data set.

6. Conclusions

In this paper we analyze the effect of unexpected monetary policy announcements on hedge funds' alpha. We examine both the hedge fund industry as a whole as well as specific fund strategies using monthly returns on the Credit Suisse Hedge Fund index and its sub-indices. Alpha, is calculated as the returns of the indices after adjusting for the Fama-French (1993) and Carhart (1997) factor exposures, as well as two fixed-income factors presented by Fung and Hsieh (2004). The monetary policy announcements are chosen based on the surprise effect they had on the markets. To investigate the potential effect of monetary policy on the alpha of various strategies we apply different econometric techniques. We start with a simple event study on the change in alpha within a three-month event window around each announcement. Here our results show that the main hedge fund index has a mean *abnormal* alpha of -2.76 percent while the strategy indices have *abnormal* alpha stretching from -3.51 percent to 2.64 percent. When adjusting for standard deviation, results indicate that *emerging market* funds are the most positively impacted by monetary policy announcements while *dedicated short bias* and *fixed-income arbitrage* funds are the most negatively affected. A major limitation of the event studies performed in this thesis is the assumption that policy announcement do not trigger changes in risk exposures. We then perform Chow tests for five pre-specified monetary policy break dates, allowing for changes in all parameters instead of just alpha. Here our results show that there exist breaks at our pre-specified dates for the *long-short equity* and *fixed-income arbitrage* strategies at the five percent significance level while other strategies show no significant signs of breaks. The limitation of the Chow tests is that we need to specify the exact dates while the effect of monetary policy on hedge funds' alpha could differ in timing both between strategies and specific announcements. To address this limitation, we proceed by performing Bai-Perron's tests for globally determined breaks. Here we are not required to pre-specify the exact break dates. From these results, we group the fund strategies into three groups based on how recurrent the effects from monetary policy announcements are on their alphas. The most impacted group includes *long-short equity* and *emerging market* funds. The second group comprises of the main hedge fund index as well as the *fixed-income arbitrage* and *global macro* sub-indices. This group also shows signs of being affected by monetary policy announcement; however, to a lesser extent than the members of the first group. The third and final group is made up by *event-driven*, *market neutral*, and *multi-strategy* funds, which seem to only occasionally be affected by monetary policy announcements. An explanation for the impact on the *long-short equity* funds could be that our data consists largely of U.S. funds which are highly exposed to movements in U.S. equity markets caused by unexpected monetary policy changes by the Fed. Regarding the effect on *emerging market* funds, a potential reason could be that a many emerging market countries have U.S. dollar denominated debt. The value of this debt and the potential fiscal stability of these countries can be martially impacted by currency appreciation and deprecation triggered by monetary policy announcements (see, e.g., Arora and Cerisol, 2001; Rowland and Torres, 2004). In addition, changes in fund flows in and out of emerging markets can significantly affect liquidity in these markets and hence the ability to generate alpha in them. Finally we investigate whether there exists a *monetary policy* regime with regime specific risk exposures and alpha by applying the Markov regime switching model. We are only able to test for two regimes because of the restricted number of observations in our data set. Results from the Markov regime switching model for all indices suggest that there does not exists a single specific *monetary policy* regime.

In summery our study finds that the alpha, after controlling for changes in risk exposures, for *long-short equity* and *emerging market* strategies seem to be recurrently affected by unexpected monetary policy announcements while other strategies only appear to be impacted occasionally. However, when analyzing regime specific estimates for the more affected strategies we do not find that policy announcements systematically increase or decrease alpha. Hence, we cannot conclude anything precise as to whether central bankers' pervasive presence in financial markets has made it easier or more difficult for funds to generate alpha. Our results simply indicate that unexpected monetary policy announcements cause variability in the alpha of a subset of commonly employed hedge fund strategies. This finding is in line with our results from the Markov switching model where we do not find the existence a single *monetary policy* regime, with regime specific risk exposures and alpha. For future research it would interesting to be able to test for more regimes, as it may be the case that there actually exists several *monetary policy* regimes with different effects on alpha. In addition, a limitation of our study is that our data consists of the average alpha for each strategy, hence we cannot differentiate between high and low performing fund managers. This is especially an issue when evaluating the *global macro* and *fixed-income* funds that aim to generate alpha from tactical bets on macro events like monetary policy announcements. It might be the case that skilled managers take advantage of the trading opportunities created by unexpected monetary policy announcements, increasing alpha, but that this result is not properly captured by studying the average performance. Therefore we think it would be interesting to segment fund performance into groups and see whether monetary policy announcements have different effects on high performing funds compared to low performing ones.

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Table 1
Event studies: Hedge fund index and all sub-indices

Sample months:	2004-11 to 2016-05		
Event dates:	2008-11, 2009-03, 2010-11, 2011-08, 2013-06, 2013-09, 2015-03, and 2016-03		

Index and sub-indices	Mean	Std. Dev	Coef. of Variation
Hedge fund index	-0.0276	0.0847	-0.3265
Long-short equity	-0.0199	0.1584	-0.1255
Event-driven	0.0006	0.1329	0.0042
Market neutral	-0.0350	0.2573	-0.1361
Dedicated short bias	-0.0296	0.0848	-0.3494
Emerging markets	0.0264	0.1546	0.1707
Fixed-income arbitrage	-0.0351	0.1035	-0.3391
Global macro	-0.0093	0.1471	-0.0629
Multi-strategy	-0.0170	0.0671	-0.2539

Table 2
Chow tests for M specified breaks: Hedge fund index and all sub-indices

Sample months:	2007-01 to 2016-05	
Specified break dates:	2009-03, 2010-11, 2011-08, 2013-06, and 2015-03	
Breaking parameters:	α_i, $\beta_{i,MKT}$, $\beta_{i,SMB}$, $\beta_{i,HML}$, $\beta_{i,MOM}$, $\beta_{i,\Delta 10y}$, and $\beta_{i,\Delta spread}$	

Index and sub-indices	F-Statistic	Prob. F(35, 71)
Hedge fund index	0.7601	0.8121
Long-short equity	1.7554*	0.0227
Event-driven	1.0310	0.4453
Market neutral	0.4601	0.9934
Dedicated short bias	0.8198	0.7375
Emerging markets	1.3492	0.1425
Fixed-income arbitrage	2.0178*	0.0062
Global macro	0.7010	0.8750
Multi-strategy	1.3673	0.1322

** Significant at the 0.05 level.*

Table 3
Bai-Perron's tests of 1 to M globally determined breaks: Hedge fund index

Sample months:	2007-01 to 2016-05
Breaking parameters:	α_i, $\beta_{i,MKT}$, $\beta_{i,SMB}$, $\beta_{i,HML}$, $\beta_{i,MOM}$, $\beta_{i,\Delta 10y}$, and $\beta_{i,\Delta spread}$

Test	No.
Sequential F-statistic determined breaks	5
Significant F-statistic largest breaks	5
UDMax determined breaks	1
WDMax determined breaks	2

Breaks	F-statistic	Scaled F-statistic	Weighted F-statistic	Critical Value
1 *	8.3887	58.7211	58.7211	22.62
2 *	7.5215	52.6502	59.4286	20.04
3 *	5.0500	35.3502	43.3340	18.45
4 *	4.2585	29.8093	39.2254	17.19
5 *	4.5682	31.9771	44.8155	16.14

UDMax statistic*	58.7211	UDMax critical value**	22.80
WDMax statistic*	59.4286	WDMax critical value**	24.34

** Significant at the 0.05 level.*
*** Bai-Perron's (Econometric Journal, 2003) critical values.*

Estimated break dates

1:	2008-03				
2:	2008-03	2009-02			
3:	2008-03	2009-05	2011-10		
4:	2007-03	2009-05	2011-10	2013-02	
5:	2007-03	2009-05	2011-10	2013-02	2015-06

Table 4
Regime specific estimates: Hedge fund index

Variable	Regime 1	Regime 2	Regime 3	Regime 4	Regime 5	Regime 6
α	-	0.0022	0.0033**	0.0064***	0.0008	-0.0062**
MKT	-	0.2992*	0.3316	0.0854	0.2507*	0.2218**
SMB	-	-0.0068	-0.0047	-0.2539	-0.1235**	0.1050
HML	-	-0.2118***	-0.1232***	-0.1167	-0.0556	0.0755
MOM	-	0.0449	-0.1181	-0.2070**	0.1630*	0.2036
Δ10y	-	0.7973	0.9776	1.9297	-1.5089**	-4.3716
Δspread	-	-2.3877**	-0.3006	0.6203	-2.5000***	-3.7769**

** significant at the 0.01 level, ** significant at the 0.05 level, *** significant at the 0.10 level*

Table 5
Bai-Perron's tests of 1 to M globally determined breaks: Long-short equity

Sample months:	2007-01 to 2016-05
Breaking parameters:	α_i, $\beta_{i,MKT}$, $\beta_{i,SMB}$, $\beta_{i,HML}$, $\beta_{i,MOM}$, $\beta_{i,\Delta 10y}$, and $\beta_{i,\Delta spread}$

Test	No.
Sequential F-statistic determined breaks	5
Significant F-statistic largest breaks	5
UDMax determined breaks	3
WDMax determined breaks	3

Breaks	F-statistic	Scaled F-statistic	Weighted F-statistic	Critical Value
1 *	3.4548	24.1840	24.1801	22.62
2 *	3.8221	26.7544	30.1988	20.04
3 *	4.7419	33.1932	40.6954	18.45
4 *	4.2408	29.6857	39.0629	17.19
5 *	4.1329	28.9306	40.5459	16.14

UDMax statistic*	33.1932	UDMax critical value**	22.80
WDMax statistic*	40.6954	WDMax critical value**	24.34

** Significant at the 0.05 level.*
*** Bai-Perron's (Econometric Journal, 2003) critical values.*

Estimated break dates

1:	2008-12				
2:	2009-05	2014-01			
3:	2008-03	2009-05	2014-01		
4:	2008-03	2009-05	2013-08	2015-02	
5:	2008-03	2009-05	2011-10	2013-08	2015-02

Table 6
Regime specific estimates: Long-short equity

Variable	Regime 1	Regime 2	Regime 3	Regime 4	Regime 5	Regime 6
α	0.0087**	-0.0043	-0.0011	0.0016	-0.0003	-0.0010
MKT	0.3240**	0.5020*	0.5049*	0.3853*	0.4435*	0.1596
SMB	-0.1757	0.1703	0.0860	-0.2288***	-0.1200**	-0.1247
HML	0.4755***	-0.5559*	-0.1853*	-0.0606	0.0431	-0.3958**
MOM	0.4035*	0.0421	-0.1449*	-0.2836*	0.5375*	-0.0550
Δ10y	-0.3953	1.2590	1.3610	0.7193	0.1176	2.6771
Δspread	-6.2471***	-0.0309	0.0744	-1.6214	-3.5013**	-0.3163

** significant at the 0.01 level, ** significant at the 0.05 level, *** significant at the 0.10 level*

Table 7
Bai-Perron's tests of 1 to M globally determined breaks: Event-driven

Sample months:	2007-01 to 2016-05
Breaking parameters:	α_i, $\beta_{i,MKT}$, $\beta_{i,SMB}$, $\beta_{i,HML}$, $\beta_{i,MOM}$, $\beta_{i,\Delta 10y}$, and $\beta_{i,\Delta spread}$

Test	No.
Sequential F-statistic determined breaks	0
Significant F-statistic largest breaks	5
UDMax determined breaks	4
WDMax determined breaks	3

Breaks	F-statistic	Scaled F-statistic	Weighted F-statistic	Critical Value
1	2.9989	20.9923	20.9923	22.62
2 *	2.9902	20.9314	23.6261	20.04
3 *	3.6297	25.4076	31.1502	18.45
4 *	3.9653	27.7570	36.5249	17.19
5 *	3.8810	27.1672	38.0746	16.14

UDMax statistic*	27.7570	UDMax critical value**	22.80
WDMax statistic*	38.0746	WDMax critical value**	24.34

** Significant at the 0.05 level.*
*** Bai-Perron's (Econometric Journal, 2003) critical values.*

Estimated break dates

1:	2015-12				
2:	2008-03	2009-05			
3:	2008-03	2009-05	2015-07		
4:	2008-03	2009-05	2010-11	2015-07	
5:	2008-03	2009-05	2011-02	2012-02	2015-07

Table 8
Regime specific estimates: Event-driven

Variable	Regime 1	Regime 2	Regime 3	Regime 4	Regime 5	Regime 6
α	0.0122*	-0.0095**	0.0075*	-0.0025	0.0016	-0.0131**
MKT	0.1078	0.2845*	0.2756*	0.1092	0.2915*	0.1843
SMB	-0.0344	0.3928**	-0.0057	0.3436	-0.0173	0.0797
HML	0.4130**	-0.3942*	-0.0266	-0.1558	0.0975	-0.1554
MOM	0.2958*	0.0364	-0.0943***	-0.1146	0.0559	0.1423
Δ10y	-0.9464	2.5256**	2.1748**	2.7585	0.2340	-9.1763
Δspread	-9.2191*	-0.2016	-0.2404	-5.8017	-3.7020**	-10.125**

** significant at the 0.01 level, ** significant at the 0.05 level, *** significant at the 0.10 level*

Table 9
Bai-Perron's tests of 1 to M globally determined breaks: Market neutral

Sample months:	2007-01 to 2016-05
Breaking parameters:	α_i, $\beta_{i,MKT}$, $\beta_{i,SMB}$, $\beta_{i,HML}$, $\beta_{i,MOM}$, $\beta_{i,\Delta 10y}$, and $\beta_{i,\Delta spread}$

Test	No.
Sequential F-statistic determined breaks	5
Significant F-statistic largest breaks	5
UDMax determined breaks	2
WDMax determined breaks	2

Breaks	F-statistic	Scaled F-statistic	Weighted F-statistic	Critical Value
1 *	4.8781	34.1470	34.1470	22.62
2 *	15.4662	108.2641	122.2011	20.04
3 *	10.5993	74.1951	90.9644	18.45
4 *	7.6595	53.6162	70.5524	17.19
5 *	5.7754	40.4281	56.6595	16.14

UDMax statistic*	108.2631	UDMax critical value**	22.80
WDMax statistic*	122.2011	WDMax critical value**	24.34

** Significant at the 0.05 level.*
*** Bai-Perron's (Econometric Journal, 2003) critical values.*

Estimated break dates

1:	2008-12				
2:	2008-01	2018-12			
3:	2008-01	2008-12	2014-01		
4:	2008-01	2008-12	2009-12	2014-01	
5:	2008-01	2008-12	2009-11	2011-01	2014-01

Table 10
Regime specific estimates: Market neutral

Variable	Regime 1	Regime 2	Regime 3	Regime 4	Regime 5	Regime 6
α	0.0048***	-0.0535	-0.0184	-0.0090**	0.0002	0.0001
MKT	0.0305	0.4615	0.4904**	0.4177*	0.2897*	-0.0001
SMB	-0.1455	0.3988	-0.5007***	0.2708***	-0.0899	0.0377
HML	0.2834***	4.2485	-0.3170	0.0129	-0.0586	-0.0061
MOM	0.1461**	0.3900	-0.0782	-0.5300**	-0.0241	0.0710
Δ10y	-1.2244	34.864	-4.4415***	-4.8000**	0.3109	1.0619
Δspread	-3.1504***	10.380	-4.5143***	-1.2831	-0.7457	0.1163

** significant at the 0.01 level, ** significant at the 0.05 level, *** significant at the 0.10 level*

Table 11
Bai-Perron's tests of 1 to M globally determined breaks: Dedicated short bias

Sample months:	2007-01 to 2016-05
Breaking parameters:	α_i, $\beta_{i,MKT}$, $\beta_{i,SMB}$, $\beta_{i,HML}$, $\beta_{i,MOM}$, $\beta_{i,\Delta 10y}$, and $\beta_{i,\Delta spread}$

Test	No.
Sequential F-statistic determined breaks	5
Significant F-statistic largest breaks	5
UDMax determined breaks	2
WDMax determined breaks	2

Breaks	F-statistic	Scaled F-statistic	Weighted F-statistic	Critical Value
1 *	3.9341	27.5384	27.5384	22.62
2 *	7.1857	50.2996	56.7753	20.04
3 *	5.2892	37.0241	45.3922	18.45
4 *	4.4437	31.1058	40.9316	17.19
5 *	3.9810	27.8670	39.0552	16.14

UDMax statistic*	50.2996	UDMax critical value**	22.80
WDMax statistic*	56.7752	WDMax critical value**	24.34

** Significant at the 0.05 level.*
*** Bai-Perron's (Econometric Journal, 2003) critical values.*

Estimated break dates					
1:	2008-11				
2:	2008-08	2009-08			
3:	2008-02	2009-01	2009-12		
4:	2008-02	2009-03	2012-01	2013-06	
5:	2008-02	2009-03	2012-01	2013-05	2014-12

Table 12
Regime specific estimates: Dedicated short bias

Variable	Regime 1	Regime 2	Regime 3	Regime 4	Regime 5	Regime 6
α	-0.0034	-0.0349***	0.0015	-0.0118	-0.0070**	-0.0019
MKT	-1.2551*	-0.2159	-0.7346*	-0.6162**	-0.3155*	-0.6475*
SMB	-0.8269	1.6311**	-0.6246*	0.8305	-0.7563*	-0.5226**
HML	-0.1627	-0.8253***	0.0463	-0.0291	-0.3621**	0.6300
MOM	-0.0277	0.5049***	-0.0249	0.6877**	-0.6729*	0.5325**
Δ10y	1.3306	2.7999	0.3396	-2.4973	3.9061**	-1.6042
Δspread	-1.2758	4.8909	0.5460	-3.8259	5.1395***	1.0677

** significant at the 0.01 level, ** significant at the 0.05 level, *** significant at the 0.10 level*

Table 13
Bai-Perron's tests of 1 to M globally determined breaks: Emerging markets

Sample months:	2007-01 to 2016-05
Breaking parameters:	α_i, $\beta_{i,MKT}$, $\beta_{i,SMB}$, $\beta_{i,HML}$, $\beta_{i,MOM}$, $\beta_{i,\Delta 10y}$, and $\beta_{i,\Delta spread}$

Test	No.
Sequential F-statistic determined breaks	5
Significant F-statistic largest breaks	5
UDMax determined breaks	1
WDMax determined breaks	2

Breaks	F-statistic	Scaled F-statistic	Weighted F-statistic	Critical Value
1 *	4.2445	29.7114	29.7114	22.62
2 *	3.8314	26.8195	30.2723	20.04
3 *	3.2564	22.7953	27.9474	18.45
4 *	2.9625	20.7373	27.2878	17.19
5 *	2.9664	20.7651	29.1020	16.14

UDMax statistic*	29.7114	UDMax critical value**	22.80
WDMax statistic*	30.2722	WDMax critical value**	24.34

** Significant at the 0.05 level.*
*** Bai-Perron's (Econometric Journal, 2003) critical values.*

Estimated break dates

1:	2008-03				
2:	2008-03	2009-02			
3:	2008-03	2009-02	2011-10		
4:	2008-03	2009-02	2011-01	2011-12	
5:	2008-03	2009-02	2011-10	2013-08	2015-04

Table 14
Regime specific estimates: Emerging markets

Variable	Regime 1	Regime 2	Regime 3	Regime 4	Regime 5	Regime 6
α	0.0135**	-0.0156	-0.0012	0.0002	-0.001	-0.0009
MKT	0.0190	0.4279**	0.5114*	0.3806*	0.2824*	0.1686
SMB	-0.2891	0.0663	0.0501	-0.4039***	-0.2693*	-0.4190**
HML	0.3611	-0.4361***	-0.3946*	0.1452	0.1065	-0.3251
MOM	0.5414*	0.2485	-0.0697	-0.3847*	0.5119*	-0.4656*
Δ10y	-2.5578	-2.7573	-1.8081	-2.4355	2.4400	9.2382**
Δspread	-12.430**	-4.9525***	-3.3280**	-0.4693	2.3095	0.3449

** significant at the 0.01 level, ** significant at the 0.05 level, *** significant at the 0.10 level*

Table 15
Bai-Perron's tests of 1 to M globally determined breaks: Fixed-income arbitrage

Sample months:	2007-01 to 2016-05
Breaking parameters:	α_i, $\beta_{i,MKT}$, $\beta_{i,SMB}$, $\beta_{i,HML}$, $\beta_{i,MOM}$, $\beta_{i,\Delta 10y}$, and $\beta_{i,\Delta spread}$

Test	No.
Sequential F-statistic determined breaks	5
Significant F-statistic largest breaks	5
UDMax determined breaks	2
WDMax determined breaks	3

Breaks	F-statistic	Scaled F-statistic	Weighted F-statistic	Critical Value
1 *	8.1217	56.8521	56.8521	22.62
2 *	8.2512	57.7586	65.1946	20.04
3 *	7.9401	55.5809	68.1431	18.45
4 *	6.2806	43.9643	57.8519	17.19
5 *	5.1018	35.7128	50.0410	16.14

UDMax statistic*	57.7586	UDMax critical value**	22.80
WDMax statistic*	68.1431	WDMax critical value**	24.34

** Significant at the 0.05 level.*
*** Bai-Perron's (Econometric Journal, 2003) critical values.*

Estimated break dates

1:	2009-01				
2:	2008-03	2009-03			
3:	2008-01	2008-12	2010-12		
4:	2008-03	2009-02	2010-05	2013-04	
5:	2008-03	2009-02	2010-05	2011-10	2013-04

Table 16
Regime specific estimates: Fixed-income arbitrage

Variable	Regime 1	Regime 2	Regime 3	Regime 4	Regime 5	Regime 6
α	0.0037	-0.0078	0.0150*	0.0046*	0.0082*	0.0012
MKT	0.1596	0.2400	0.0802	0.1205*	0.0087	0.0434
SMB	-0.0061	0.1820	-0.1077	-0.3109*	-0.2258*	-0.0275
HML	0.4662***	-0.1656	-0.0829	-0.2479**	-0.0293	0.0074
MOM	0.0974	-0.0278	-0.0373	0.1441	-0.0983*	0.0144
Δ10y	-2.2003	0.2718	-3.5600	1.9633**	-0.4776	-0.3103
Δspread	-3.4603	-6.2939***	-2.8604**	-0.0347	-0.7441	-2.6358*

** significant at the 0.01 level, ** significant at the 0.05 level, *** significant at the 0.10 level*

Table 17
Bai-Perron's tests of 1 to M globally determined breaks: Global macro

Sample months:	2007-01 to 2016-05
Breaking parameters:	α_i, $\beta_{i,MKT}$, $\beta_{i,SMB}$, $\beta_{i,HML}$, $\beta_{i,MOM}$, $\beta_{i,\Delta 10y}$, and $\beta_{i,\Delta spread}$

Test	No.
Sequential F-statistic determined breaks	5
Significant F-statistic largest breaks	5
UDMax determined breaks	2
WDMax determined breaks	2

Breaks	F-statistic	Scaled F-statistic	Weighted F-statistic	Critical Value
1 *	3.8034	26.6237	26.6237	22.62
2 *	4.6244	32.3710	36.5385	20.04
3 *	3.8790	27.1528	33.2898	18.45
4 *	3.2076	22.4535	29.5461	17.19
5 *	2.8908	20.2355	28.3598	16.14

UDMax statistic*	32.3710	UDMax critical value**	22.80
WDMax statistic*	36.5385	WDMax critical value**	24.34

** Significant at the 0.05 level.*
*** Bai-Perron's (Econometric Journal, 2003) critical values.*

Estimated break dates

1:	2008-03				
2:	2008-03	2009-02			
3:	2008-03	2009-02	2015-02		
4:	2008-03	2009-02	2013-06	2015-06	
5:	2008-03	2009-02	2010-03	2011-08	2015-02

Table 18
Regime specific estimates: Global macro

Variable	Regime 1	Regime 2	Regime 3	Regime 4	Regime 5	Regime 6
α	0.0170**	-0.0145***	0.0099	0.0070***	0.0011	-0.0045
MKT	-0.0003	0.1846	0.0578	0.0700	0.1513*	0.3516**
SMB	-0.5270	0.4514	-0.2106	0.1461	-0.1683**	0.1367
HML	0.9477***	-0.6295**	-0.0655	-0.3670	-0.1122	0.3076
MOM	0.2321	0.2918**	-0.0124	-0.2175	0.0236	0.2565
Δ10y	-0.6215	-1.8364	-5.3942	0.6301	-2.6736*	-1.8630
Δspread	-3.6451	-2.0577	-1.5051	-4.6967	-1.0514	-0.7140

** significant at the 0.01 level, ** significant at the 0.05 level, *** significant at the 0.10 level*

Table 19
Bai-Perron's tests of 1 to M globally determined breaks: Multi-strategy

Sample months:	2007-01 to 2016-05
Breaking parameters:	α_i, $\beta_{i,MKT}$, $\beta_{i,SMB}$, $\beta_{i,HML}$, $\beta_{i,MOM}$, $\beta_{i,\Delta 10y}$, and $\beta_{i,\Delta spread}$

Test	No.
Sequential F-statistic determined breaks	5
Significant F-statistic largest breaks	5
UDMax determined breaks	1
WDMax determined breaks	2

Breaks	F-statistic	Scaled F-statistic	Weighted F-statistic	Critical Value
1 *	4.3646	30.5525	30.5525	21.87
2 *	3.9124	27.3868	31.5568	18.98
3 *	2.8790	20.1533	25.5806	17.23
4 *	2.4167	16.9170	23.7926	15.55
5 *	2.0589	14.4062	23.5121	13.40

UDMax statistic*	30.5525	UDMax critical value**	22.04
WDMax statistic*	31.5568	WDMax critical value**	23.81

** Significant at the 0.05 level.*
*** Bai-Perron's (Econometric Journal, 2003) critical values.*

Estimated break dates

1:	2009-02				
2:	2009-02	2014-03			
3:	2009-06	2011-10	2013-02		
4:	2009-01	2010-05	2011-11	2013-03	
5:	2009-01	2010-05	2011-11	2013-06	2015-02

Table 20
Regime specific estimates: Multi-strategy

Variable	Regime 1	Regime 2	Regime 3	Regime 4	Regime 5	Regime 6
α	0.0007	0.0081**	0.0024	0.0087*	0.0024**	0.0023***
MKT	0.2192**	0.1624**	0.2450*	0.0450	0.1453*	0.0208
SMB	0.0104	0.0110	-0.2908**	-0.3620**	-0.1504*	-0.0117
HML	-0.3128	-0.2356**	-0.2869**	-0.1010	0.0059	-0.1305
MOM	0.0229	-0.0408	0.2667**	-0.2634*	0.3550*	0.0427
Δ10y	1.1744	-5.0010**	2.2642**	1.3077	-0.7760	-0.6464
Δspread	-3.7076**	-3.7410*	-1.2162	1.2810	-3.2334**	-3.0317*

** significant at the 0.01 level, ** significant at the 0.05 level, *** significant at the 0.10 level*

Table 21
Markov regime specific estimates: Hedge fund index

Normal regime		**Monetary policy regime**	
Variable	Coefficient	Variable	Coefficient
α	0.001750	α	0.001856*
MKT	0.252503*	MKT	0.231170*
SMB	-0.006844	SMB	-0.283739*
HML	-0.158188*	HML	0.011013
MOM	0.015871	MOM	0.228595*
Δ10y	0.096513*	Δ10y	2.502045*
Δspread	-3.204763*	Δspread	1.401258*

** significant at the 0.01 level, ** significant at the 0.05 level, *** significant at the 0.10 level*

Table 22
Markov regime specific estimates: Long-short equity

Normal regime		**Monetary policy regime**	
Variable	Coefficient	Variable	Coefficient
α	0.001445	α	-0.003098
MKT	0.405544*	MKT	0.497988*
SMB	0.043685	SMB	-0.097957
HML	0.018216	HML	-0.320669*
MOM	0.133830*	MOM	0.016326
Δ10y	-0.783145	Δ10y	1.503350
Δspread	-0.282243	Δspread	-3.211487**

** significant at the 0.01 level, ** significant at the 0.05 level, *** significant at the 0.10 level*

Table 23
Markov regime specific estimates: Event-driven

Normal regime		**Monetary policy regime**	
Variable	Coefficient	Variable	Coefficient
α	0.005063*	α	-0.012147*
MKT	0.247224*	MKT	0.268785*
SMB	0.001091	SMB	-0.020445
HML	-0.051316	HML	-0.140846
MOM	0.037240**	MOM	0.015029
Δ10y	0.665152	Δ10y	3.343606*
Δspread	-3.535352*	Δspread	-0.316916
log(σ)	-4.947764*	log(σ)	-5.007031*

** significant at the 0.01 level, ** significant at the 0.05 level, *** significant at the 0.10 level*

Table 24
Markov regime specific estimates: Market neutral

Normal regime		**Monetary policy regime**	
Variable	Coefficient	Variable	Coefficient
α	0.002080**	α	-0.039124*
MKT	0.138909*	MKT	0.733478*
SMB	-0.003578	SMB	1.191045*
HML	-0.061181	HML	1.009363*
MOM	-0.009560	MOM	0.219022
Δ10y	1.055688**	Δ10y	-19.96897*
Δspread	-0.271818	Δspread	-46.73462*

** significant at the 0.01 level, ** significant at the 0.05 level, *** significant at the 0.10 level*

Table 25
Markov regime specific estimates: Dedicated short bias

Normal regime		**Monetary policy regime**	
Variable	Coefficient	Variable	Coefficient
α	0.001133	α	-0.017905*
MKT	-0.844193*	MKT	0.024521
SMB	-0.487429*	SMB	-0.341651***
HML	0.297793*	HML	-0.686954*
MOM	0.103980	MOM	0.070607
Δ10y	0.071882	Δ10y	9.301976*
Δspread	4.588796*	Δspread	4.475569*

** significant at the 0.01 level, ** significant at the 0.05 level, *** significant at the 0.10 level*

Table 26
Markov regime specific estimates: Emerging markets

Normal regime		**Monetary policy regime**	
Variable	Coefficient	Variable	Coefficient
α	0.002338	α	-0.000570
MKT	0.307324*	MKT	0.433230*
SMB	-0.325371**	SMB	0.058618
HML	-0.078980	HML	-0.225837**
MOM	0.060557	MOM	-0.043890
Δ10y	-0.386196	Δ10y	-0.548163
Δspread	-1.055479	Δspread	-5.125333*

** significant at the 0.01 level, ** significant at the 0.05 level, *** significant at the 0.10 level*

Table 27
Markov regime specific estimates: Fixed-income arbitrage

Normal regime		Monetary policy regime	
Variable	Coefficient	Variable	Coefficient
α	0.004537*	α	-0.038560*
MKT	0.071477*	MKT	0.414513*
SMB	-0.070390**	SMB	-1.788867*
HML	0.007012	HML	-0.644065***
MOM	-0.028476***	MOM	0.362018
Δ10y	-0.414208	Δ10y	3.463943
Δspread	-2.519242*	Δspread	-5.884647**

** significant at the 0.01 level, ** significant at the 0.05 level, *** significant at the 0.10 level*

Table 28
Markov regime specific estimates: Global macro

Normal regime		Monetary policy regime	
Variable	Coefficient	Variable	Coefficient
α	0.000374	α	0.010829*
MKT	0.216667*	MKT	-0.140957***
SMB	-0.204213*	SMB	0.383425**
HML	-0.274278*	HML	0.058700
MOM	0.015871	MOM	-0.031939
Δ10y	-1.199591***	Δ10y	-2.284404
Δspread	-2.391083*	Δspread	1.614931

** significant at the 0.01 level, ** significant at the 0.05 level, *** significant at the 0.10 level*

Table 29
Markov regime specific estimates: Multi-strategy

Normal regime		Monetary policy regime	
Variable	Coefficient	Variable	Coefficient
α	0.003597*	α	-0.000419
MKT	0.183879*	MKT	0.304898*
SMB	-0.019320	SMB	0.086251
HML	-0.074831**	HML	-0.330453*
MOM	0.001279	MOM	0.121641***
Δ10y	-0.258976	Δ10y	-0.430522
Δspread	-2.662574*	Δspread	-7.840909*

** significant at the 0.01 level, ** significant at the 0.05 level, *** significant at the 0.10 level*

Figure 1
Filtered regime probabilities: Hedge Fund Index

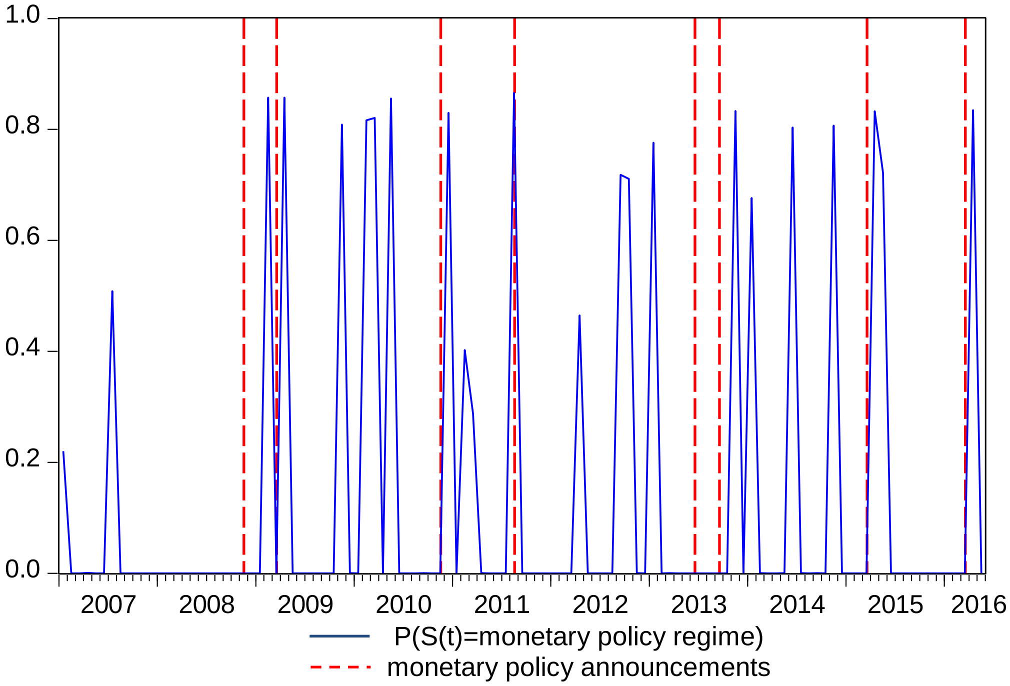

Figure 2
Filtered regime probabilities: Long-short equity

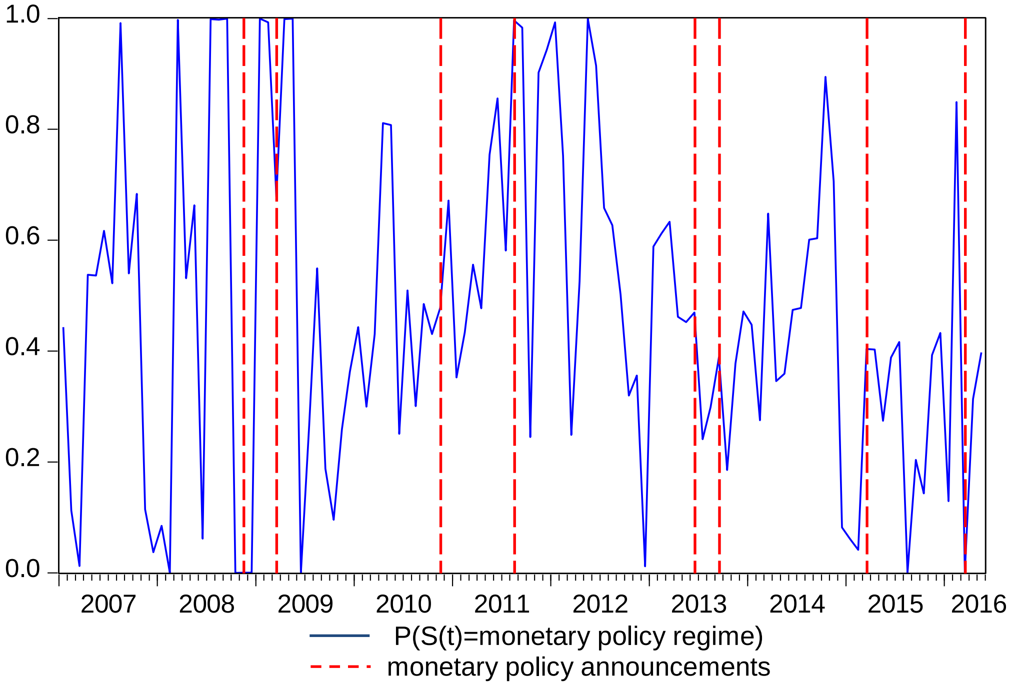

Figure 3
Filtered regime probabilities: Event-driven

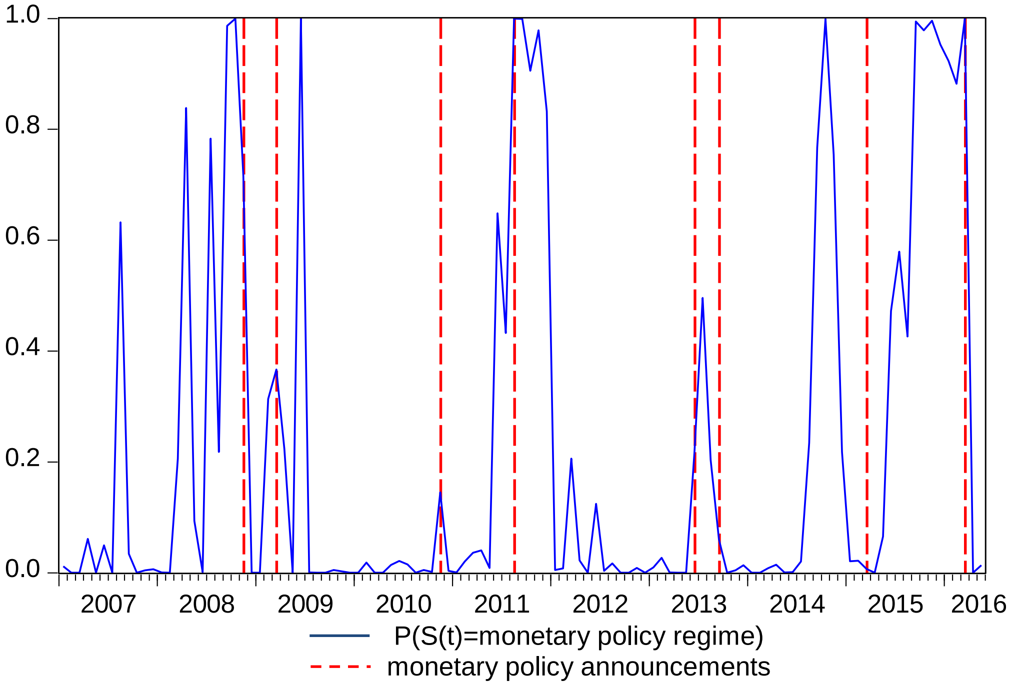

Figure 4
Filtered regime probabilities: Market neutral

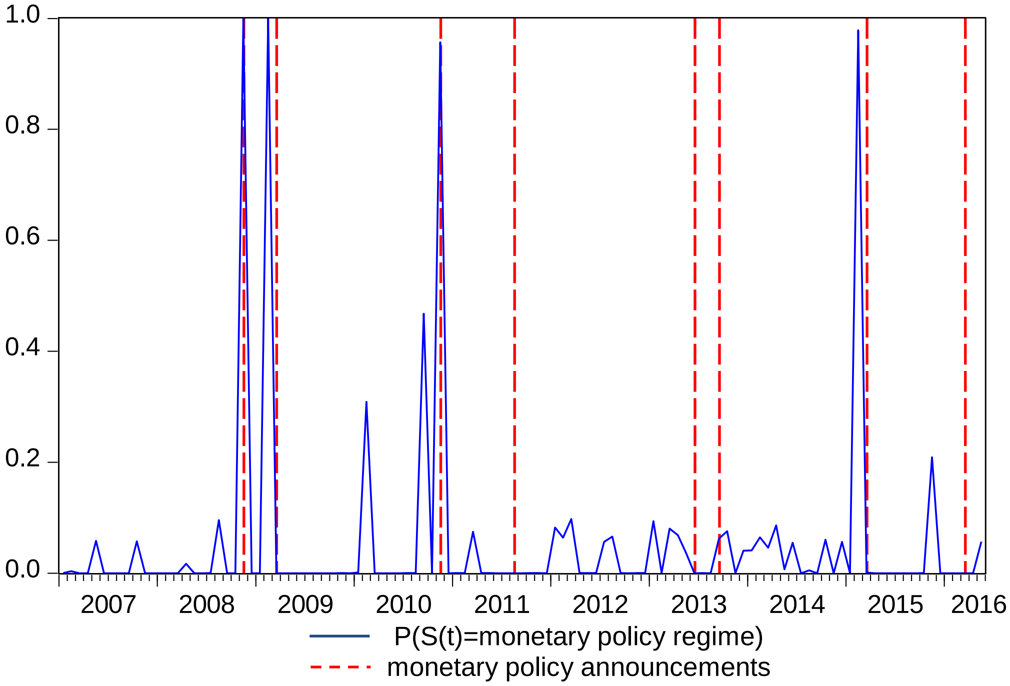

Table 5
Filtered regime probabilities: Dedicated short bias

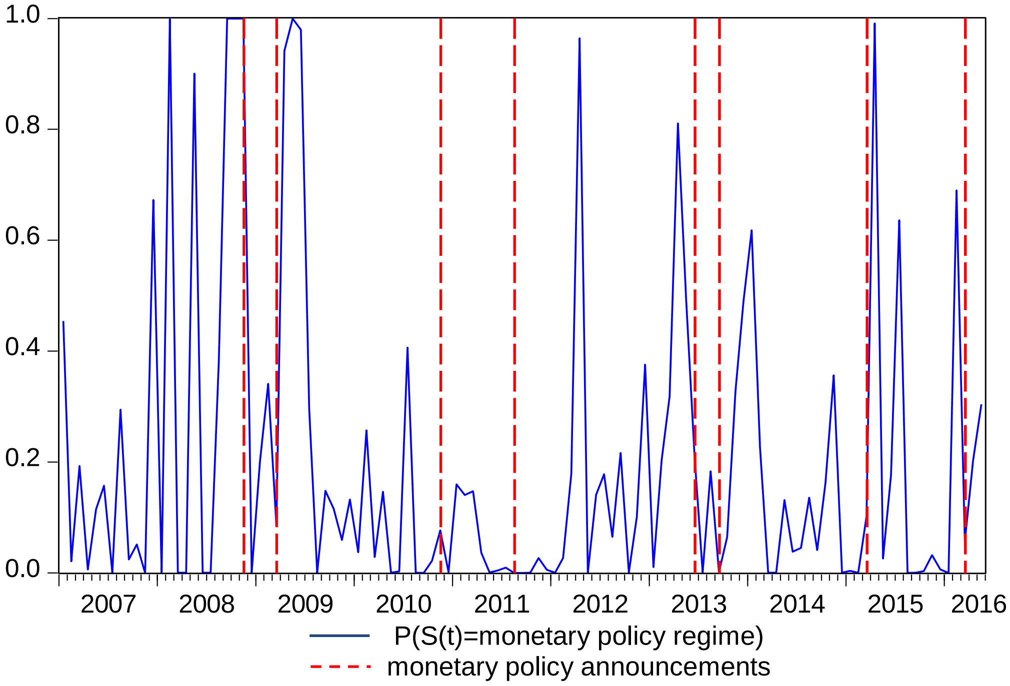

Figure 6
Filtered regime probabilities: Emerging markets

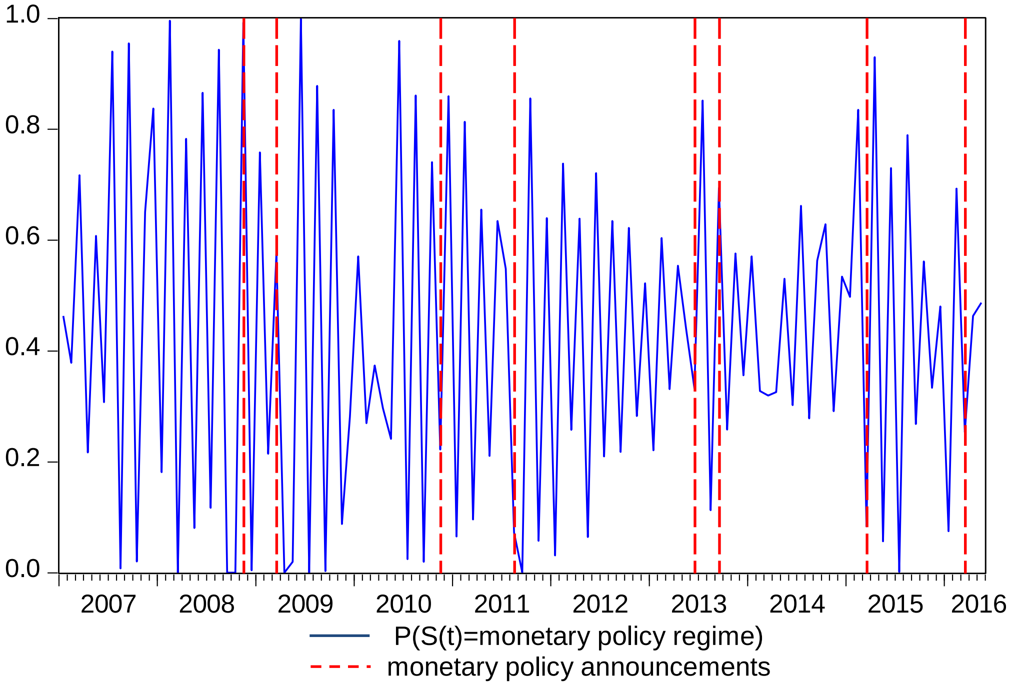

Figure 7
Filtered regime probabilities: Fixed-income arbitrage

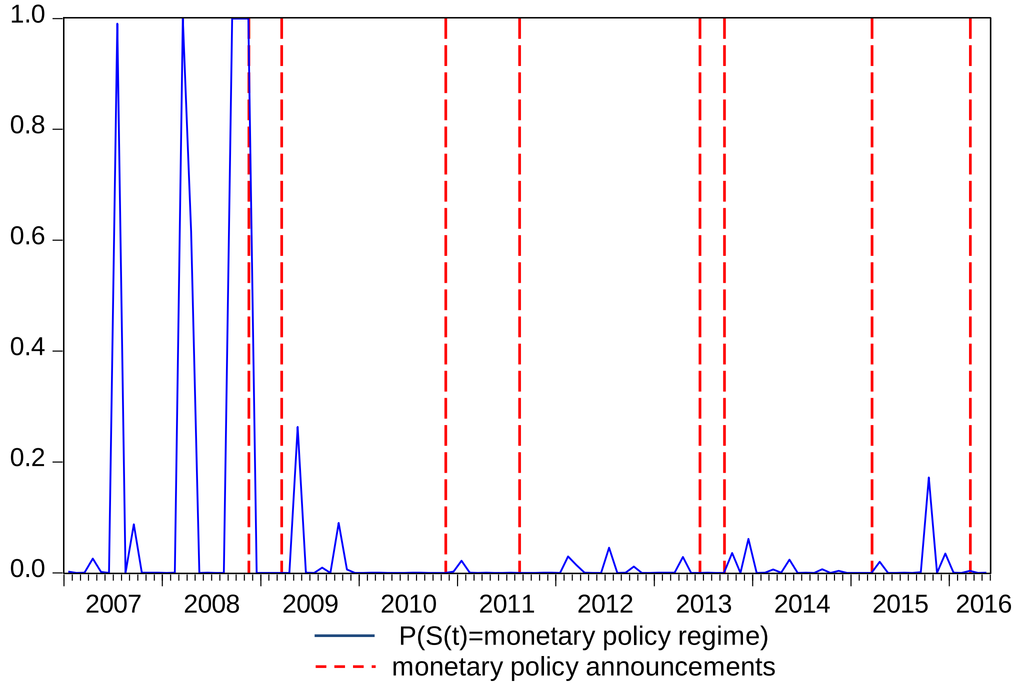

Figure 8
Filtered regime probabilities: Global macro

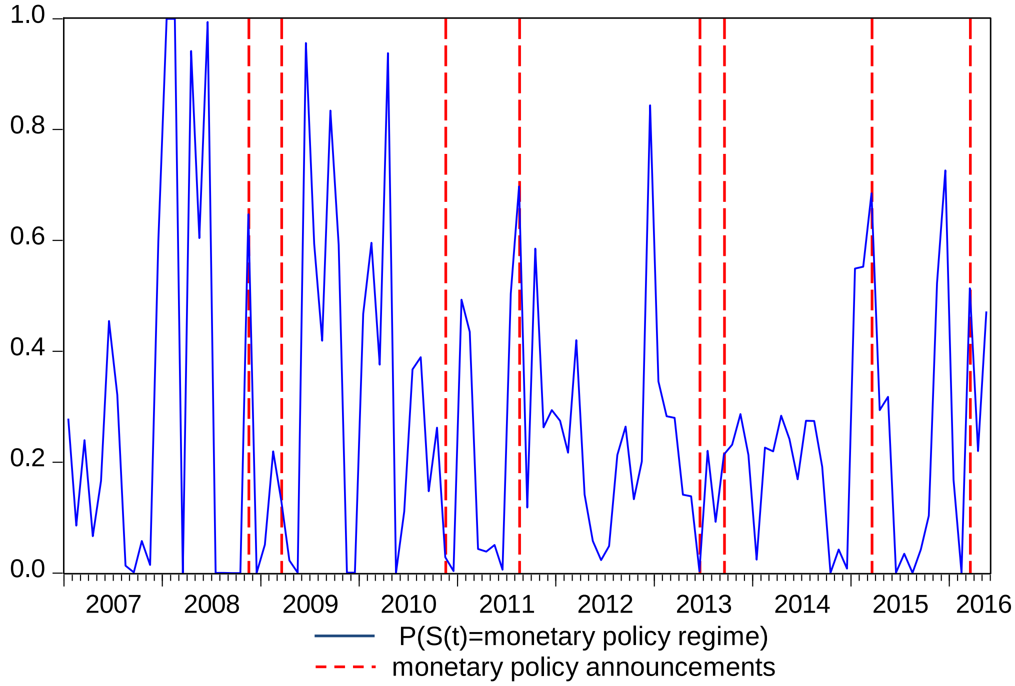

Figure 9
Filtered regime probabilities: Multi-strategy