Stock Market Responses to Monetary Policy Worry:
A Further Analysis of the Impact of Monetary Policy on the Stock Market

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Abstract

Past literature has studied the impact of monetary policy and uncertainty on stock returns. To understand the linkage further, we introduced an additional layer in this relationship by defining a monetary policy worry (MPW) variable to act like a wedge between the stock market response and the underlying monetary policy change and uncertainty based on psychological theory about human behavior in times of uncertainty. For this purpose, we defined and constructed an MPW index and examined the information content of the index. We provided empirical evidence of how stock market returns and volatilities respond to MPW.

Keywords: Monetary Policy Worry, Stock Market Return and Volatility, Market Sentiments, Investor Behavior

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1. Introduction

The stock market can generally be influenced by two types of factors: the fundamentals and expectations based on the fundamentals. There is no doubt that monetary policy is a fundamental factor. The news media often reports that the stock market is worried about monetary policy and its impact on the market. For example, a report titled "Fed Raises Interest Rates, Showing Confidence in Health of Economy" in *The New York Times* on December 19, 2018, mentioned that despite the market's awareness that the Federal Reserve has raised interest rates and signaled more rate increases in a display of confidence in the economy, the financial market was still worried about future rate increases and political pressure to suspend rate increases. Also, as financial stability is one of the triple mandates of the Federal Reserve, the Federal Open Market Committee (FOMC) often has financial market worry in mind when it implements monetary policy. In the meantime, any uncertainty regarding monetary policy weighs on the financial markets and dampens the mood for investors.[1]

There are two distinct elements in the discussions above. The first is monetary policy uncertainty (MPU) and the second is the behavioral response of the market to monetary policy and uncertainty about it. The result of these market behavioral changes is the stock market price change.[2] Thus this second element—namely, monetary policy worry (MPW)—places a wedge between the stock market reactions represented by stock price changes and the ultimate sources of the stock price changes such as fundamental changes in the market and expectation of market fundamental changes. Therefore, the link between monetary policy and investor sentiment may have important implications for both market practitioners and policymakers, as emphasized in Lutz (2015). However, based on the viewpoint of Nandwani and Verma (2021), the traditional measurement of investor sentiment may be insufficient for showing the exact behavioral response of the market if its construction does not account for an individual's emotional or mental state, such as worry about monetary policy that comes from information available in the media.

From the perspective of psychology, worry is a human emotional response to the intolerance of uncertainty. Worry has several characteristics. First, the negative emotion represented by worry is

[1] Oet and Lyytinen (2017) showed evidence that, for the Fed, financial stability is as important as price stability and long-run growth. Ellis and Liu (2021) showed that economic policy uncertainty affects the monetary policy preferences of the FOMC.

[2] As discussed in Baker and Wurgler (2007), there has been a large and growing literature on the effects of sentiment on financial markets, e.g., Shiller (2000), Brown and Cliff (2004), Tetlock (2007), Kurov (2008), Brunnermeier (2009), Schmeling (2009), Fung et al. (2010), Gençay et al. (2010), Chen (2011), Chung et al. (2012), Singer et al. (2013), Garcia (2013), and Lutz (2016).

impacted by the intolerance of uncertainty; second, no matter what the chance of negative events is, the intolerance of uncertainty leads to individuals being inclined to concern themselves only with the unexpected negative events; third, the intolerance of uncertainty makes people hold negative attitudes toward uncertain events; and lastly, the intolerance of uncertainty leads to people overestimating the impact of the negative events (Dugas, Marchand, and Ladouceur, 2005; Dugas, Schwartz, and Francis, 2004; Dugas, Gosselin, and Ladouceur, 2001; Ladouceur, Gosselin, and Dugas, 2000). Thus, worry has its roots in uncertainty and reflects people's intolerance of it.

Other research points out that emotions impact decision-making. As pointed out in Garcia (2013), the psychology literature forcefully argues that emotions affect people's decision-making and their information processing in particular. Lad and Tailor (2016) studied various emotional biases that influence investors' investment decisions and concluded that various cognitive and emotional biases have an impact on investors when they make investment decisions. In the financial literature, it has been shown that emotion may be about individuals' oversensitivity to monetary shocks (Kurov, 2010; Bernanke and Kuttner, 2005); this is especially true of naive investors, who may overreact to financial news more often than sophisticated investors (Mahani and Poteshman, 2008).

However, we believe that the financial literature is limited to investigating the impact of MPU but not MPW, even though the two can be related; moreover, the investor sentiment measured in past work is insufficient to reflect the exact behavioral response of the market because it lacks information about emotions like worry. Representative studies of MPU include Husted, Rogers, and Sun (2020), Tillmann (2020), Gospodinov and Jamali (2018), Gu, Kurov, and Wolfe (2018) and Baker, Bloom, and Davis (2016), and those works regarding investor sentiment toward monetary policy include Kurov (2010), Lutz (2015), Li (2015), Dahmene, Boughrara, and Slim (2021), Cepni and Gupta (2021), Guo, Hung, and Kontonikas (2021), and Galariotis, Makrichoriti, and Spyrou (2018). To our knowledge, there is no study of the impact of MPW. MPU is related to the outcome of monetary policy, but MPW directly measures investors' perception of and response to unexpected monetary policy that is unfavorable. In this sense, we directly incorporate investors' sentiments toward uncertainty about unfavorable monetary policy results into our measurement and analysis. Thus, our objective in this paper is to study the impact of MPW directly. For this purpose, we construct an index that can be used to measure MPW and then examine its impact.

The financial literature has already seen studies focused on MPU, or surprises or shocks, for example, De Pooter, Favara, Modugno, and Wu (2021), Gürkaynak, Kara, Kısacıkoğlu, and Lee (2021), Sequeira (2021), Fausch and Sigonius (2018), Basistha and Kurov (2015), Fawley and Neely (2014), León and Sebestyén (2012), Claus and Dungey (2012), Bredin, Hyde, and Reilly (2010), Bohl, Siklos, and Sondermann (2008), Kuttner (2001), Andrade and Ferroni (2021), Bu, Rogers, and Wu (2021), Alves, Kaplan, Moll, and Violante (2020), Chava and Hsu (2020), Claus and Nguyen (2020), Mumtaz and Theodoridis (2020), Pasten, Schoenle, and Weber (2020), Alessi and Kerssenfischer (2019), Keating, Kelly, Smith, and Valcarcel (2019), Castelnuovo and Pellegrino (2018), Furceri, Loungani, and Zdzienicka (2018), and Nelson, Pinter, and Theodoridis (2018). Monetary policy surprise and monetary policy shock raise the level of MPU and thus trigger worry in the financial market. However, monetary policy surprises and then uncertainty can only be inferred from investors' responses through changes in the financial markets. We improve the literature further by providing a missing link between MPU and reactions in the financial markets.

As MPW is not a directly observable variable, we need to come up with a suitable measurement index, which is also a major issue in the behavioral finance literature that focuses on investor emotions. For this reason, we modified the method of Da et al. (2015) and Fernandez-Perez, Fuertes, Gonzalez-Fernandez, and Miffre (2020), who formulated a measurement of MPU employing the relationship between the Google Trends search volume index (SVI) and asset returns. The Google Trends SVI is the statistical summary of keyword searches in the Google search engine. Researchers can set the area and time of the search as they wish. The SVI reflects the degree of search interest by noting how many times a given search term is entered into Google's search engine relative to the site's total search volume over a given period of time. SVI is a standardized value between 0 and 100, with 100 representing the time period with the most searches and 0 the time period with the relatively fewest searches (not necessarily 0 searches). In more recent years, the SVI has been used in the study of retail investor attention, financial and economic attitudes revealed by search (FEAR), fear of hazards, fear of the coronavirus, gambling sentiment, and other emotional sentiments (e.g., Da, Engelberg, and Gao, 2011; Da et al. 2015; Fernandez-Perez et al., 2020; Lyócsa, Baumöhl, Výrost, and Molnár, 2020; Chen, Kumar, and Zhang, 2021). In this study, we extend it to measuring investors' sentiment of MPW in the context of financial market movement.

To consider the characteristics of the emotion of worry described in psychology, we differ from Da et al. (2015) and Fernandez-Perez et al. (2020) in measuring MPW. The most important difference is that the empirical relationship that we use to measure MPW is between the value at risk of a single asset and search query terms rather than the link between asset returns (representing market response to the full spectrum of events) and search query terms, as in past works. The employment of value at risk to measure worry is an important difference from the past literature. The downside risk of asset return measured by value at risk is essential for our purpose of gauging worry. The methods in Da et al. (2015) and Fernandez-Perez et al. (2020), which were based on an empirical link between asset return and search query terms, specify no aspect of worry and are therefore not suitable for measuring the emotion of worry in this article.

In addition to the major measurement issue just mentioned, several other differences make our study stand out. First, in our measurement, the asset holding time is assumed to be related to the investor's investment horizon, which could be as short as just days or as long as months or a year. Considering that the asset holding period could affect the degree of worry, we rely on a cumulative daily return for different holding times to calculate the degree of risk. We consider asset holding periods of 1 day, 5 days, 20 days, 60 days, and 240 days to capture the downside risk investors face when they have respective investment horizons of 1 day, 1 week, 1 month, and 1 year. We then obtain the first principal component as the MPW measurement index through principal component analysis. In comparison, the past literature has not considered impact that could vary with the investment horizon or asset holding time. We believe ignoring the investment horizon could lead to measurement errors, especially when the measurement index is supposed to reflect the return on an asset for the holding period (e.g., 5 days or 20 days) and the holding periods are typically not the same as the data frequency (such as daily data) in the studies.

Second, differing from Da et al. (2015) and Fernandez-Perez et al. (2020), who used the return of multiple assets, we employed the return of a single asset, namely, the return of crude oil futures. We did this for three reasons.

The first is that Gospodinov and Jamali (2018) showed that the prices of the commodity futures of the same group could have different responses to monetary policy surprises. Among the 20 commodity futures they analyzed, only gold and platinum had responses similar to that of crude oil futures price to monetary policy surprises. Fernandez-Perez et al. (2020) found that the correlation between asset return and SVI can still differ quite significantly among the commodity futures in the same industry (energy, agriculture, metal, and soft goods). For this reason, an asset return calculated using inappropriate commodity futures could lead to errors when market emotions are measured.

The second is that empirical studies have already shown that crude oil is easily influenced by monetary policy and it is a financial instrument that is highly sensitive to monetary policy. For example, Rosa (2014) provided evidence that an unexpectedly high federal funds target rate could negatively influence the price of West Texas Intermediate crude oil futures. Basistha and Kurov (2015), employing intraday data, obtained the same result as Rosa (2014) and further revealed that the effect was stronger especially when no FOMC meeting was scheduled. Employing event study methodology, Marfatia, Gupta, and Cakan (2021) studied the impact of unexpected monetary policy announcements on crude oil futures and concluded that when there was an increase in MPU, unexpected monetary policy announcements by the FOMC would reduce the impact of the policy on the return and realized volatility of crude futures. In addition, using the unexpected variations in the Italian risk premium as the unconventional monetary policy, Soriano and Torró (2021) analyzed the impact of European Central Bank (ECB) monetary policy on crude oil price and found that the price of Brent crude futures could be negatively impacted by unexpected variation in the risk premium; however, the price of Brent could be positively impacted by unexpected variations in short-term interest rates.

The third is that Mensi, Hammoudeh, Shahzad, and Shahbaz (2017) pointed out that, in addition to the available fundamental information in the stock markets, investors make decisions based on information prevailing in the oil market since changes in oil prices contain crucial information about the relationship between oil and the stock markets. Using the copula method, Mensi et al. (2017) showed that crude oil prices are linked to stock market indexes from the aspect of tail dependence and such tail dependence is up to short- and long-run time horizons and upside and downside risk. More importantly, since one of the variables that Mensi et al. (2017) used to examine tail dependence is value at risk, their empirical findings can serve as support for our use of crude oil futures as the only asset and employing its value at risk to measure market-level worry.

Our empirical study first analyzes the information content of MPW to ascertain whether it contains any information related to MPU. This is because being able to reflect the uncertainty is the necessary first step in measuring the emotion of worry from the point of psychology. For this reason, we investigate the connection between the MPW index and the three MPU indexes of Husted et al. (2020; henceforth HRS), Gospodinov and Jamali (2018; henceforth GJ), and Baker et al. (2016; henceforth BBD). We examine whether the information from these MPU indexes can be reflected in the MPW index we construct. Our sample covers the period of October 2006 to April 2020. Our empirical results reveal that the MPW index contains the relevant information from MPU for the current and previous month. In addition, when we divide future monetary policy into unexpected monetary contraction and unexpected monetary expansion, MPW reflects better the information content in the MPU index, which suggests that the MPW index contains the market worry about the two expected monetary policy directions. In the meantime, we are able to find differences among the MPU indexes. That is, the uncertainty detected in BBD and GJ was mainly related to unexpected monetary contraction, and the uncertainty detected by HRS was mainly related to unexpected expansionary monetary policy. This finding helps us to understand the information content of MPU and enables us to use MPU as a variant of MPW to analyze the impact of MPW on asset return and volatility; it also helps us to better explain the estimation results. This way, we can investigate investors' worry about unexpected monetary contraction through the indexes of BBD and GJ and investigate investors' worry about unexpected monetary expansion through the HRS index. This is an important and useful discovery for this study, as suggested by Gospodinov and Jamali (2018); the impact of unexpected monetary policy on crude oil price depends on the target interest rate set by the Federal Reserve, whether the policy is expected to be expansionary or contractionary, and the economic condition at the time. During recessions, only unexpected expansionary monetary policy affects MPU (i.e., there is no effect from unexpected monetary contraction), and it causes a decline in the return of near-month futures contracts. By contrast, during nonrecessionary periods, only unexpected contractionary monetary policy affects MPU (i.e., unexpected expansionary monetary policy is ineffective), and the return of near-month futures contracts increases as a result.

Next, we analyze the impact of the MPW index on the return of market indexes including the S&P 500 index and the Russel 3000 index. Through generalized method of moments (GMM) estimation, we found endogeneity between the contemporaneous incremental changes of MPW and index returns.

When the future 6-month index returns were analyzed, the endogeneity disappeared. We also found that the increase in the contemporaneous incremental MPW index could lead to worsening index returns, and there is no reversal of that result in the next 6 months whether we add BBD and GJ or HRS to our list of instrumental variables. The result of a net negative effect suggests that worry about the market is a negative factor that affects stock market performance, and the result of no subsequent reversal of the effect differs from the findings of past research on investor sentiments.[3] Then, using the components of the S&P 500, we further searched to see if the MPW index affects the performance of an individual stock including its risk premium and abnormal returns. To deal with the econometric issues arising from the unobservable individual effect, we estimated the models with GMM using the Arellano-Bond difference. Our results reveal that the information about unexpected monetary contraction contained in the BBD and GJ indexes does not enable us to explain individual stock performance; that could be explained only by the unexpected monetary expansion information contained in the HRS index. This reveals a distinctive difference between the effects of the MPW index on the market index and its effects on individual stocks. Another difference is the dynamic effect of the impact of MPW: even though the increase in contemporaneous incremental MPW leads to lower same-period returns of individual stocks, there is a reversal of the stock performance after four months, which offsets most of the initial negative impact. That being the case, we tend to believe that, as implied by the market index, investors do not tend to adjust the decisions they have made under the influence of worry, but individual investors make adjustments subsequently. However, compared to the time needed (several months) for investors to reverse the initial impact of emotion, it takes a relatively long time to reverse the impact of worry.

To investigate the impact of MPW on individual stocks, we further examine whether the risk premium can be determined by the cross-sectional difference between the individual stocks. Our results suggest that the risk premium of MPW shows up in the risk premium of individual stocks; in other words, the higher the risk premium of individual stocks due to contemporaneous incremental MPW, the higher the overall risk premium. However, the significance of the effect is reduced due to the addition of an intercept to the model. We suspect that in the risk premium of incremental MPW, some effects are similar for all individual stocks, so the impact is diluted when an intercept is added into time series regression models of individual stock returns. Finally, we investigate through component regression the impact of MPW on index return volatility including the VIX index (implied volatility) and realized volatility measured by the return of the S&P 500 and Russel 3000. We use the 20th, 50th, and 80th percentiles to represent low, medium, and high volatility, respectively. We find that when the index is in a period of high volatility, MPW added in the same month lead to higher volatility; however, when the index is in periods of median and low volatility, the contemporaneous incremental MPW does not

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[3] As illustrated in the behavioral models in De Long et al. (1990), investor sentiment is expected to be able to predict stock market return reversals. Studies that also find evidence of reversal include Obaid and Pukthuanthong (2021), Weißofner and Wessels (2020), Zhu, Sun, and Chen (2019), Koo, Chae, and Kim (2019), Renault (2017), Sun, Najand, and Shen (2016), Da et al. (2015), Ni, Wang, and Xue (2015), Chui, Titman, and Wei (2010), and Tetlock (2007).

have any significant impact. In addition, the contemporaneous incremental MPW does not have any one-period lagged effect regardless of the volatility state.

To our knowledge, this is the first paper in the literature that deals with MPW. We contribute to the financial literature in the area of constructing an MPW index, verifying its information content, and investigating its impact on the stock market, including the index returns and volatility and individual stocks' returns and risk premium. The paper is organized as follows: in section 2, we detail the method of constructing the MPW index, describe its characteristics, and compare it to the MPU index. We also explain the control variables that we use in our empirical analysis. Section 3 details the empirical methods, including the setup of the empirical model and estimation, and explains the empirical findings. Section 4 provides robustness checks. The conclusion is given in section 5.

2. Data and Methodology

2.1 MPW index construction

We begin by illustrating the construction of our MPW index, which is the main variable in our analysis. Our method is inspired by extant literature such as Da et al. (2015) and Fernandez-Perez et al. (2020); these studies resort to the relation between Google search volume and asset-price returns to construct the proxy for fear. However, because we are concerned with the role of market worry about monetary policy, our search query terms are monetary policy keywords instead of the economic words and hazard-fear terms employed by Da et al. (2015) and Fernandez-Perez et al. (2020). We resorted to recent literature in finance to build a list of 39 search terms related to monetary policy, which are listed in column 1 of Table 1 (Boguth, Grégoire, and Martineau, 2019; Gu, Kurov, and Wolfe, 2018; Wohlfarth, 2018; Altavilla and Giannone, 2017; Baker, Bloom, and Davis, 2016).[4] To understand how the words might be searched in Google by American households, we specified the query region as "United States" and input each word into Google Trends to download the daily SVI.[5] Columns 3 and 4 of Table 1 display the sample mean and *t*-test statistics for the SVIs over the period from January 1, 2004, to April 30, 2021. It shows that irrespective of the difference in geographical regions, *t*-test statistics are all significant at a 1% level, which suggests that American households pay attention to the monetary policies of major economies all over the world. Figure 1 draws time series graphs of average SVIs for different geographical regions; because the SVI level in Figure 1(a) is higher than that in Figure 1(b) and Figure 1(c), we conclude that American households are most concerned with America's monetary policy, less concerned with Europe's, and least concerned with Asia's.

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[4] As our search terms have all either appeared in news stories or been employed in Google Trends, we ignore the process in Da et al. (2015) and Fernandez-Perez et al. (2020) which examined the top ten related searches of each term to filter out the irrelevant keywords.

[5] We found it impossible to set five different time periods in Google Trends for comparison as suggested in Chronopoulos, Papadimitriou, and Vlastakis (2018), so we resorted to the "gsvi 0.2.2" Python code to retrieve daily SVIs.

----- Insert Table 1 here -----

----- Insert Figure 1 here -----

Next, we defined the daily change in the SVI of the k-th search term as:

$$\Delta\text{SVI}_{k,t} = \ln(1 + \text{SVI}_{k,t}) - \ln(1 + \text{SVI}_{k,t-1}),\ k = 1, \tag{1}$$

Column 6 in Table 1 shows that no t-test statistics of the sample mean of $\Delta\text{SVI}_{k,t}$ are significantly different from zero. Similar to the findings of Da et al. (2015), our time-series data of daily change in SVIs fluctuate close to the horizontal axis, indicating zero expected value for daily $\Delta\text{SVI}_{k,t}$. Moreover, in order to mitigate any concerns about seasonality and heteroscedasticity, we follow Da et al. (2015) and Fernandez-Perez et al. (2020) and employ the method of Baker and Wurgler (2006) to regress daily $\Delta\text{SVI}_{k,t}$ on dummies for weekdays and months, and then we standardize the residuals by the time-series standard deviation for the preceding L days (our setting here is $L = 31$). This processing leaves us deseasonalized and standardized data for the daily $\Delta\text{SVI}_{k,t}$ of our 39 query terms; we also follow the literature by naming it as change in abnormal SVIs and denoting it by $\Delta\text{ASVI}_{k,t}$.[6]

Our final step in constructing the MPW index is also based on the procedure in Da et al. (2015) and Fernandez-Perez et al. (2020), but it is different from them in three aspects. First, we focused on examining the influence of $\Delta\text{ASVI}_{k,t}$ on crude oil futures as the only asset rather than on the entire equity market or numerous commodity futures as considered in Da et al. (2015) and Fernandez-Perez et al. (2020). This is because crude oil futures have been shown to be more sensitive to monetary policy and more influential for equity and macroeconomic variables than equities and other commodity futures (Jiang and Liu, 2021; Zhang, He, Nakajima, and Hamori, 2020; Chiang and Hughen, 2017; Basistha and Kurov, 2015; Hammoudeh, Nguyen, and Sousa, 2015). Second, based on the psychological insight that people worry about uncertainty and uncertainty then leads to negative thoughts (Dugas, Marchand, and Ladouceur, 2005; Dugas, Schwartz, and Francis, 2004; Dugas, Gosselin, and Ladouceur, 2001; Ladouceur, Gosselin, Dugas, 2000), we resorted to a risk measure, value at risk, to capture market worry rather than the return variable employed by Da et al. (2015) and Fernandez-Perez et al. (2020). Third, because market participants' worry may depend on how long they expect to hold assets, we examined our value at risk for various investment periods, including 1, 5, 20, 60, and 240 trading days, to facilitate the capture of the behavior of value at risk by day, week, month, quarter, and year.

We followed the approach of Da et al. (2015) and Fernandez-Perez et al. (2020) and constructed MPW based on the historical relationship between changes in daily abnormal SVI and the contemporaneous

[6] Different from Da et al. (2015) and Fernandez-Perez et al. (2020), we are interested in extreme behavior (i.e., the lower tail of equity returns); therefore, in order to preserve the extreme results of each series, we chose not to change the original results of abnormal SVIs.

value at risk of the assets represented by crude oil futures. Specifically, we used the data to run expanding backward rolling regressions of $\Delta\text{ASVI}_{k,s+j-1}$ on value at risk. Given the window of W trading days and the period of N trading days required for the historical simulation approach to trace out value at risk with a probability of 1% (our default settings here were $W = 120$ and $N = 1200$), the regression model can be specified as

$$\text{VaR}^{P}_{s+j-1} = \alpha + \beta^{P}_{k,s+j-1} \cdot \Delta\text{ASVI}_{k,s+j-1} + \varepsilon^{P}_{s+j-1}, \tag{2}$$

$$s = 1, \cdots, W, \text{ for all } j = 1, \cdots, T - W - N - K,$$

where VaR^{P}_{s+j-1} denotes value at risk, ε^{P}_{s+j-1} is the error term and stands for idiosyncratic risk, and $P = 1, 5, 20, 60, 240$ represents the periods that assets have been held by market participants. Using the case of $P = 1$ for illustration, for September 14, 2005, we used the data from March 31 to September 14, 2005, to run a regression of $\Delta\text{ASVI}_{k,s+j-1}$ for each of our 39 search terms on value at risk, and throughout the sample from January 1, 2004, to April 30, 2021, the OLS estimate for $\hat{\beta}^{1}_{k,s+j-1}$ is available for all $k = 1, \cdots, 39$ from September 14, 2005, to April 30, 2021. Figure 2(a) shows the graphs of value at risk available from the historical simulation of a 1200-day window. From that figure, we found that holding assets for a longer period is riskier because of larger drops in daily returns in general, such as the periods from 2009 to 2013 and from 2015 to 2021, but during the period from 2021, it seems that holding assets for 20 days can be riskier than holding assets for 60 days.

----- Insert Figure 2 here -----

Then we ranked the OLS estimate for $\hat{\beta}^{P}_{k,s+j-1}$ from the most negative to the most positive for each P (i.e., asset holding period), and we selected the most negative effects to form our MPW index. So we defined the MPW of market participants that hold assets for P trading days on day $\tilde{t}$ as

$$\text{MPW}^{P}_{\tilde{t}} = \sum_{i=1}^{\leq 20} \left|\hat{\beta}^{P}_{k,\tilde{t}}\right|, \ \tilde{t} = s + j - 1, \tag{3}$$

where $\text{MPW}^{P}_{\tilde{t}}$ denotes the MPW index for a certain period of P trading days, and $\left|\hat{\beta}^{P}_{k,\tilde{t}}\right|$ indicates the absolute value of the OLS estimate available from equation (2). Since our search query terms were few and we observed that the number of negative estimates of $\hat{\beta}^{P}_{k,\tilde{t}}$ may be less than 20, we chose at most 20 terms to aggregate the MPW index rather than setting a fixed number to be a cutoff point as in Da et al. (2015). Despite this, we observed that the negative estimates of $\hat{\beta}^{P}_{k,\tilde{t}}$ typically accounted for a dominant percentage and the MPW index was still characterized by enough negative estimates. Again, using the case of $P = 1$ (i.e., holding an asset for one day) for illustration, among the 3949 data points of the MPW index from September 14, 2005, to April 30, 2021, there were 3651 data points constructed by the sum of at least 15 negative estimates of $\hat{\beta}^{P}_{k,\tilde{t}}$ (more than 92%) and only 9 data points constructed by the sum of less than 10 negative estimates of $\hat{\beta}^{P}_{k,\tilde{t}}$ (less than 1%). As documented in Da et al. (2015), there are several advantages to employing such a historical and regression-based approach for selecting terms since it is an objective way to let the data speak for themselves. We drew the graphs of MPW_t^P in Figure 2(b). In that figure, the peaks during 2007-2009 may be due to the subprime-lending financial crisis; other large peaks during 2014-2015 may reflect the Fed's intention to change monetary policy from quantitative easing to tapering, and smaller peaks that occurred during 2020 may be associated with the COVID-19 epidemic.

To measure the market worry about monetary policy by a single MPW index, we resorted to principal component analysis to integrate the MPW available from equation (3) by the first principal component. This is similar to ways in the literature in which sentiment indexes are constructed (Yang and Hu, 2021; Gao, Liang, Xu, and Xie, 2020; Zhou and Huang, 2020; Rao and Zhou, 2019; Gao and Yang, 2018; Yang and Zhou, 2016; Irresberger, Mühlnickel, and Weiß, 2015; Yang and Zhou, 2015; Peterson and Smedema, 2011). Then we summed daily MPW within the same calendar month to be the monthly MPW index. The data start from October 2005 because daily data for MPW in September 2005 are not complete. Figure 2(c) depicts the time series process of our monthly MPW index with the legend "MPW (1st PC)," and it can be seen that the time-series behavior is similar to the daily MPW of various asset-holding periods in Figure 2(b). In addition, Figure 2(c) also draws on MPU indexes in extant literature. Figure 2(c) reveals that investors do not need to worry about monetary policy even when an economy is under a high level of uncertainty, such as the periods from the middle of 2010 to the end of 2013 and from the middle of 2017 to the beginning of 2019. This is a remarkable feature that distinguishes the MPW index from the MPU index. Intuitively, MPU may be triggered by FOMC meetings when the U.S. is in recession, but people often do not need to worry about monetary policy unless business conditions have not recovered for a while.

2.2 Other variables

As illustrated above, the data of SVIs and crude oil futures returns are essential to the construction of our MPW index. We collected the data of daily SVIs from Google Trends and the data of crude oil futures prices from Yahoo Finance, ticker "CL=F." Throughout this paper, we measure returns by this formula:

$$R_\ell = [\ln(P_\ell) - \ln(P_{\ell-1})] \times 100, \tag{4}$$

where R_ℓ and P_ℓ represent return and level of price or index at the ℓ-th period, respectively. The most important thing to us was to make sure that the MPW index yielded information about uncertainty due to monetary policy. To verify this, we employed three MPU indexes developed in extant literature, and their behaviors are as illustrated in Figure 2. The data from Baker et al. (2016) and Husted et al. (2020) are directly available from the authors' websites; the data from Gospodinov and Jamali (2018) was calculated by us using data of euro-dollar futures prices, which is also available from Yahoo

Finance, ticker "GE=F." [7] As pointed out in Husted et al. (2020), BBD and HRS are constructed by a news-based approach using newspaper coverage frequency, and such MPU indexes available from textual analysis can complement measures like those of GJ, which use a market-based approach.[8]

After verifying the existence of the link between MPW and MPU, we investigated how MPW affects stock market assets, including return variables and volatility variables. Except for the data of the S&P 500 VIX futures prices obtained from Investing.com, ticker "VX," other data were collected from Yahoo Finance, including the S&P 500 index, the Russel 3000 index, the Chicago Board Options Exchange (CBOE) market volatility index (VIX), and the S&P 500 component stocks' prices (the many tickers used include "GSPC," "RUA," and "VIX").[9] Given these, we could measure the stock market returns by the S&P 500 and Russel 3000 indexes, the individual stocks' returns by the component stocks' prices, the VIX futures returns by the S&P 500 VIX futures prices, and the stock market volatility by the VIX (30-days implied volatility of S&P 500 index) and the realized volatility of the S&P 500 and Russel 3000 indexes as computed by the following formula:

$$RV_d = 250 \times \left(\sum_{\tilde{\ell}=1}^{M_d} R_{d,\tilde{\ell}}^2\right)/M_d, \quad (5)$$

where RV_d represents realized volatility in the d-th month, which has M_d trading days, and $R_{d,\tilde{\ell}}^2$ is the square of return at the $\tilde{\ell}$-th trading day in that month. In Equation (5), we follow Da et al. (2015) and consider the annualized realized volatility by a multiplier of 250, and we divide the sum of the square of returns by the number of trading days within the calendar month to avoid bias due to the difference in the number of total trading days in calendar months.

Moreover, when examining the impact of MPW on stock market assets, we followed Da et al. (2015) and control for the impact of the lagged dependent variables and the macroeconomic conditions represented by the VIX, changes in the economic policy uncertainty (EPU) index, and changes in the Aruoba, Diebold, and Scotti (ADS) index (Aruoba et al., 2009). Specifically, the VIX is well known as a gauge of investor fear (Da et al. 2015) and is considered an alternative market sentiment measure in Baker and Wurgler (2007). We included the VIX as a control variable in specifications except where it is specified as a dependent variable. The EPU measure is developed by Baker et al. (2016) by counting the number of U.S. newspaper articles collected in the News Bank Access World News database with at least one term associated with the categories "economic," "uncertainty," and "the authorities." As shown in Baker et al. (2016), such a news-based index is good at capturing perceived

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[7] Data for BBD and HRS can be found at http://www.policyuncertainty.com/index.html and https://sites.google.com/site/lucasfhusted/data, respectively.

[8] Examples of market-based approaches also include Chang and Feunou (2013), Bauer (2012), Emmons, Lakdawala, and Neely (2006), Swanson (2006), Carlson, Craig, and Melick (2005), and Neely (2005). As documented in Husted et al. (2020), the market-based approach may reflect only the perception of households participating in the options market, may have a component due to time-varying risk aversion and/or state-dependent marginal utility rather than uncertainty, and may fail to include the part of monetary policy uncertainty that is not caused by interest rate uncertainty.

[9] We resorted to the "yfinance" Python library to collect the data.

EPU. The ADS index uses a battery of seasonally adjusted macroeconomic variables that have mixed frequencies, including weekly data of initial jobless claims, monthly data of payroll employment, industrial production, personal income less transfer payments, and manufacturing and trade sales, as well as quarterly data of real gross domestic product. As mentioned in Da et al. (2015), changes in the ADS reflect innovations from macroeconomic conditions, and thus an increase in the ADS indicates progressively better-than-average conditions, while a decrease means progressively worse-than-average conditions.

Table 2 presents the descriptive statistics from our data. It can be seen in columns 3 to 6 that an increased sample mean, standard deviation, and maximum and minimum of daily down-side risk correlate with an increased investment horizon. But when the results of value at risk are divided by the number of days that people hold assets, the mean of daily down-side risk, its volatility, and the maximum and minimum of daily loss all decrease with the number of days that people hold assets. Likewise, the statistics of MPW before being mixed by principal component analysis show similar results. That is, a market participant who holds assets for a long period can be less worried than one who holds for a short period about short-term monetary policy, whether it is measured by the average level, the degree of variation, or the maximum or minimum level. As to the MPW index measured by the first principal component of MPW, we scaled the original results to a range from 0 to 100 to facilitate comparison with the MPU index measures. The adjusted results range from 8.92 to 100, with average and standard deviation between those for the results for the MPW of someone who holds assets for 5 days and 60 days.[10]

----- Insert Table 2 here -----

In Table 2, we also find from the statistics of MPU that HRS is larger and GJ smaller than the other two indexes, and their values move in respectively larger and smaller ranges; however, this does not mean that HRS and GJ measure respectively more or less uncertainty than the other two; their units are not measured in the same way. Statistics for the S&P 500 and the Russel 3000 show that the latter is slightly more profitable and riskier than the former, consistent with a knowledge of additional risk premiums for small-capitalized stocks. Moreover, it can be seen that the return of S&P 500 individual stocks is higher on average and has a larger standard deviation than the return of the S&P 500 index, consistent with a consensus that individual stocks are riskier than the stock market index. Finally, the EPU index, the ADS index, and the FOMC meeting dummy variables are macroeconomic conditions

[10] The original results of the 1st principal component of MPW spans from −0.56 to 3.95. Such a wide range is difficult to compare with MPUs, so we adjusted it by shifting it by 1 unit to make it all positive, and then we divided each datum by its maximum value. For example, the first observation, 0.64 at September 2006, is transferred as $[(1 + 0.64) / (1 + 3.95)] \times 100 = 33.13$. As depicted in Figure 2(c), this keeps the main features of MPW, as can be observed from Figure 2(b). Throughout this paper, we employ the original 1st principal component results of MPW for our empirical study rather than the adjusted results for drawing Figure 2(c).

that we employed as control variables. The maximum and minimum of the EPU index are positive, which means that the EPU index is a variable of positive values, unlike the ADS index, which seems to fluctuate up and down around zero since its maximum value is positive and the minimum value is negative. In addition, it seems that the EPU index owns a large scale so that its mean and standard deviation are larger than those for the ADS index. The mean of the FOMC meeting dummy is 0.65, which suggests that in 65% of the observations in our sample the Fed held an FOMC meeting.

3. Empirical Results

3.1 Information content of MPW

We begin by checking whether our MPW index is informative to MPU by examining the effects of contemporary and first-lag MPU on the MPW index. To do this, we resort to the following regressions:

$$\mathrm{Y}_d^{MPW} = \text{Constant} + \beta_1 \cdot \mathrm{MPU}_d + \boldsymbol{\gamma}_1' \boldsymbol{Control}_{1,d} + \varepsilon_{1,d}^{MPW}, \tag{6}$$

$$\mathrm{Y}_d^{MPW} = \text{Constant} + \beta_2 \cdot \mathrm{MPU}_{d-1} + \boldsymbol{\gamma}_2' \boldsymbol{Control}_{2,d} + \varepsilon_{2,d}^{MPW}, \tag{7}$$

$$\mathrm{TRS}_d = \frac{1}{M_d} \sum_{\tilde{\ell}=1}^{M_d} i_{\tilde{\ell}} - \mathrm{FR}_{d-1,M_d}^{(1)}, \tag{8}$$

where $\mathrm{Y}_d^{MPW} = \{\mathrm{MPW}_d, \mathrm{MPW}_d \times \mathbb{I}(\mathrm{TRS}_d > 0), \mathrm{MPW}_d \times \mathbb{I}(\mathrm{TRS}_d < 0)\}$ denotes a set of dependent variables at time point d; TRS_d denotes target rate surprise (TRS), which is calculated by the difference between the average funds rate target of month d and the one-month-ahead futures rate on the last day of month $d-1$, written as equation (8); MPU_d refers to MPU; $\boldsymbol{Control}_{1,d} = (\mathrm{EPU}_d, \mathrm{ADS}_d, \mathrm{FOMC}_d, \mathrm{MPW}_{d-1}, \mathrm{MPW}_{d-2}, \cdots, \mathrm{MPW}_{d-H})'$ is a vector of control variables including the EPU index, the ADS index, a dummy variable that indicates if an FOMC meeting is held in month d, the first H lags of MPW; and $\boldsymbol{Control}_{2,d} = \boldsymbol{Control}_{1,d}$.[11] Our formula to compute the TRS as written in equation (8) follows Bernanke and Kuttner (2005), and the TRS was applied by Gospodinov and Jamali (2018) to identify the MPU index in cases of positive and negative target rate surprise. Here we used it to help us examine if the positive or negative TRS affects the informativeness of our MPW index to MPU.

Panel A in Table 3 shows the empirical results of estimating equation (6); the effects using contemporary MPU and the first lag of MPU are listed in panel B. From panel A, we find that the adjusted R squared is between 0.78 and 0.79, which shows that the model fits well whether TRS is positive or negative. The direction of the OLS estimates of MPU can be positive or negative, depending on whether TRS is positive or negative. Specifically, columns 4 to 6 show that if the Fed were to set an unexpected higher target rate (i.e., positive TRS), the greater uncertainty would cause more worry,

[11] The data for the FOMC's target federal funds rate or range is available from https://www.federalreserve.gov/, and the data for the federal funds futures rate is calculated by subtracting 100 from the price of 30-day Fed fund futures from Yahoo Finance, ticker "ZQ=F."

which is consistent with the positive estimates of BBD and GJ at a 5% significance level and HRS at a 10% significance level. By contrast, columns 7 to 9 reveal that if an unexpected lower target rate is set by the Fed, households would be less worried about monetary policy, so the negative estimate of HRS is as expected, but the other two MPU measures are insignificant. Moreover, without identifying positive or negative TRS, columns 1 to 2 show that MPW is positively affected by BBD and GJ at a 10% significance level, which is consistent with the results in columns 4 to 5 and 7 to 8: BBD and GJ contain more information from unexpected contractionary monetary policy than from unexpected expansionary monetary policy, whereas the insignificant result of HRS in column 3 reflects that it contains almost as much information from unexpected contractionary monetary policy as from unexpected expansionary monetary policy. We then examined panel B to see whether, based on equation (7), the MPW index is informative to MPU in the previous month and found that most of the results in panel B are similar to those contained in panel A, including adjusted R squares, positive effects of BBD and GJ given positive TRS, and a negative effect of HRS given negative TRS. BBD and HRS are news-based measures, and we think that the use of the human auditing index based on human reading that is employed in Husted et al. (2020) to address concerns about automated news-based computer search may be why the direction of MPU's effects of HRS on the MPW without identifying the condition of positive or negative TRS are opposite to those of BBD and GJ.

----- Insert Table 3 here -----

Our findings show that the MPW index is informative to MPU in the current month and previous months. Moreover, we find that introducing TRS to identify unexpected monetary policy as contractionary or expansionary helps to clarify the link between the MPW index and MPU. According to the detected link, MPU may serve as a valid instrument to measure MPW, especially when market worry is mainly toward unexpected contractionary or expansionary monetary policy. Specifically, BBD and GJ may be employed as instruments for the MPW index when households worry about the Fed's unexpected contractionary monetary policy, and HRS may be a suitable instrument if the Fed's unexpected expansionary monetary policy is a source of worry for households. Besides, although many of the control effects are almost insignificant, the significant results have intuitive explanations. Specifically, the positive effects of the EPU and ADS indexes reveal that an increase in EPU and good macroeconomic conditions can lead people to be more worried about monetary policy. In actuality, the EPU index is a more general measure for macroeconomic uncertainty than the MPU index. This means that the EPU index contains information about the MPU index, and it thus explains the positive effect of the EPU index on our MPW index. Moreover, improvements in the ADS index may cause people to be more worried than setbacks in the ADS index because it is typical that the Fed's monetary policy holds unchanged unless macroeconomic conditions are sufficiently good. Regarding the poor effects of the FOMC meeting dummy, one possible explanation is that the dates of FOMC meetings are not regular. For example, an FOMC meeting held in the first or final few days of a calendar month may lead people to be worried about the Fed's monetary policy in the previous or the same month, and this thus explains why the effect of the FOMC meeting dummy variable is poor.

3.2 MPW and stock index returns

Motivated by the analysis in Da et al. (2015), which uses the change in the EPU as an explanatory variable to explain asset returns, we employ change in MPW, $\Delta\text{MPW}_d = \Delta\text{MPW}_d - \Delta\text{MPW}_{d-1}$, to explain the stock index.[12] Then we run the following regression to examine how MPW affects stock market index returns:

$$R_{d+f} = \text{Constant} + \beta_3 \cdot \Delta\text{MPW}_d + \boldsymbol{\gamma}_3' \boldsymbol{Control}_{3,d} + \varepsilon_d^R, \quad (9)$$

where $R_{d+f} = \{R_d, R_{d+1}, \cdots, R_{d+6}\}$ is a set of dependent variables that are stock market returns forward for f months to be used in turn in equation (9), $f = 0,1,\cdots,6$, ΔMPW_d represents changes in MPW, and $\boldsymbol{Control}_{3,d} = (\text{VIX}_d, \Delta\text{EPU}_d, \Delta\text{ADS}_d, R_d, R_{d+f-1}, \cdots, R_{d+f-F})'$ represents a vector of control variables including the level of VIX, the change in EPU, and the change in ADS, as well as the contemporaneous stock market return (not be specified only when the independent variable is R_d) and its lag is no more than F months. The selection of the control variables also follows Da et al. (2015). Since the performance of the stock market index may affect households' worry about monetary policy, we resort to GMM to estimate coefficients in equation (9) to avoid the problem of endogeneity.[13] Based on the findings in Table 3 that the MPW index contains information about MPU and different levels of MPU are associated with differences in the status of unexpected monetary policy, here we use changes in MPW and MPU to be instruments for running GMM. Defining $\boldsymbol{IV}_d^{MPW} = (\Delta\text{MPW}_{d-1}, \cdots, \Delta\text{MPW}_{d-q})'$, $\boldsymbol{IV}_d^{MPU1} = (\Delta\text{BBD}_d, \Delta\text{GJ}_d, \Delta\text{BBD}_{d-1}, \Delta\text{GJ}_{d-1}, \cdots, \Delta\text{BBD}_{d-g}, \Delta\text{GJ}_{d-g})'$, and $\boldsymbol{IV}_d^{MPU2} = (\Delta\text{HRS}_d, \cdots,, \Delta\text{HRS}_{d-g})$, we can establish two instrument matrixes:

$$\boldsymbol{IV}_\mathbf{1}^\boldsymbol{R} \equiv \begin{bmatrix} \text{Constant} & \boldsymbol{o}' \\ 0 & \boldsymbol{IV}_d^{MPW'}, \boldsymbol{IV}_d^{MPU1'} \end{bmatrix} \text{ and } \boldsymbol{IV}_\mathbf{2}^\boldsymbol{R} \equiv \begin{bmatrix} \text{Constant} & \boldsymbol{o}' \\ 0 & \boldsymbol{IV}_d^{MPW'}, \boldsymbol{IV}_d^{MPU2'} \end{bmatrix},$$

where $\boldsymbol{IV}_\mathbf{1}^\boldsymbol{R}$ and $\boldsymbol{IV}_\mathbf{2}^\boldsymbol{R}$ corresponds to the Fed's unexpected contractionary and expansionary monetary policy, respectively; and the upper index $\boldsymbol{R}$ which is the same as the notation of stock market returns in equation (9) is used to indicate what the instrument matrix is specified for.

In Tables 4 and 5, based on a setting of $q = 2$ and $g = 1$, we examine the returns of the S&P 500 index and the Russel 3000 index, which stand for large-capitalized stocks and a pool of U.S. stocks with various market capitalizations, respectively.[14] We first examine the results for the S&P 500. In Table 4, column 1 demonstrates that when $f = 0$, the effects of MPW are found to be significant from cases using $\boldsymbol{IV}_\mathbf{2}^\boldsymbol{R}$, as shown in panel B, but not from cases using $\boldsymbol{IV}_\mathbf{1}^\boldsymbol{R}$, as shown in panel A.

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[12] We also tried to fit the data by the level of MPW, but the effects were poor.

[13] Another concern about endogeneity is on the measurement error of our MPW index since our method of using the value at risk of holding asset for 1 day, 5 days, 60 days, and 240 days is only a simplified way to deal with it.

[14] The result holds if we consider a setting of $q = 3$ and $g = 2$ or another setting of $q = 2$ and $g = 1$.

Specification tests reveal that, although the Sargan and IV validity tests do not reject the use of $\boldsymbol{IV_1^R}$, $\boldsymbol{IV_1^R}$ is unsuitable because of its poor instrument orthogonality and significant residual serial correlations. Moreover, $\boldsymbol{IV_1^R}$ fails to detect the endogeneity found in $\boldsymbol{IV_2^R}$, with a test statistic of 5.74 and a significance level less than 5%. This suggests that, for the index of large-capitalized stocks, contemporaneous returns are driven by households' worry about unexpected contractionary monetary policy since instruments that measure unexpected contractionary monetary policy are not orthogonally unrelated to the moment conditions of stock index returns. Using $\boldsymbol{IV_2^R}$, the estimate of the effect of MPW is significant at a 5% level, which means that a 1-percentage-point increase in the incremental change in MPW contemporaneously corresponds to an 8.02-percentage-point decline in the S&P 500 index return after possible influences from contemporaneous VIX, changes in EPU and ADS, and the first four lags of dependent variables are controlled for. In contrast, the out-of-sample results from columns 2 to 7 in Table 4 reveal that, when cases from $f = 1$ to $f = 6$ are examined, the instruments remain valid and the endogeneity problem no longer exists, yet none of the coefficients of MPW are significantly different from zero. This means that those point estimates are statistically negligible, confirming that the effect of MPW on market-level asset prices occurs in the contemporaneous months but not in the future months.

----- Insert Table 4 here -----

We follow by examining how the MPW index affects Russel 3000 index returns. The Russel 3000 index is different from the S&P 500 index in that it contains not only large-capitalized stocks but also small-capitalized ones. We show the results in Table 5. In general, the results in Table 5 are similar to the results in Table 4. Specifically, the Sargan's test statistics in column 1 of panels A and B are insignificant, which means that $\boldsymbol{IV_1^R}$ and $\boldsymbol{IV_2^R}$ are not rejected, but as seen in Table 4, $\boldsymbol{IV_1^R}$ seems unsuitable since it cannot deal with residual serial correlations and cannot detect endogeneity. Thus, we ensure that only the additional information of households' worry about unexpected expansionary monetary policy be used to explain the behavior of contemporaneous stock index returns. The coefficient of MPW is −8.45, which shows a larger negative effect than the influence on the S&P 500 index shown in Table 4. This result implies that an incremental change in MPW causes a greater decrease in the contemporaneous returns of stocks that have smaller market capitalization than those stocks included in the S&P 500 index. Again, similar to the result in Table 4, Table 5 shows that an incremental change in MPW cannot affect the future returns of the Russel 3000 index, and thus we conclude that we find no evidence of significant reversal of the initial negative effect during the subsequent six months.[15] To sum up, the results in Table 4 and Table 5 show that an incremental change in MPW leads to lower contemporaneous stock index returns, but it fails to cause a future

[15] We also examined cases in which $f \geq 7$, but the effects of change in the MPW on stock index returns remain insignificant.

reversal of the effect whether the stock market capitalization is large or small. Such a finding is different from the existence of reversal effects of sentiment index such as the FEARS index as shown in Da et al. (2015).[16] Perhaps the nonnegativity truncation feature of the MPW index may serve as a reason to explain such a distinction between sentiment and worry. Different from the investor sentiment index in Baker and Wurgler (2006) and Baker and Wurgler (2007), the MPW index is limited to being nonnegative, and thus the value is unable to decrease from positive values to negative values (or increase from negative values to positive values), so these parts may be related to reversal effects.

----- Insert Table 5 here -----

3.3 MPW and individual stock returns

In view of the contemporaneous response of S&P 500 index returns to the MPW index as discussed above, we further investigated how incremental changes in MPW affect the component stocks of the S&P 500 index. To do this, we collected the data on 239 stocks listed in the S&P 500 index during our sampling period (i.e., from October 2006 to April 2021); the graphs in Figure 3 show the characteristics of those stocks. The negative relationship presented in graph (a) suggests that stocks with larger standard deviation may not be positively associated with higher average returns. Graph (b) and graph (c) show leftward skewing and leptokurtosis for most of the stock returns, and graph (d) reveals that the returns spread in a range from 0% to 2%, with the mean close to 1%.

Defining $rp_{i,d} = r_{i,d} - Rf_d$ as risk premiums (the amount of returns exceeding the risk-free rate Rf_d) and following the literature such as Amihud and Stoyanov (2017), Borgers, Derwall, Koedijk, and Ter Horst (2013), Fernando, May, and Megginson (2012), Kolari and Pynnonen (2011) to define $ar_{i,d} = rp_{i,d} - \widehat{rp}_{i,d}$ as abnormal returns that are unable to be included in the predicted risk premiums $\widehat{rp}_{i,d}$, we considered the following regressions:

$$rp_{i,d+f} = \alpha_{4,i} + \beta_4 \cdot \Delta\mathrm{MPW}_d + \boldsymbol{\gamma}_4' \boldsymbol{Control}_{4,d} + \varepsilon_d^{rp}, \tag{10}$$

$$ar_{i,d+f} = \alpha_{5,i} + \beta_5 \cdot \Delta\mathrm{MPW}_d + \boldsymbol{\gamma}_5' \boldsymbol{Control}_{5,d} + \varepsilon_d^{ar}, \tag{11}$$

where $rp_{i,d+f}$ and $ar_{i,d+f}$ denote monthly risk premiums and abnormal returns forward for f months ($f \geq 0$), and $\alpha_{4,i}$ and $\alpha_{5,i}$ are stock-specific fixed effects that reflect unobserved heterogeneity. The following vectors of control variables,

[16] In fact, no reversal is also found in the literature on the effect of the sentiment, including sentiment shocks from media discourse in Hanna, Turner, and Walker (2020), sentiment effect on institutional and foreigner investors in Koo et al. (2019), sentiment related to open market share repurchases in Liang (2016), sentiment of the losers' portfolio in Watkins (2003), and so on.

$$\boldsymbol{Control}_{4,d} = (\mathrm{VIX}_d, \Delta\mathrm{EPU}_d, \Delta\mathrm{ADS}_d, R_d, rp_{i,d}, rp_{i,d-1}, \cdots, rp_{i,d-F}, \mathrm{DUM}_1, \mathrm{DUM}_2, \cdots, \mathrm{DUM}_{11})'$$

and

$$\boldsymbol{Control}_{5,d} = (\mathrm{VIX}_d, \Delta\mathrm{EPU}_d, \Delta\mathrm{ADS}_d, ar_{i,d}, ar_{i,d-1}, \cdots, ar_{i,d-F}, \mathrm{DUM}_1, \mathrm{DUM}_2, \cdots, \mathrm{DUM}_{11})',$$

include macroeconomic conditions such as VIX, change in EPU and ADS, stock market returns (only when risk premiums are employed as dependent variables), and lags of dependent variables up to F months ($rp_{i,d}$ and $ar_{i,d}$ are introduced if $f > 0$). DUM_1, DUM_2,…, DUM_{11} are monthly dummy variables that we used to indicate calendar months from January to November. Again, since stock returns may affect people's worry about monetary policy, we resorted to GMM to estimate coefficients in equation (10) and (11) to avoid the problem of endogeneity. Different from estimating coefficients in equation (9), here we employed Arellano-Bond difference GMM estimation to deal with the econometrics of individual effects. We also employed White's robust standard errors to account for serial correlations and heteroscedasticity to calculate robust *t* statistics.

Once again, taking $f = 0$ as an example for illustration, performing a first difference transformation on equation (10) results in the following equation:

$$\Delta rp_{i,d} = \beta_4 \cdot (\Delta\mathrm{MPW}_d - \Delta\mathrm{MPW}_{d-1}) + \boldsymbol{\gamma}_4'(\boldsymbol{Control}_{4,d} - \boldsymbol{Control}_{4,d-1}) + \Delta\varepsilon_d^{rp}. \quad (12)$$

This implies four sets of valid instruments for GMM: (1) $\Delta\boldsymbol{IV}_d^{MPW}$, $\Delta\boldsymbol{IV}_d^{MPU1}$, and $\Delta\boldsymbol{IV}_d^{MPU2}$ as instruments for $\Delta\mathrm{MPW}_d - \Delta\mathrm{MPW}_{d-1}$; (2) the first difference of VIX_d, $\Delta\mathrm{EPU}_d$, $\Delta\mathrm{ADS}_d$, and ΔR_d as instruments for $\boldsymbol{Control}_{4,d} - \boldsymbol{Control}_{4,d-1}$; (3) given our default setting of $F = 4$, $rp_{i,d-2}$ and $\Delta rp_{i,d-2}, \Delta rp_{i,d-3}, \Delta rp_{i,d-4}$ as instruments for the first four lags of dependent variables; and (4) the level of monthly dummy variables as instruments for themselves.[17] We define

$$\boldsymbol{A_1} \equiv \begin{bmatrix} \Delta\boldsymbol{IV}_d^{MPW\prime}, \Delta\boldsymbol{IV}_d^{MPU1\prime} & 0 & 0 & 0 & 0 \\ \boldsymbol{o}' & \Delta\mathrm{VIX}_d & 0 & 0 & 0 \\ \boldsymbol{o}' & 0 & \Delta\mathrm{EPU}_d - \Delta\mathrm{EPU}_{d-1} & 0 & 0 \\ \boldsymbol{o}' & 0 & 0 & \Delta\mathrm{ADS}_d - \Delta\mathrm{ADS}_{d-1} & 0 \\ \boldsymbol{o}' & 0 & 0 & 0 & \Delta R_d \end{bmatrix},$$

$$\boldsymbol{A_2} \equiv \begin{bmatrix} \Delta\boldsymbol{IV}_d^{MPW\prime}, \Delta\boldsymbol{IV}_d^{MPU2\prime} & 0 & 0 & 0 & 0 \\ \boldsymbol{o}' & \Delta\mathrm{VIX}_d & 0 & 0 & 0 \\ \boldsymbol{o}' & 0 & \Delta\mathrm{EPU}_d - \Delta\mathrm{EPU}_{d-1} & 0 & 0 \\ \boldsymbol{o}' & 0 & 0 & \Delta\mathrm{ADS}_d - \Delta\mathrm{ADS}_{d-1} & 0 \\ \boldsymbol{o}' & 0 & 0 & 0 & \Delta R_d \end{bmatrix},$$

[17] Using $\Delta ar_{i,d-1}$ as the instrument would result in a problem of endogeneity because $ar_{i,d-1}$ appears in the left-hand side of equation (11) after the first difference transformation, but when $f > 0$, $\Delta ar_{i,d-1}$ is no longer endogenous, and it thus can be employed as an instrument for GMM estimation.

$$\boldsymbol{B} \equiv \begin{bmatrix} rp_{i,d-2} & 0 & 0 & 0 \\ 0 & \Delta rp_{i,d-2} & 0 & 0 \\ 0 & 0 & \Delta rp_{i,d-3} & 0 \\ 0 & 0 & 0 & \Delta rp_{i,d-4} \end{bmatrix}, \text{and } \boldsymbol{C} \equiv \begin{bmatrix} \text{DUM}_1 & 0 & \cdots & 0 \\ 0 & \text{DUM}_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \text{DUM}_{11} \end{bmatrix},$$

where $\Delta \boldsymbol{IV}_d^{MPU1}$ and $\Delta \boldsymbol{IV}_d^{MPU2}$ are included as additional instruments to examine if worry about unexpected monetary policy can be used to explain how changes in MPW affect risk premiums and abnormal returns. Given these, when analyzing equation (12), we consider the following matrices:

$$\boldsymbol{IV}_{\mathbf{1}}^{\boldsymbol{rp}} = \begin{bmatrix} \boldsymbol{A}_1 & \boldsymbol{O} & \boldsymbol{O} \\ \boldsymbol{O} & \boldsymbol{B} & \boldsymbol{O} \\ \boldsymbol{O} & \boldsymbol{O} & \boldsymbol{C} \end{bmatrix} \text{ and } \boldsymbol{IV}_{\mathbf{2}}^{\boldsymbol{rp}} = \begin{bmatrix} \boldsymbol{A}_2 & \boldsymbol{O} & \boldsymbol{O} \\ \boldsymbol{O} & \boldsymbol{B} & \boldsymbol{O} \\ \boldsymbol{O} & \boldsymbol{O} & \boldsymbol{C} \end{bmatrix},$$

where $\boldsymbol{IV}_{\mathbf{1}}^{\boldsymbol{rp}}$ is a 25×52 matrix that includes additional information about worry about unexpected contractionary monetary policy, $\boldsymbol{IV}_{\mathbf{2}}^{\boldsymbol{rp}}$ is a 23×52 matrix that includes additional instruments regarding households' worry about unexpected expansionary monetary policy, and both $\boldsymbol{IV}_{\mathbf{1}}^{\boldsymbol{rp}}$ and $\boldsymbol{IV}_{\mathbf{2}}^{\boldsymbol{rp}}$ are used to construct orthogonal conditions for GMM estimation. By dropping ΔR_d from $\boldsymbol{A_1}$ and $\boldsymbol{A_2}$ and replacing the risk premiums in $\boldsymbol{B}$ by abnormal returns, such as replacing $rp_{i,d-2}$ by $ar_{i,d-2}$, we can get instrument matrixes for estimating equation (11), the upper index $\boldsymbol{rp}$ is used to indicate risk premiums examined in equation (10), and we denote the resulting instrument matrixes as $\boldsymbol{IV}_{\mathbf{1}}^{\boldsymbol{ar}}$ and $\boldsymbol{IV}_{\mathbf{2}}^{\boldsymbol{ar}}$ using another upper index $\boldsymbol{ar}$ to indicate abnormal returns as examined in equation (11), respectively.

We need to obtain the values of risk premiums and abnormal returns of S&P 500 component stocks for our regressions in (10) and (11). Risk premiums are calculated by subtracting raw returns (adjusted for dividends and splits) from the risk-free rate, and abnormal returns are measured by residuals of regressing risk premiums on the five factors of Fama and French (2015). Panel A of Table 6 shows significant Sargan's test J statistics when $\boldsymbol{IV}_{\mathbf{1}}^{\boldsymbol{rp}}$ is used, which means that the instruments are overidentified and thus $\boldsymbol{IV}_{\mathbf{1}}^{\boldsymbol{rp}}$ is an unsuitable specification for the conditional moment of equation (12). Likewise, many results of Sargan's test using $\boldsymbol{IV}_{\mathbf{2}}^{\boldsymbol{rp}}$ are also significant, exceptions being $rp_{i,d}$ in column 1 and $rp_{i,d+3}$ in column 4. The significance of difference in the J test statistics are almost consistent with the results of Sargan's test. These findings imply that additional information about households' worry about monetary policy is not useful for explaining risk premiums, which is contrary to our finding from the stock index returns in Table 4 and Table 5. Significant GMM estimates in columns 1 and 4 mean that an increase of 1 percentage point in MPW this month results in a decrease of risk premiums of 1.08 percentage points in the same month, and this will cause a greater decline of 1.97 percentage points in risk premiums after 3 months. However, since Table 6 shows that too many effects on risk premiums within the future 6 months are insignificant, we are unable to infer the total effect of incremental change in MPW and so cannot conclude if a reversal exists.

----- Insert Table 6 here -----

In panel B of Table 6, the Sargan's test *J* statistics using $\boldsymbol{IV_1^{ar}}$ are found to be insignificant for $ar_{i,d}$, $ar_{i,d+4}$, and $ar_{i,d+6}$; but if $\boldsymbol{IV_2^{ar}}$ is used instead of $\boldsymbol{IV_1^{ar}}$, they become insignificant for all the examined returns. This is consistent with the significant statistics of difference in *J* tests, which show that adding additional instruments including $\Delta\boldsymbol{IV}_d^{MPU1}$ into $\boldsymbol{IV_1^{ar}}$ is unsuitable; but on the contrary, $\Delta\boldsymbol{IV}_d^{MPU2}$ is suitable to be included as an additional instrument so that the difference in *J* test statistics using $\boldsymbol{IV_2^{ar}}$ is insignificant. By comparing these findings with panel A, we confirm that additional information about market worry about monetary policy is useful for explaining abnormal returns rather than risk premiums, and $\boldsymbol{IV_2^{ar}}$ is a better choice than $\boldsymbol{IV_1^{ar}}$. It seems that, different from market-level findings, as we show in Table 4 and Table 5, only households' worry about unexpected expansionary monetary policy, such as quantitative easing, can be useful for explaining firm-level returns, and the incremental change in MPW mainly affects the abnormal part of individual stocks' returns rather than the premiums for systematic risk, such as characterized by the five factors of Fama and French (2015). GMM estimates using $\boldsymbol{IV_2^{ar}}$ show that an increase in the incremental change in MPW leads to an initial effect to decrease abnormal returns for 58 basis points, and it is offset by an opposite effect to increase abnormal returns for 45 basis points after four months in the future. This reversal means that the negative impacts of change in MPW on risk premiums as shown in panel A can be attributed to the premiums for risk factors of Fama and French (2015). But in contrast to the finding of Barber, Odean, and Zhu (2008) and Joseph, Wintoki, and Zhang (2011), which show it takes 5 to 8 weeks to achieve reversal for sentiment effects, we find that it takes longer for the effects of incremental change in MPW to achieve reversal.

3.4 MPW and volatility

As motivated by the findings of Gospodinov and Jamali (2018) that monetary policy shocks are associated with greater volatility during recessions and Baker et al. (2016) and Husted et al. (2020) that uncertainty is significantly associated with an increase in firm-level implied volatility and VIX, we further examined the link between MPW and volatility. Moreover, to examine if the impact of MPW depends on the degree of volatility, we resorted to quantile regression in the following forms:[18]

$$\text{Volatility}_d = \text{Constant} + \beta_7 \cdot \Delta\text{MPW}_d + \boldsymbol{\gamma}_7'\boldsymbol{Control}_{7,d} + \varepsilon_d^{Volatility}, \quad (13)$$

$$\text{Volatility}_d = \text{Constant} + \beta_8 \cdot \Delta\text{MPW}_{d-1} + \boldsymbol{\gamma}_8'\boldsymbol{Control}_{8,d} + \varepsilon_d^{Volatility}, \quad (14)$$

where $\text{Volatility}_d = \{IV_d, RV_d\}$ includes the log of implied volatility (denoted as IV_d) and the log of realized volatility (denoted as RV_d), which we use in turn as the dependent variable for equations (13) and (14).

[18] Different from our method, Da et al. (2015) modeled daily volatility using ARFIMA, but we find that ARFIMA is not suitable for monthly volatility.

$$\boldsymbol{Control}_{7,d} = \boldsymbol{Control}_{8,d} = (\Delta\text{EPU}_d, \Delta\text{ADS}_d, \text{Volatility}_{d-1}, \cdots, \text{Volatility}_{d-F}, \text{DUM}_1, \cdots, \text{DUM}_{11})'$$

is a vector of control variables, including macroeconomic conditions ΔEPU_d and ΔADS_d, lags of dependent variables up to the previous F months, and monthly dummy variables.

We investigated whether MPW affects stock market volatility using data from the VIX, S&P 500, and Russel 3000 index returns to calculate realized volatility. Following Da et al. (2015), who removed seasonality from the volatility variables, we based our investigation on X13 seasonally adjusted results to measure volatility. Moreover, as shown in the literature, volatility is associated with uncertainty contemporaneously, and, as seen in our empirical result, MPW is induced mainly by uncertainty in the previous month. Here we did not use GMM for equation (13) and (14) to deal with the potential problem of endogeneity.[19] Columns 1 and 2 of Table 7 show that, given different quantiles, adjusted R squares are from 0.44 to 0.48. However, the coefficients of change in MPW and its first lag are unable to affect the VIX significantly, which means that implied volatility can be free from the influences of the variations in MPW. Differently, column 3 shows some significant effects when the effects of MPW in the 80% quantile of the S&P 500 realized volatility are examined, although the significance level is only 10%. As with the VIX, columns 3 and 4 show that the effects of change in MPW on volatility in the 20% and 50% quantiles remain insignificant, and changes in the MPW of the previous month cannot significantly affect the volatility of different quantiles. The positive contemporaneous effect of incremental change in MPW reveals that an increase in worry about monetary policy of 1 percentage point can cause an increase in realized volatility of 33 basis points. Column 5 also shows that the influence of the change in MPW on volatility is more notable for small-capitalized stocks than for the large-capitalized stocks shown in column 3 because the contemporaneous effect of change in MPW on the volatility of the Russel 3000 in the 80% quantile has a 5% significance level. To sum up, these findings show that the change in MPW motivates stock market volatility only contemporaneously, only when volatility is high enough, and more evidently for small-capitalized stocks. Besides, we observe smaller adjusted R squares from the S&P 500 and the Russel 3000 than from the VIX, which suggests that the realized volatility is more difficult to be modeled than the VIX; the most difficult case is the volatility of the Russel 3000 reaching 80% quantile since the Ljung-Box statistic is found to be significant at 5% level.

----- Insert Table 7 here -----

[19] Recent studies by Megaritis, Vlastakis, and Triantafyllou (2021) and Kaminska and Roberts-Sklar (2018) examine the link between volatility and uncertainty.

4. Robustness Checks

4.1 Sensitivity to different settings to calculate MPW

The results obtained in previous sections employed the monthly data for the MPW index with two default settings including historical simulation of the risk using 1200 trading days and only the negative effect of MPW on risk when the daily MPW was summarized; this differs from the method in the literature, in which a fixed number of estimation results were summarized. Therefore, in this section, we checked to see whether these two default settings would impact the information content of the MPW index. First, we calculated historical simulations of the risk and MPW index based on 480 and 2400 trading days. Next, we ranked the degree of risk from low to high and picked the 20 smallest regression coefficients to arrive at the monthly sum of the MPW index based on daily data. Table 8 reports the empirical results based on both changes.

----- Insert Table 8 here -----

Panel A shows that when we reduced the time period in the historical simulation from 1200 trading days (about 5 years) to 480 days (about two years), the MPW index still contained the information on contemporaneously unexpected contractionary monetary policy measured by the GJ index. However, there is no information on unexpected expansionary policy anymore. In comparison, under the setting of 480 trading days, the information related to previous MPU is still contained in the MPW index, including the contemporaneously unexpected contractionary and expansionary policy measured by the GJ and HRS indexes. This suggests that the MPW index can still be used to appropriately measure MPW.

However, not all information in BBD is contained in the MPW index. If we extend the historical simulation to 2400 trading days (about 10 years), the MPW index does not contain the contemporaneous MPU information anymore, but it still contains the information about the previous month’s unexpected monetary contraction and expansion. Therefore, based on the psychological concept that worry originates from uncertainty, we believe the MPW index is stable with respect to different historical simulation periods. However, when the historical simulation is no longer based on 1200 trading days, as it is more appropriate to analyze the previous month’s MPW as an explanatory variable in empirical modeling, the MPW index could at most reflect the contemporaneous MPU. In addition, we observe from the result in panel B that there is not much impact on the information content of MPW if we fix the regression coefficient at 20 when we summarize the daily MPW values to obtain the monthly MPW value. Significant differences only occur to information related to previously unexpected monetary expansion with historical simulations using the 480-trading-day data.

4.2 Sensitivity to different specifications for instrumental variables

We next examined whether the use of the instrumental variable could lead to differences in empirical results. We looked at two areas.

First, when dealing with previously unexpected contractionary monetary policy, we used BBD and GJ as the instruments for the MPW index and HRS as the only instrument in the case of unexpected expansionary monetary policy. Using more instruments is likely to impact the estimates and test results, so we looked at how the results differed when we used BBD or GJ separately.

Second, in previous sections, we separated the use of BBD and GJ to measure unexpected contractionary policy from the use of HRS to measure unexpected expansionary policy when we measured the impact of MPW in order to not offset the effects. The method implied that there is no coexistence of worry about contractionary policy and worry about expansionary policy. However, worry about both could exist at the same time in the market. There is no method in the literature that can be used to distinguish the source of the worry. Thus, it is worthwhile to see how the result would be different if we use BBD, GJ and HRS at the same time. The drawback is that the number of instruments will increase, and we do not have any preconceptions about the result of the analysis. In Table 9, we report the result using BBD and GJ alone; Table 10 reports the results of using all three indexes at the same time.

----- Insert Table 9 here -----

Table 9 shows that when there is worry about unexpected monetary contraction, the effect of the contemporaneous incremental change of MPW on stock index returns does not change as the result of BBD and GJ being used simultaneously or one of them being used as the instrument; this indicates that the previous findings are robust. However, the test results are slightly different. First, the Sargan's test result in Table 9 shows that the hypothesis that GJ alone can be used as the instrument to explain the Russell 3000 index returns after 6 months is inappropriate and can be rejected at the 10% significance level. In addition, the endogeneity test result suggests that, when the effect of the contemporaneous incremental change of the MPW index on the same-period index return is analyzed, whether we use the S&P 500 index or the Russel 3000 index, we can detect endogeneity by using BBD alone, just as we did with HRS. This result suggests that we should use BBD as the instrumental variable when we estimate the impact of the contemporaneous incremental change of the MPW index, as employing GJ as the instrument or both BBD and GJ at the same time could lead to errors in detecting endogeneity. A similar situation can be observed from Table 10, as seen from the estimation results: using all MPU as the instruments generates the same results as using HRS only in our previous empirical implementation. These effects include a significantly positive effect on contemporaneous stock index returns and an insignificant effect on future six-month index returns. These empirical findings suggest that the results are insensitive to the instrumental variable choice of MPU and the policy direction, whether contractionary or expansionary. Furthermore, Table 10 shows that Sargan's test does not reject the model setting of using all MPU information, but the endogeneity test result becomes insignificant when the contemporaneous incremental MPW's impact on stock index returns is analyzed. We suspect that these changes are due to the use of GJ as the instrument, which was also the reason for the changes in the results in Table 9.

----- Insert Table 10 here -----

We next examine whether the empirical results on individual stock returns would be impacted by the use of instruments. The Sargan's test result in Table 11 suggests that the models using BBD or GJ separately as an instrument or using them together can be rejected significantly. The result obtains when all MPUs are used as the instruments. Even HRS, which has a better performance, could pass the test only when it was used as the instrument in the case of the dependent variable being the contemporaneous and 4-month-after individual stock returns. In comparison, in panel B, all the Sargan's test results when HRS is the sole instrumental variable show insignificances. This result implies that the effect of market worry is on individual stocks' abnormal returns, not risk premium. This also tells us that when we are analyzing the impact of MPW on individual stocks returns, it is difficult to pass Sargan's test if we do not eliminate the part of the risk premium that is related to systematic risk in individual stocks. The Sargan's test results in panel B also suggest that the worst scenario is to use BBD and GJ as the instruments and use all MPUs as the instruments. This finding suggests that the impact of a larger number of instrumental variables on Sargan's test mainly shows up when individual stock returns, not stock index returns, are analyzed. Furthermore, the estimation results in panel B suggest that the significance of the estimation can be different with respect to instrument variables. We find the significant negative effect insensible when we use BBD, BBD and GJ together, GJ separately, or all MPUs as extra instrumental variables to study the impact of contemporaneous incremental MPW on 6-month-after individual stocks' abnormal returns. This corroborates with the rejection results of Sargan's test. Overall, our results suggest that the GMM estimation and test results are not robust to the use of instrumental variables when our analysis focuses on individual stock returns, which is different from when we analyze stock index returns.

----- Insert Table 11 here -----

5. Further Discussion

5.1 To what extent do people become intolerant of downside risk?

Our empirical results in earlier sections indicate that there are significant effects of MPW on stock index return and volatility, and individual stocks' abnormal returns. We also provided a robustness check. All of these are based on the intolerance of worry measured by risks represented by the left 1% of asset return distribution. We would like to explore how more downside risk could affect the stock market. Thus, we adopted a risk measure with 5% and 10% tail values and reinvestigated the impact of MPW on index returns and volatility. The empirical results are reported in Tables 12 and 13.

Sargan's test in Table 12 shows insignificance, which indicates that all instrumental variable settings can pass Sargan's test whether BBD and GJ or HRS are used as extra instrumental variables. Regarding the estimation result, column 1 shows that there is no significant impact on the contemporaneous index return of the MPW index measured with the left 5% or 10% of the asset returns regardless of whether BBD and GJ or HRS is being used as the instrumental variables. The only negative effect occurs with the original measure of the left tail 1% return as the MPW index. This suggests that downside risk below the left tail 1% may still be within the tolerance range of investors, so the index return will not be affected as market participants' worry about monetary policy is still tolerable. In addition, the results in columns 2 through 7 show that the MPW index measured with the lower 5% and 10% asset returns do not generate significant impacts on index returns within the following 6 months, which is the same as we have found using the lower 1% return as the measure of MPW. This also suggests that the lower downside risk is within the range of tolerance.

----- Insert Table 12 here -----

To understand how the downside risk affects the stock market, we need to look at not only the index returns but also the return volatilities. As shown in the adjusted *R* squares in Table 13, the explanatory power of the model is between 25% and 49%, among which the goodness of fit for the VIX is best at between 44% and 49%. The next is for the Russell 3000, whose goodness of fit is between 26% and 31%. The last one is for the S&P 500 index, for which the goodness of fit is between 25% and 30%. This result shows that the model fits the data better with implied volatility than with realized historical volatility. In addition, seen from the strength of the volatility, the models fit the data better at high volatility levels than at low, indicating that the model fits better for high volatility states. Looking at the estimation result, it appears that there is no observable significant effect of the MPW index when we use the left 5% and 10% of the asset return distribution to measure MPW. The only exception is the downside risk of the left tail 10%: the contemporaneous incremental MPW affects the Russell 5000 index volatility positively, with an estimated value of 0.25 and a significance level of 5%. This result suggests that under the circumstance of relatively low index volatility, the contemporaneous incremental MPW measured with lower downside risk leads to higher index volatility. This suggests that the effect of MPW on volatility may be nonlinear, and it may not increase as the volatility level increases.[20] Furthermore, MPW starts to affect the stock market when downside risk is at least 10% or higher, but its impact is mainly on volatility, not on returns.

----- Insert Table 13 here -----

We also investigated whether the size of the downside risk could impact the previously found impact of MPW on individual stocks. Based on the findings in Table 11, we only provide analysis with HRS in Table 14. Panel A shows that Sargan's test rejects most of the instrumental variables, which is the same as before, suggesting that individual stock risk premiums that have not taken out systematic risk are not suitable for the analysis of the impact of MPW. In comparison, the Sargan's test results in panel B are all insignificant, suggesting that all the instrument variables can be accepted. Differing from the results of 1% downside risk in Table 6, the results in column 1 of Table 14 are also insignificant, suggesting that when the downside risks are at 5% and 10% levels, individual investors in the S&P 500 will not adjust their holdings due to MPW. However, in the absence of the contemporaneous effect, we can observe almost the same significantly positive effect in column 5 as in column 6 with a 5% downside risk. Also note that in column 7, there are some negative effects, which is different from column 6. The regression coefficients are 0.56 and −0.65 respectively, suggesting that the individual investors in the S&P 500 would adjust their holdings after 6 months to sell the stocks they bought after 4 months. We suspect this is due to smaller investors selling individual stocks due to MPW for the month. However, investors in large stocks such as stocks in the S&P 500 did not sell; so, after 4 months, the smaller investors bought back the originally sold small stocks in addition to large stocks (S&P 500 stocks) due to investment reversals. Therefore, this negative effect of MPW is offset due to arbitrage under the return to long-term equilibrium.[21]

----- Insert Table 14 here -----

5.2 Can the risk premium for MPW be priced by cross-sections of individual stocks?

We complement the panel-data findings with cross-sectional pricing tests to examine if the effects of the MPW index is priced over and above the extant risk factors. We perform this extension because we

[20] It would be interesting to investigate the relationship between the volatility of the market and MPW, but it goes beyond the scope of this study.

[21] We have simply made some conjectures regarding this effect. Proof of the conjectures would require additional and more careful execution of the empirical investigations, which is beyond the scope of this paper.

can observe from Table 5 and Table 6 that the MPW index's impact on individual stocks' abnormal returns is more significant than it is on index returns. This implies that the impacts of the MPW index on individual stocks have offset each other so no overall effect at the index level can be shown. Also, Table 14 shows that when the downside risk of asset returns reaches 5%, the stock market starts to generate MPW. As a result, pressure exists for selling smaller stocks but not larger stocks. These results suggest that there are differentiated effects of the MPW index on individual stocks and different risk premiums associated with MPW. Furthermore, as monetary contraction or expansion would directly affect liquidity, we base our subsamples on individual stocks' liquidity and investigate whether the contemporaneous incremental MPW risk premium could be priced by individual stocks' risk premium in the cross-section. Methodologically, we resorted to the regression method of Fama and Macbeth (1973) to estimate full-sample betas using OLS time-series regressions. Thus, for each individual stock i, we ran the following regressions:

$$rp_{i,d} = \text{Constant}_{6i} + \beta_{6,i} \cdot \Delta\text{MPW}_d + \boldsymbol{\gamma}'_{6,i}\boldsymbol{Control}_{6,d} + u^{r6}_{i,d}, \quad (15)$$

$$rp_{i,d} = \text{Constant}_{7i} + \beta_{7,i} \cdot \Delta\text{MPW}_d + \boldsymbol{\gamma}'_{7,i}\boldsymbol{Control}_{7,d} + u^{r7}_{i,d}, \quad (16)$$

where $\boldsymbol{Control}_{6,d} \equiv (\text{VIX}_d, \Delta\text{EPU}_d, \Delta\text{ADS}_d, R_d - Rf_d, \text{SMB}_d, \text{HML}_d, \text{RMW}_d, \text{CMA}_d, \text{DUM}_1, \text{DUM}_2, \cdots, \text{DUM}_{11})'$ and $\boldsymbol{Control}_{7,d} \equiv (\boldsymbol{Control}_{6,d}, rp_{i,d-1})'$ are vectors of control variables that include macroeconomic conditions (i.e., VIX_d, ΔEPU_d and ΔADS_d), Fama and French's (2015) systematic risk factors (i.e., $R_d - Rf_d$, SMB_d, HML_d, RMW_d, and CMA_d), the monthly dummy variables, and the first lag of $rp_{i,d}$. Using the data of 239 component stocks in the S&P 500 index, we got the estimated full-sample betas denoted as $\widehat{\text{Constant}}_{6i}$ and $\hat{\beta}_{6,i}$ and $\hat{\boldsymbol{\gamma}}_{6,i}$ as well as $\widehat{\text{Constant}}_{7i}$ and $\hat{\beta}_{7,i}$ and $\hat{\boldsymbol{\gamma}}_{7,i}$, respectively, and based on these, we further estimated the following cross-sectional regression of average risk premiums:

$$\overline{rp}_i = \lambda_{10} \cdot \widehat{\text{Constant}}_{6i} + \lambda_{11} \cdot \hat{\beta}_{6,i} + \boldsymbol{\lambda}'_{12}\hat{\boldsymbol{\gamma}}_{6,i} + u^{\overline{r6}}_i, \quad (17)$$

$$\overline{rp}_i = \lambda_{20} \cdot \widehat{\text{Constant}}_{7i} + \lambda_{21} \cdot \hat{\beta}_{7,i} + \boldsymbol{\lambda}'_{2}\hat{\boldsymbol{\gamma}}_{7,i} + u^{\overline{r7}}_i, \quad (18)$$

where $\overline{\boldsymbol{rp}}_i = \sum_{d=1}^{T} rp_{i,d}$ stands for average of risk premium of stock i.

We utilized three liquidity variables (trading volume, liquidity ratio, and Amihud's illiquidity measure) to distinguish among the different levels of liquidity in the samples. Demsetz (1968) and Benston and Hagerman (1978) pointed out in their studies that the bid-ask spread is smaller for stocks of larger trading volumes. So trading volume is used as a measurement of liquidity. The liquidity ratio was proposed by Cooper, Groth, and Averta (1985), and it is calculated as the ratio of trading volume to the sum of the squared stock price change. Therefore, the larger the ratio, the smaller the impact on stock price in the case of a large trading volume. The illiquidity (ILLIQ) index was proposed by Amihud (2002). It is calculated as the absolute value of stock returns divided by trading volume. This measure captures the intuition that a security is less liquid if a given trading volume generates a greater move in its price and vice versa. Table 15 reports full sample results and liquidity subsample results, including the OLS estimates and the significance of *t*-test statistics based on White's robust standard errors.[22] First, the adjusted *R* squares for the whole sample are between 0.73 and 0.87. Adjusted *R* squares for subsamples vary with the variables dividing the subsamples. The goodness of fit numbers for the subsamples divided by trading volumes and liquidity ratios are relatively smaller, between 0.71 and 0.89. In comparison, the goodness of fit numbers for subsamples distinguished by ILLIQ are higher, between 0.69 and 0.93.

Regarding the estimation result, column 1 in Table 15 reveals that for the whole sample, individual stock risk premium is influenced by the contemporaneous incremental MPW only when the downside risk is 5%. But the effect becomes insignificant when the lagged one-period effect of the individual stock risk premium is controlled for. In comparison, the result in column 2 suggests that in the absence of a control for the one-period lagged impact of the individual stock's risk premium, no matter whether the downside risk is 1%, 5%, or 10%, the risk premiums of individual stocks with smaller trading volumes are affected significantly by the contemporaneous incremental MPW. The regression coefficients are between 0.02 and 0.04, suggesting that if the incremental MPW risk premium is 1% higher, individual stocks' risk premiums will be higher by 0.02 to 0.04%. When the one-period lagged effect of the individual risk premium is added, the effect is still significant when the downside risk is 1% and 5% but insignificant when the downside risk is 10%. This suggests that the MPW index with a downside risk of 5% starts to influence the risk premium of the individual stocks of the S&P 500. In contrast, column 3 reveals that no matter whether the one-period lagged risk premium effect is included or whether the downside risk is 1%, 5%, or 10%, the risk premium of the contemporaneous incremental MPW does not affect the returns of the individual stocks. These findings taken together imply that the MPW index can be reflected in the risk premium of individual stocks with worse liquidity, and the risk from MPW can probably be priced by liquid individual stocks; similarly, MPW cannot be reflected in the risk premium of individual stocks with better liquidity, and MPW risk can probably not be priced by illiquid individual stocks.

However, the result in column 4 is similar to that of column 2, when the one-period lagged effect of individual stock risk premiums are not controlled for and when the downside risk is at 1% or 5% of the asset returns. But these results become insignificant when the one-period lagged effects of the individual stocks' risk premiums are controlled for. Because adding the one-period lagged effect of individual stocks' risk premiums can lead to a decline in the adjusted *R* squared, we intend to adopt the result in panel A. That is, dividing samples by liquidity ratio could also support the empirical findings with subsamples based on trading volumes. Regarding the empirical result in column 5, we could also judge by the result of the model with a higher adjusted *R* squared that the contemporaneous incremental changes in MPW do not affect the risk premium of individual stocks when the downside risk is 5%, as in panel B. This result is consistent with the result in column 3, which is based on

[22] We also tried computing Shanken (1992) errors-in-variables corrected *t* statistics, yet the results were less significant than the reported results based on White's heteroscedasticity-consistent standard errors.

subsamples divided by trading volumes. However, the results in columns 6 and 7 show that the results are totally different when we base the subsamples on ILLIQ values, whether we incorporate the one-period lagged effect of individual stocks' risk premiums or not, the risk premium of the contemporaneous incremental change in the MPW index does not affect the risk premium of individual stocks. As we are using monthly trading volume, the liquidity ratio, and the ILLIQ index, not the daily or intra-day values of these indexes as in the existing literature, we suspect that the liquidity measure obtained from the monthly ILLIQ index may not be able to reflect the degree of liquidity, but the trading volume and liquidity ratio can still appropriately measure liquidity, thus leading to different empirical results.

----- Insert Table 15 here -----

6. Concluding Remarks

To gauge market worry about monetary policy, we resorted to the sensitivity of the down-side risk of crude oil futures returns to query terms like "central bank," "fed," and "federal reserve" to construct a monetary policy worry (MPW) index. We show that the MPW index predicts both stock market returns and individual stocks' returns, but the two patterns are different. Specifically, by examining S&P 500 component stocks, we find that the MPW index is correlated with low returns in the current month but predicts high returns after four months, which is a reversal pattern that takes a longer time than sentiment induced temporary mispricing. By contrast, for stock market-level aspects, we examine the S&P 500 and Russel 3000 indexes and find that MPW affects returns in contemporaneous months but not future returns, and thus no reversal exists; this can serve as a feature different from temporary mispricing due to sentiment. In addition, using Fama and Macbeth's (1973) regression method, we demonstrate that although the cross-sectional premium for change in the MPW index is small and similar across stocks, it cannot be fully priced by the systematic risk factors found by Fama and French (2015). Finally, our MPW index is related to the transitory component of the monthly realized volatility of the S&P 500 and Russel 3000 indexes, but it is not correlated with the VIX, which is unlike the finding of FEARS in Da et al. (2015). Thus, this paper underscores the usefulness of search data in financial applications for measuring worry. Because of the unavailability of data, we are unable to discuss worry from speculative investors who are interested in intraday trading or other people who hold assets for a long time horizon as pension funds. Moreover, although it would be feasible to discuss other financial segments, such as the bond and real estate markets, and different forms of value at risk that can be used to construct the MPW index, such as parametric value at risk, such discussion is beyond the scope of this paper. So we leave these applications for future research.

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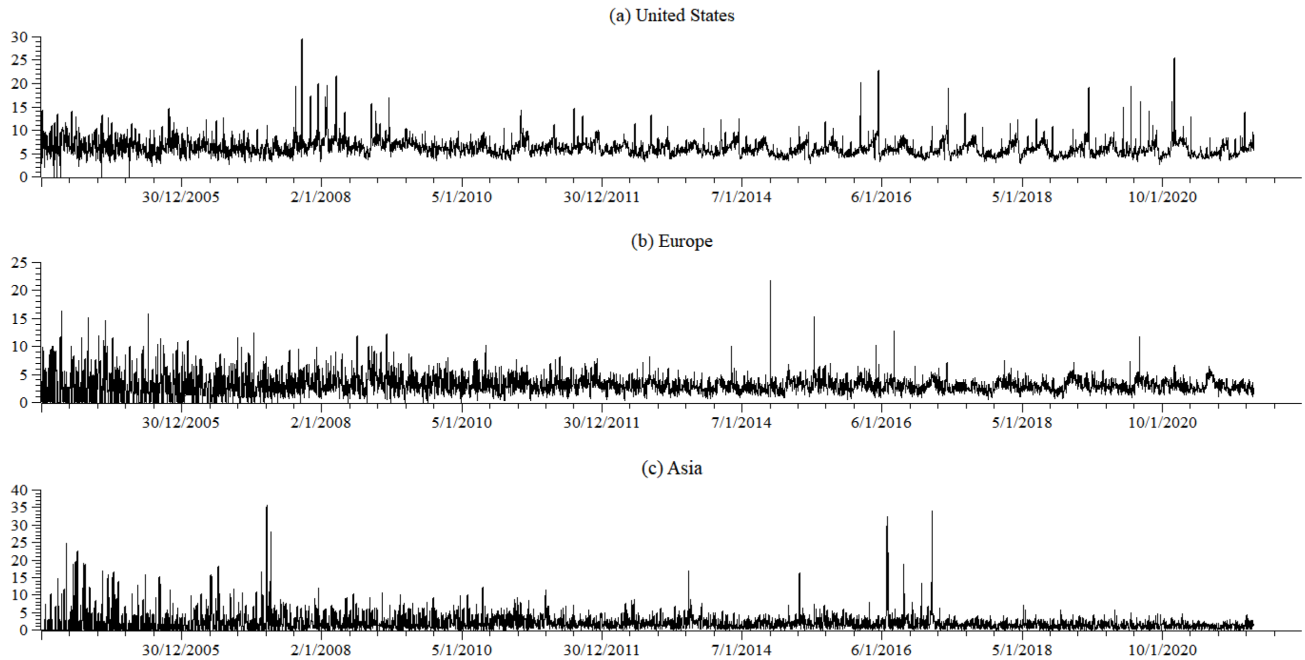

FIGURE 1

SVI in the region of the United States about monetary policy in category area

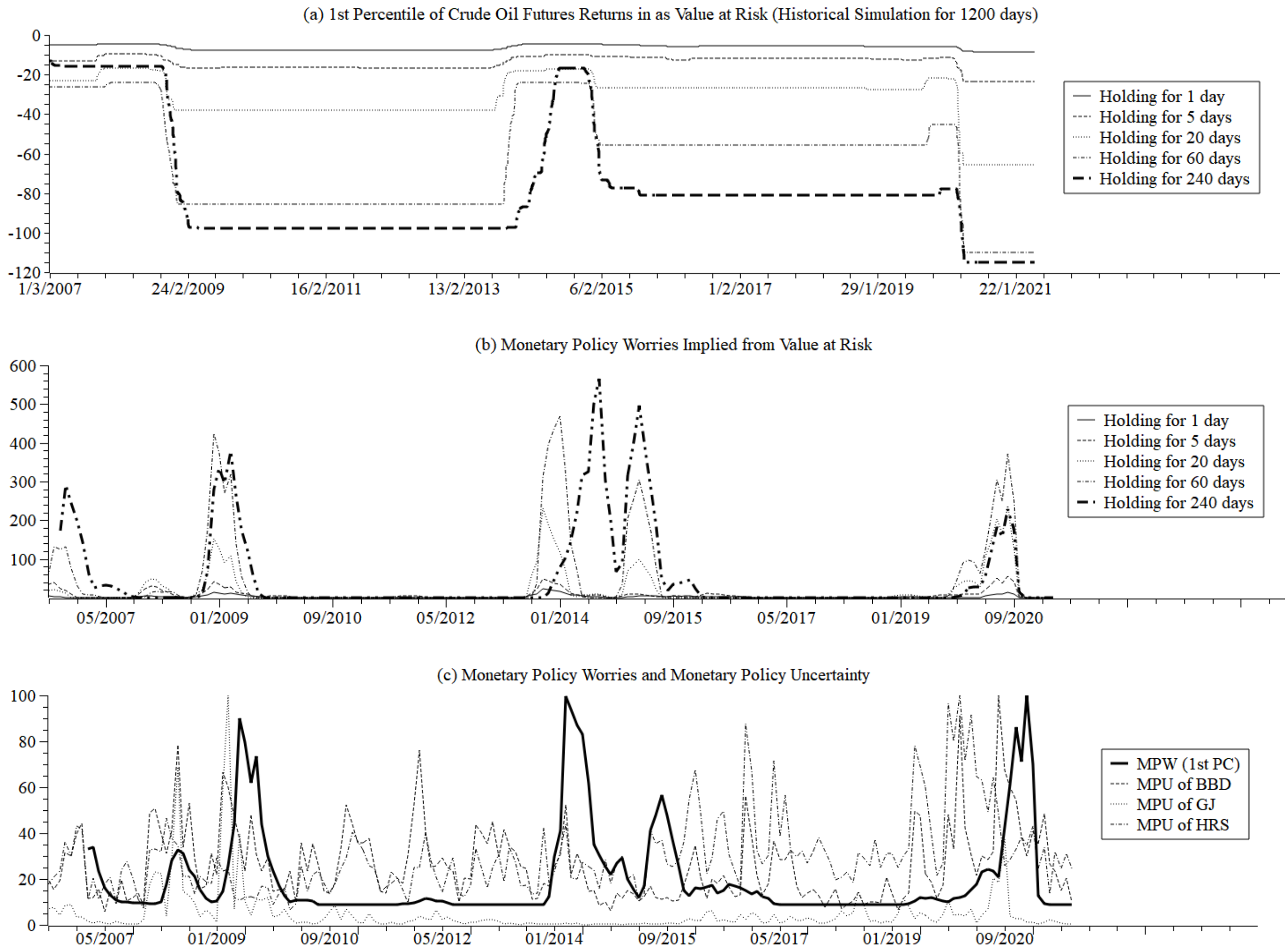

FIGURE 2

Value at risk, monetary policy worry, and monetary policy uncertainty

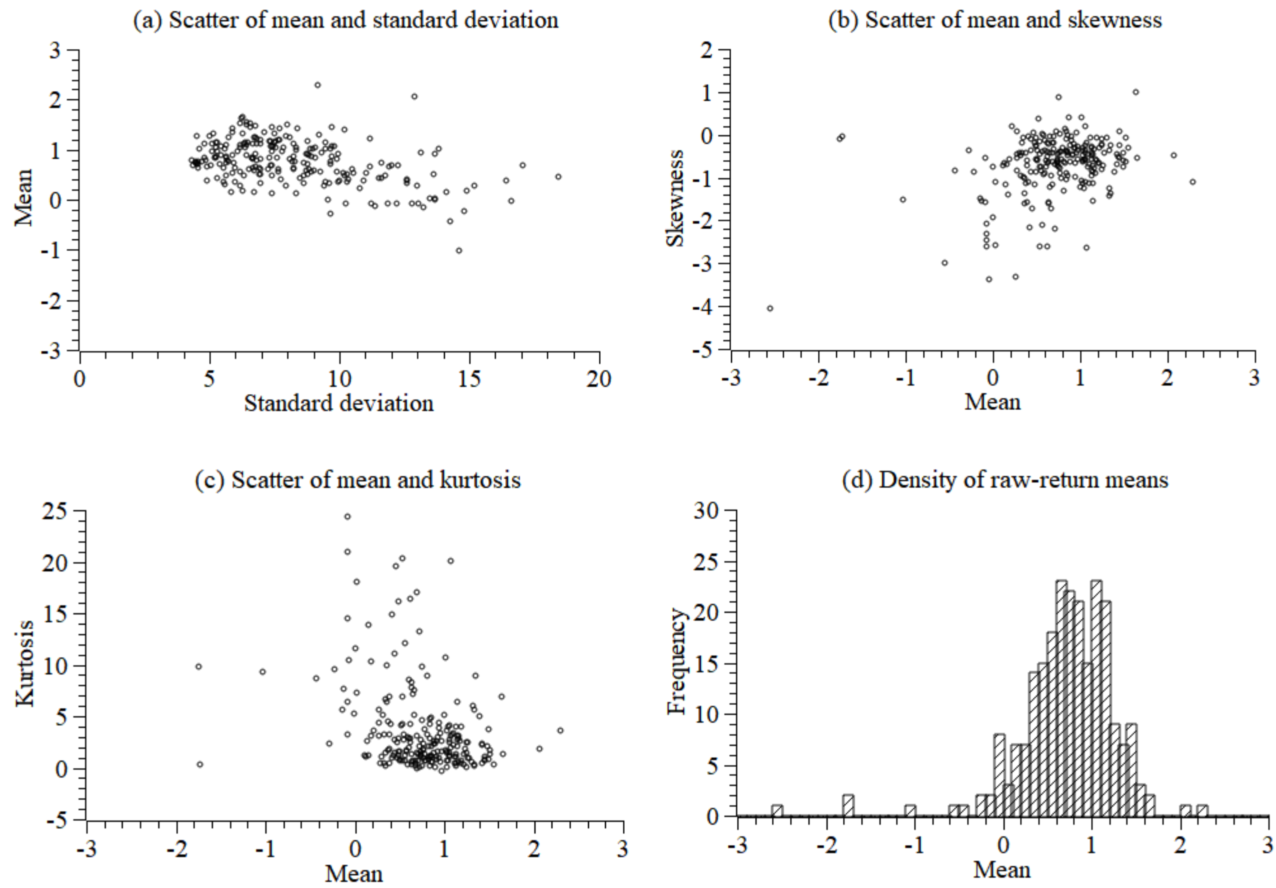

FIGURE 3

Scatters and density of summary statistics of S&P500 component stocks' raw returns

TABLE 1

Mean and *t*-test statistics of daily SVI and its changes regarding monetary-policy related keywords

		SVI		ΔSVI	
Keywords	Related studies	Mean	t-stat.	Mean	t-stat.
United States (26 Keywords)					
central bank	BBD	26.69	199.62***	<|0.01|	-0.01
fed	Wohlfarth	23.55	226.78***	<|0.01|	-0.02
federal reserve	BBD, Wohlfarth	12.28	128.27***	<0.01	0.05
money supply	BBD	10.76	83.38***	<0.01	0.03
monetary policy	BBD	10.61	80.20***	<0.01	0.03
the fed	BBD, Wohlfarth	8.34	118.42***	<0.01	0.04
federal reserve bank	Wohlfarth	7.69	88.81***	<0.01	0.02
interest rates	BBD	5.93	149.11***	<0.01	<0.01
tapering	AG	5.93	63.07***	<0.01	0.01
federal reserve system	Wohlfarth	4.74	58.75***	<0.01	0.02
fomc	BGM	3.72	42.64***	<0.01	<0.01
quantitative easing	BBD, AG	2.97	40.84***	<0.01	0.02
greenspan	BBD	2.89	53.63***	<0.01	0.01
discount window	BBD	2.81	38.85***	<0.01	0.01
fed meeting	GKW	2.56	30.12***	<0.01	0.01
fed funds rate	BBD	2.12	39.70***	<0.01	0.01
fed rate	Wohlfarth	1.70	37.11***	<0.01	0.01
fed chair	BBD	1.32	24.07***	<0.01	<0.01
volker	BBD	1.16	35.74***	<0.01	<0.01
fed interest	Wohlfarth	1.08	34.40***	<0.01	0.03
open market operations	BBD	0.92	30.35***	<0.01	0.01
lender of last resort	BBD	0.60	15.97***	<0.01	<0.01
fed chairman	BBD	0.58	23.90***	<0.01	<0.01
bernanke	BBD	0.54	25.15***	<0.01	<0.01
operation twist	AG	0.35	11.13***	<0.01	<0.01
overnight lending rate	BBD	0.16	5.60***	<0.01	<0.01
Europe (10 Keywords)					
bce	Wohlfarth	12.10	96.93***	<0.01	0.02
ecb	BBD, Wohlfarth	5.01	63.60***	<0.01	0.01
bank of England	BBD	4.23	52.78***	<|0.01|	-0.02
bank of Italy	BBD	1.66	27.56***	<0.01	0.02
bank of France	BBD	1.18	27.26***	<0.01	<0.01
European central bank	BBD, Wohlfarth	1.02	24.21***	<0.01	<0.01
ecb rate	Wohlfarth	0.97	16.88***	<0.01	<0.01
Bundesbank	BBD	0.88	16.03***	<0.01	<0.01
ezb	Wohlfarth	0.79	14.52***	<0.01	<0.01
banco central europeo	Wohlfarth	0.17	5.76***	<0.01	<0.01
Asia (3 Keywords)					
boj	BBD	2.38	33.06***	<0.01	0.01
bank of China	BBD	2.01	56.64***	<0.01	0.02
bank of Japan	BBD	1.24	24.94***	<0.01	<0.01

Note: The time-series sample of SVI spans a period from January 1, 2004, to April 30, 2021. BBD, Wohlfarth, AG, GKW, and BGM refer to Baker et al. (2016), Wohlfarth (2018), Altavilla and Giannone (2017), Gu et al. (2018), and Boguth et al. (2019), respectively. Mean and *t*-stats are based on daily data of SVI in the United States, spanning the period from January 1, 2004, to April 30, 2021, and *t*-stats are evaluated by Newey-West HAC standard errors. We use "<0.01" and "<|0.01|" to identify positive values smaller than 0.01 and negative values between 0 and −0.01, respectively. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

TABLE 2
Descriptive statistics

	Sample Period	Obs.	Mean	St.D.	Max.	Min.
Value at Risk (Daily)						
1D	2005/3/31–2021/4/30	4068	-6.21	1.27	-4.38	-8.40
5D	2005/4/6–2021/4/30	4064	-14.29	3.47	-9.58	-23.48
20D	2005/4/27–2021/4/30	4049	-30.93	11.70	-16.85	-65.85
60D	2005/6/22–2021/4/30	4009	-59.97	25.91	-23.97	-110.05
240D	2006/3/1–2021/4/30	3829	-74.49	31.20	-9.09	-115.15
Monetary Policy Worry (Monthly)						
1D	2005/10–2021/4	187	2.12	3.78	22.49	0.00
5D	2005/10–2021/4	187	6.53	11.33	54.34	0.00
20D	2005/11–2021/4	186	19.08	44.20	236.92	0.00
60D	2006/1–2021/4	184	43.01	99.52	468.84	0.00
240D	2006/9–2021/4	176	54.30	112.28	565.00	0.00
1st PC	2006/9–2021/4	176	20.19	20.25	100.00	8.92
Monetary Policy Uncertainty (Monthly)						
BBD	2005/10–2021/4	187	79.34	49.46	304.07	17.62
GJ	2005/10–2021/4	187	5.13	10.91	99.13	0.15
HRS	2005/10–2021/4	187	121.02	69.36	407.37	25.88
Return Variables (Monthly)						
S&P 500	2005/10–2021/4	187	0.65	4.36	11.94	-18.56
Russell 3000	2005/10–2021/4	187	0.67	4.53	12.32	-19.58
S&P 500 stocks	2005/10–2021/4	187	0.74	17.79	427.94	-422.94
Volatility Variables (Monthly)						
VIX (implied volatility of S&P 500)	2005/10–2021/4	187	19.66	8.83	59.89	9.51
Realized volatility of S&P 500	2005/10–2021/4	187	396.65	905.34	8493.03	19.70
Realized volatility of Russell 3000	2005/10–2021/4	187	408.39	921.03	8640.90	22.10
Macroeconomic Conditions (Monthly)						
EPU	2005/10–2021/4	187	144.69	72.05	503.96	44.78
ADS	2005/10–2021/4	187	0.01	2.48	21.13	-21.85
FOMC meeting dummy	2005/10–2021/4	187	0.65	0.48	1.00	0.00

Note: "1D," "5D," "20D," "60D," "240D" indicate 1, 5, 20, 60, 240 days for which assets are held by market participants; "1st PC" means the first principal component; and "BBD," "GJ," and "HRS" refer to Baker et al. (2016), Gospodinov and Jamali (2018), and Husted et al. (2020), respectively. The statistics of "S&P 500 stocks" returns were calculated from 239 stocks included in the S&P 500 index during the period from October 2005 to April 2021, and the "Max." and "Min." are available from RTX (i.e., Raytheon Technologies) for April 2006 and September 2008, respectively.

TABLE 3
Information-content analysis for MPW

	MPW			$\text{MPW} \times \mathbb{I}(\text{TRS} > 0)$			$\text{MPW} \times \mathbb{I}(\text{TRS} < 0)$		
Panel A									
MPU in contemporary month									
BBD	<0.01			<0.01			<|0.01|		
	1.91*			2.18**			-0.91		
GJ		<0.01			<0.01			<0.01	
		1.68*			2.49**			0.88	
HRS			<|0.01|			<0.01			<|0.01|
			-0.17			1.81*			-2.58**
Control Variable									
Constant	-0.17	-0.15	-0.15	-0.14	-0.15	-0.18	-0.15	-0.17	-0.14
	-2.15**	-1.82*	-1.81*	-1.75**	-1.71*	-2.06**	-1.84**	-2.08**	-1.69*
EPU	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
	0.16	1.23	1.57	0.80	1.42	1.48	1.57	1.55	1.81*
ADS	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.01
	2.18**	1.99**	1.76*	0.93	1.75*	1.62	1.08	2.00**	1.45
FOMC meeting dummy	<0.01	-0.01	<0.01	-0.01	<|0.01|	-0.01	<|0.01|	<|0.01|	<|0.01|
	0.05	-0.17	0.03	-0.23	-0.08	-0.20	-0.04	-0.02	-0.14
Lags of dependent variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.79	0.79	0.78	0.79	0.78	0.79	0.78	0.79	0.79
Panel B									
MPU in previous month									
BBD	<0.01			<0.01			<|0.01|		
	1.96*			2.16**			-0.68		
GJ		<0.01			<0.01			<|0.01|	
		1.33			4.41***			-0.91	
HRS			<|0.01|			<0.01			<|0.01|
			-0.73			1.07			-2.07**
Control Variable									
Constant	-0.20	-0.17	-0.14	-0.15	-0.15	-0.17	-0.15	-0.14	-0.14
	-1.00	-2.07**	-1.48	-1.71*	-1.75*	-1.90*	-1.75*	-1.70*	-1.67*
EPU	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
	0.85	1.41	1.79*	0.82	1.22	1.56	1.64	1.62	1.70*
ADS	0.01	0.01	0.01	0.01	0.01	0.02	0.01	0.01	0.01
	1.55	1.78*	1.64	1.69*	1.67*	2.07**	1.99**	1.86*	1.87*
FOMC meeting dummy	<|0.01|	0.01	<0.01	<0.01	0.01	<0.01	<0.01	<|0.01|	<0.01
	-0.09	0.16	0.05	0.01	0.19	0.04	0.07	<|0.01|	0.06
Lags of dependent variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.79	0.78	0.78	0.79	0.79	0.78	0.78	0.78	0.78

Note: The sample spans a period from September 2006 to April 2021. The dependent variables are MPW, $\text{MPW} \times \mathbb{I}(\text{TRS} > 0)$, and $\text{MPW} \times \mathbb{I}(\text{TRS} < 0)$. MPW denotes monetary policy worry, TRS denotes target rate surprise as defined by Bernanke and Kuttner (2005), and $\mathbb{I}(\cdot)$ is an indication function which is equal to one if TRS is positive or negative as indicated in the brackets; otherwise it equals zero. The explanatory variables include three measures of MPU, respectively denoted by "BBD," "GJ," and "HRS"; the control variables contain EPU, ADS, FOMC dummy variables; the first two lags of MPW that are used to control effects from economic policy uncertainty, macroeconomic activities, the holding of FOMC meetings, and autoregression effects. The reported t statistics are evaluated by White's robust standard errors. We use "<0.01" and "<|0.01|" to identify positive values smaller than 0.01 and negative values between 0 and −0.01. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

TABLE 4

Effects of monetary policy worry on S&P 500 index returns

	R_d	R_{d+1}	R_{d+2}	R_{d+3}	R_{d+4}	R_{d+5}	R_{d+6}
Panel A: Using $\boldsymbol{IV_1^R}$							
Change in MPW	-0.69	-2.09	1.77	2.42	-0.37	2.08	-0.34
	-0.32	-0.91	0.77	1.02	-0.18	1.23	-0.17
Control Variable							
Constant	5.65	-1.24	-1.65	-1.64	-2.08	-1.57	-0.61
	6.78***	-1.22	-1.52	-1.43	-1.89*	-1.34	-0.57
VIX	-0.24	0.10	0.10	0.10	0.13	0.11	0.07
	-5.83***	2.14**	2.19**	2.11**	3.02***	2.34**	1.58
ΔEPU	-0.01	<0.01	<0.01	<0.01	<0.01	<|0.01|	<0.01
	-2.73***	0.51	1.01	1.16	0.23	-0.99	1.27
ΔADS	0.26	0.03	0.06	0.02	-0.14	-0.20	0.34
	2.20**	0.17	0.58	0.27	-1.17	-2.04**	3.75
Lags of dependent variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sargan's test							
J statistic	8.21	5.48	2.90	0.64	3.69	3.01	8.02
(d.f.)	5.00	5.00	5.00	5.00	5.00	5.00	5.00
Endogeneity test							
difference in *J* statistic	0.13	1.25	0.87	2.04	0.15	1.66	0.04
(d.f.)	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Instrument orthogonality test							
difference in *J* statistic	7.88*	5.30	2.49	0.58	1.33	2.95	6.99
(d.f.)	4.00	4.00	4.00	4.00	4.00	4.00	4.00
Ljung-Box test							
Q(10) statistic	33.96***	15.40	7.21	4.36	7.82	7.03	9.24
Q(20) statistic	42.65***	27.93	14.98	12.46	17.82	17.79	18.21
Observation	173.00	172.00	171.00	170.00	169.00	168.00	167.00
Panel B: Using $\boldsymbol{IV_2^R}$							
Change in MPW	-8.02	-2.22	-0.70	1.66	-0.29	1.85	3.44
	-1.79*	-0.76	-0.27	0.65	-0.12	0.80	1.25
Control Variable							
Constant	6.11	-1.13	-1.19	-1.52	-1.67	-1.40	-1.46
	4.66***	-1.02	-1.20	-1.32	-1.43	-1.17	-1.25
VIX	-0.25	0.07	0.08	0.09	0.11	0.09	0.09
	-4.04***	1.34	1.98**	1.87*	2.28**	1.91*	1.89*
ΔEPU	-0.02	<0.01	<0.01	<0.01	<0.01	-0.01	<0.01
	-2.48**	0.76	0.04	1.25	0.59	-1.55	1.11
ΔADS	0.47	-0.06	0.11	0.03	-0.22	-1.23	0.31
	1.95*	-0.30	0.80	0.33	-1.60	-1.91*	2.55**
Lags of dependent variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sargan's test							
J statistic	0.54	4.16	2.72	0.21	5.31	1.79	1.77
(d.f.)	3.00	3.00	3.00	3.00	3.00	3.00	3.00
Endogeneity test							
difference in *J* statistic	5.74**	0.23	<0.01	0.91	0.07	1.15	1.81
(d.f.)	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Instrument orthogonality test							
difference in *J* statistic	0.48	4.02	1.92	0.15	2.70	1.73	1.50
(d.f.)	2.00	2.00	2.00	2.00	2.00	2.00	2.00
Ljung-Box test							
Q(10) statistic	11.52	11.30	5.66	4.16	6.33	5.84	5.84
Q(20) statistic	22.32	25.20	13.96	11.78	15.42	15.90	15.80
Observation	173.00	172.00	171.00	170.00	169.00	168.00	167.00

Note: The sample spans from October 2006 to April 2021. The dependent variables are the index returns of the S&P500 and the Russell 3000. The independent variables include changes in MPW, VIX, EPU, and ADS and the current and the first 4 lags of the dependent variable. For all models, we employ lags of change in MPW from 1 to 2 periods and change in MPU from 0 to 1 period as instruments to account for possible endogeneity. Instruments from "BBD" and "GJ" are denoted as "$\boldsymbol{IV_1^R}$," and instruments from "HRS" are denoted as "$\boldsymbol{IV_2^R}$." The reported *t* statistics of the estimates are evaluated by White's weighting matrix and robust standard errors. $Q(\cdot)$ is the chi-square statistic for the number of lags of residuals as shown in the brackets. We use "<0.01" and "<|0.01|" to identify positive values smaller than 0.01 and negative values between 0 and −0.01, respectively. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

TABLE 5

Effects of monetary policy worry on Russel 3000 index returns

	R_d	R_{d+1}	R_{d+2}	R_{d+3}	R_{d+4}	R_{d+5}	R_{d+6}
Panel A: Using $\boldsymbol{IV_1^R}$							
Change in MPW	-3.00	-2.36	1.82	2.48	0.13	2.34	-0.38
	-1.03	-0.99	0.75	1.00	0.06	1.29	-0.19
Control Variable							
Constant	5.91	-1.41	-1.91	-1.85	-2.10	-1.72	-0.70
	6.30***	-1.35	-1.72*	-1.58	-1.90*	-1.44	-0.64
VIX	-0.26	0.11	0.11	0.11	0.13	0.12	0.07
	-5.72***	2.26**	2.39**	2.26**	3.07***	2.41**	1.71*
ΔEPU	-0.02	<0.01	<0.01	<0.01	<0.01	<|0.01|	<0.01
	-2.68***	0.49	1.10	1.12	0.17	-0.90	1.10
ΔADS	0.40	0.04	0.04	0.01	-0.16	-0.18	0.38
	2.44**	0.24	0.43	0.13	-1.25	-1.74*	4.10***
Lags of dependent variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sargan's test							
J statistic	4.16	5.63	2.84	0.45	4.31	3.59	7.74
(d.f.)	5.00	5.00	5.00	5.00	5.00	5.00	5.00
Endogeneity test							
difference in *J* statistic	0.27	0.36	0.84	2.02	0.01	2.05	0.11
(d.f.)	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Instrument orthogonality test							
difference in *J* statistic	3.94	5.43	2.33	0.44	1.43	2.95	6.79
(d.f.)	4.00	4.00	4.00	4.00	4.00	4.00	4.00
Ljung-Box test							
Q(10) statistic	25.76***	15.73	7.13	4.15	7.17	6.31	8.93
Q(20) statistic	38.19***	28.60*	15.26	12.33	17.95	16.60	18.04
Observation	173.00	172.00	171.00	170.00	169.00	168.00	167.00
Panel B: Using $\boldsymbol{IV_2^R}$							
Change in MPW	-8.45	-2.61	-0.47	2.01	0.05	2.39	3.42
	-1.76*	-0.85	-0.17	0.72	0.02	0.94	1.21
Control Variable							
Constant	6.19	-1.17	-1.43	-1.81	-1.78	-1.55	-1.56
	4.59***	-1.01	-1.42	-1.54	-1.50	-1.23	-1.34
VIX	-0.25	0.07	0.10	0.10	0.11	0.10	0.10
	-3.93***	1.33	2.22**	2.08**	2.39**	1.95*	2.05**
ΔEPU	-0.02	<0.01	<0.01	<0.01	<0.01	-0.01	<0.01
	-2.47**	0.72	0.11	1.23	0.48	-1.44	1.05
ΔADS	0.51	-0.06	0.10	0.01	-0.23	-0.23	0.35
	2.13**	-0.26	0.67	0.15	-1.59	-1.78*	3.02***
Lags of dependent variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sargan's test							
J statistic	0.58	3.97	2.62	0.17	5.22	1.69	1.70
(d.f.)	3.00	3.00	3.00	3.00	3.00	3.00	3.00
Endogeneity test							
difference in *J* statistic	5.51**	0.36	0.02	1.15	0.01	1.65	1.48
(d.f.)	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Instrument orthogonality test							
difference in *J* statistic	0.51	3.80	1.69	0.16	2.20	1.67	1.38
(d.f.)	2.00	2.00	2.00	2.00	2.00	2.00	2.00
Ljung-Box test							
Q(10) statistic	11.12	11.59	5.40	4.00	5.99	5.11	5.39
Q(20) statistic	21.79	26.38	13.98	11.80	15.97	14.99	15.44
Observation	173.00	172.00	171.00	170.00	169.00	168.00	167.00

Note: The sample spans from October 2006 to April 2021. The dependent variables are the index returns of the S&P500 and the Russell 3000. The independent variables include VIX, changes in MPW, EPU, and ADS, and the current and the first 4 lags of the dependent variable. For all models, we employ lags of change in MPW from 1 to 2 periods and change in MPU from 0 to 1 period as instruments to account for possible endogeneity. Instruments from "BBD" and "GJ" are denoted as "$\boldsymbol{IV_1^R}$," and instruments from "HRS" are denoted as "$\boldsymbol{IV_2^R}$." The reported *t* statistics of the estimates are evaluated by White's weighting matrix and robust standard errors. $Q(\cdot)$ is the chi-square statistic for the number of lags of residuals as shown in the brackets. We use "<0.01" and "<|0.01|" to identify positive values smaller than 0.01 and negative values between 0 and −0.01, respectively. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

TABLE 6
Effects of monetary policy worry on S&P 500-index component stocks

	Return variables						
	d	$d+1$	$d+2$	$d+3$	$d+4$	$d+5$	$d+6$
Panel A: Simple risk premiums							
Change in MPW							
Using $\boldsymbol{IV_1^{rp}}$	-1.05	3.00	-0.94	-1.15	0.62	-0.11	-2.75
	-3.36***	9.55***	-3.11***	-3.69***	2.56**	-0.32	-4.26***
Using $\boldsymbol{IV_2^{rp}}$	-1.08	2.84	-0.48	-1.97	0.92	-0.74	-1.62
	-3.68***	5.79***	-0.92	-3.23***	3.76***	-2.78***	-2.70***
Control Variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation							
Cross section	239.00	239.00	239.00	239.00	239.00	239.00	239.00
Period	172.00	171.00	170.00	169.00	168.00	167.00	166.00
Sargan's test J statistic							
Using $\boldsymbol{IV_1^{rp}}$	67.86***	393.86***	71.68***	71.52***	46.06***	107.11***	65.11***
(d.f.)	5.00	5.00	5.00	5.00	5.00	5.00	5.00
Using $\boldsymbol{IV_2^{rp}}$	2.58	40.62***	7.39*	3.94	43.48***	20.27***	28.27***
(d.f.)	3.00	3.00	3.00	3.00	3.00	3.00	3.00
Difference in J test							
Adding $\Delta\boldsymbol{IV_d^{MPU1}}$	67.64***	353.24***	66.19***	69.87***	46.01***	106.92***	60.07***
(d.f.)	4.00	4.00	4.00	4.00	4.00	4.00	4.00
Adding $\Delta\boldsymbol{IV_d^{MPU2}}$	2.36	34.15***	1.90	2.29	43.43***	20.08***	23.23***
(d.f.)	2.00	2.00	2.00	2.00	2.00	2.00	2.00
Panel B: Abnormal returns based on Fama-French five factors							
Change in MPW							
Using $\boldsymbol{IV_1^{ar}}$	-0.55	0.48	-0.24	-0.20	0.43	0.13	-0.92
	-2.74***	2.01**	-0.98	-0.90	2.40**	0.44	-1.67*
Using $\boldsymbol{IV_2^{ar}}$	-0.58	0.30	0.11	-0.56	0.45	-0.14	-0.77
	-2.95***	0.91	0.24	-1.16	2.37**	-0.73	-1.60
Control Variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation							
Cross section	239.00	239.00	239.00	239.00	239.00	239.00	239.00
Period	172.00	172.00	172.00	171.00	171.00	171.00	170.00
Sargan's test J statistic							
Using $\boldsymbol{IV_1^{ar}}$	5.05	10.80*	11.31**	15.81***	5.40	12.44**	1.06
(d.f.)	5.00	5.00	5.00	5.00	5.00	5.00	5.00
Using $\boldsymbol{IV_2^{ar}}$	2.76	1.89	1.72	1.22	3.16	1.74	0.36
(d.f.)	3.00	3.00	3.00	3.00	3.00	3.00	3.00
Difference in J test							
Adding $\Delta\boldsymbol{IV_d^{MPU1}}$	4.95	9.81**	9.93**	15.13***	5.32	11.51**	1.05
(d.f.)	4.00	4.00	4.00	4.00	4.00	4.00	4.00
Adding $\Delta\boldsymbol{IV_d^{MPU2}}$	2.66	0.90	0.34	0.54	0.52	0.81	0.35
(d.f.)	2.00	2.00	2.00	2.00	2.00	2.00	2.00

Note: The sample spans a period from October 2006 to April 2021 and contains 239 stocks that remained S&P 500 component stocks during the period. The dependent variables include simple risk premiums and abnormal returns. The former is excess returns of raw returns (adjusted for dividends and splits) more than the risk-free rate, and the latter refer to abnormal returns adjusted for the five factors of Fama and French (2015). The explanatory variables include changes in MPW and control variables, and control variables includes VIX, changes in EPU and ADS, monthly dummy variables, and lags of the dependent variable from 1 to 4 periods. For each regression, we employ White's period correction for residual serial correlation and heteroscedasticity for difference GMM estimation, and we employ lags of change in MPW from 1 to 2 periods and change in MPU from 0 to −1 periods as instruments to account for possible endogeneity. Instruments from the MPU of "BBD" and "GJ" are denoted as "IV-1" and instruments from the MPU of "HRS" are denoted as "IV-2". We use "<0.01" and "<|0.01|" to identify positive values smaller than 0.01 and negative values between 0 and −0.01, respectively. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

TABLE 7

Effects of monetary policy worry on volatility

	VIX		S&P 500		Russel 3000	
Panel A: 20% quantile of volatility						
Change in MPW						
ΔMPW	0.01		0.04		-0.06	
	0.34		0.08		-0.22	
ΔMPW, 1st lag		0.03		-0.13		-0.15
		1.22		-0.69		-0.80
Control Variable						
ΔEPU	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
	1.17	1.46	2.63***	3.13***	2.39**	2.80***
ΔADS	<|0.01|	<|0.01|	-0.04	-0.02	-0.03	-0.02
	-0.99	-1.02	-1.06	-0.52	-0.73	-0.71
Constant, lags of dependent, and monthly dummies	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.44	0.44	0.25	0.26	0.26	0.26
Ljung-Box test						
Q(10) statistic	15.26	19.75**	11.69	8.67	11.76	10.26
Q(20) statistic	33.22**	38.25***	16.98	14.17	16.95	16.49
Observation	175.00	174.00	175.00	174.00	175.00	174.00
Panel B: 50% quantile of volatility						
Monetary Policy Worry						
ΔMPW	<|0.01|		0.10		0.16	
	-0.18		0.78		0.83	
ΔMPW, 1st lag		0.03		0.01		0.02
		0.87		0.19		0.21
Control Variable						
ΔEPU	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
	1.40	1.19	2.81***	2.67**	2.57**	2.90***
ΔADS	<|0.01|	-0.01	-0.05	-0.05	-0.05	-0.06
	-1.26	-1.33	-2.59**	-2.72***	-2.73***	-3.06***
Constant, lags of dependent, and monthly dummies	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.46	0.46	0.28	0.27	0.30	0.29
Ljung-Box test						
Q(10) statistic	8.90	10.99	12.89	8.38	11.83	12.73
Q(20) statistic	23.96	27.68	18.68	14.96	17.87	20.91
Observation	175.00	174.00	175.00	174.00	175.00	174.00
Panel C: 80% quantile of volatility						
Monetary Policy Worry						
ΔMPW	0.01		0.33		0.36	
	0.33		1.95*		2.31**	
ΔMPW, 1st lag		<|0.01|		0.25		0.22
		-0.15		1.29		1.13
Control Variable						
ΔEPU	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
	1.84*	2.09**	3.07***	3.15***	2.97***	3.15***
ΔADS	-0.02	-0.02	-0.01	-0.01	-0.03	-0.01
	-2.69***	-4.01***	-0.63	-0.31	-1.15	-0.39
Constant, lags of dependent, and monthly dummies	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.48	0.48	0.30	0.29	0.31	0.30
Ljung-Box test						
Q(10) statistic	17.35*	12.14	15.83	12.33	18.91**	12.44
Q(20) statistic	27.03	19.44	19.82	18.32	22.98	17.92
Observation	175.00	174.00	175.00	174.00	175.00	174.00

Note: The sample spans from October 2006 to April 2021. The dependent variables are log of VIX and realized volatility of S&P 500 and Russel 3000. The independent variables are changes in MPW and the 1st lag, and control variables include changes in EPU and ADS, monthly dummy variables, and lags of the dependent variable from 1 to 2 periods. The reported *t* statistics are evaluated by covariance using Huber sandwich estimators. We use "<0.01" and "<|0.01|" to identify positive values smaller than 0.01 and negative values between 0 and −0.01, and *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

TABLE 8

Sensitivity of MPW's informativeness to MPU given different historical simulation periods

	MPW			$MPW \times \mathbb{I}(TRS > 0)$			$MPW \times \mathbb{I}(TRS < 0)$		
	No. of days for simulation			No. of days for simulation			No. of days for simulation		
	1200	480	2400	1200	480	2400	1200	480	2400
Panel A: MPW by no-more-then-20 negative effects of ASVI on value at risk									
Scenario 1: MPU in contemporary month									
MPU measures									
BBD	<0.01	<0.01	<|0.01|	<0.01	<0.01	<0.01	<|0.01|	<|0.01|	<|0.01|
	1.91*	0.86	-0.07	2.18**	0.92	0.71	-0.91	-0.24	-0.69
GJ	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
	1.68*	1.60	0.42	2.49**	2.29**	0.39	0.88	0.68	0.28
HRS	<|0.01|	<|0.01|	<|0.01|	<0.01	<|0.01|	<0.01	<|0.01|	<|0.01|	<|0.01|
	-0.17	-1.89*	-0.60	1.81*	-0.06	0.18	-2.58**	-1.41	-0.54
Control Variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.78 ~0.79	0.79	0.74	0.78 ~0.79	0.79	0.74	0.78 ~0.79	0.79	0.74
Scenario 2: MPU in previous month									
MPU measures									
BBD	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<|0.01|	<|0.01|	<|0.01|
	1.96*	0.85	0.05	2.16**	0.98	0.90	-0.68	-0.36	-1.13
GJ	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<|0.01|	<|0.01|	-0.01
	1.33	0.83	0.71	4.41***	2.91***	2.02**	-0.91	-1.19	-1.14
HRS	<|0.01|	<|0.01|	<|0.01|	<0.01	<0.01	<0.01	<|0.01|	<|0.01|	<|0.01|
	-0.73	-1.72*	-1.28	1.07	0.16	1.56	-2.07**	-1.70*	-2.11**
Control Variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.78 ~0.79	0.79	0.74	0.78 ~0.79	0.79 ~0.80	0.75 ~0.76	0.78	0.79	0.74 ~0.75
Panel B: MPW by equal-to-20 effects of ASVI on value at risk (some of the effects may be positive)									
Scenario 1: MPU in contemporary month									
MPU measures									
BBD	<0.01	<0.01	<|0.01|	<0.01	<0.01	<0.01	<|0.01|	<|0.01|	<|0.01|
	1.85*	0.83	-0.02	2.21**	0.86	0.68	-0.90	-0.16	-0.63
GJ	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
	1.66*	1.43	0.23	2.62***	2.60***	0.08	0.90	0.68	0.23
HRS	<|0.01|	<|0.01|	<|0.01|	<0.01	<0.01	<0.01	<|0.01|	<|0.01|	<|0.01|
	-0.02	-1.53	-0.53	1.90*	0.05	0.15	-2.48**	-1.08	-0.46
Control Variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.76 ~0.77	0.76	0.72	0.77 ~0.78	0.76	0.72	0.77 ~0.78	0.76	0.72
Scenario 2: MPU in previous month									
MPU measures									
BBD	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<|0.01|	<|0.01|	<|0.01|
	2.03**	0.76	0.08	2.34**	1.11	1.02	-0.86	-0.65	-1.31
GJ	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<|0.01|	<|0.01|	-0.01
	1.35	0.83	0.61	4.57***	3.30***	2.17**	-0.91	-1.41	-1.37
HRS	<|0.01|	<|0.01|	<|0.01|	<0.01	<0.01	<0.01	<|0.01|	<|0.01|	<|0.01|
	-0.65	-1.64	-1.21	1.23	0.23	1.64	-2.07**	-1.64	-2.12**
Control Variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.76 ~0.77	0.76	0.72	0.77	0.76	0.72 ~0.73	0.77	0.76	0.72

Note: The sample spans a period from September 2006 to April 2021. The dependent variables are MPW, $MPW \times \mathbb{I}(TRS > 0)$, and $MPW \times \mathbb{I}(TRS < 0)$. MPW denotes monetary policy worry, TRS denotes target rate surprise as defined by Bernanke and Kuttner (2005), and $\mathbb{I}(\cdot)$ is an indication function equal to one if TRS is positive or negative as indicated in the brackets and otherwise equal to zero. The explanatory variables include three measures of MPU, respectively denoted by "BBD," "GJ," and "HRS," and control variables contain EPU, ADS, the FOMC dummy variable, and the first two lags of MPW that are used to control effects from economic policy uncertainty, macroeconomic activities, the holding of FOMC meetings, and autoregression effects. The reported t statistics are evaluated by White's robust standard errors. We use "<0.01" and "<|0.01|" to identify positive values smaller than 0.01 and negative values between 0 and −0.01. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

TABLE 9

Sensitivity of MPW's impact on stock market given a part of the additional instrument from MPUs

	R_d	R_{d+1}	R_{d+2}	R_{d+3}	R_{d+4}	R_{d+5}	R_{d+6}
Panel A: S&P 500							
Change in MPW							
BBD and GJ as additional instrument	-0.69	-2.09	1.77	2.42	-0.37	2.08	-0.34
	-0.32	-0.91	0.77	1.02	-0.18	1.23	-0.17
Only BBD as additional instrument	-5.93	-3.10	1.90	2.02	-0.80	2.48	2.32
	-1.38	-1.14	0.80	0.79	-0.38	0.97	0.90
Only GJ as additional instrument	1.65	-3.62	-1.72	2.65	0.35	2.07	0.22
	0.62	-1.37	-0.64	1.06	0.16	1.24	0.11
Control Variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sargan's test J statistic							
BBD and GJ as additional instrument	8.21	5.48	2.90	0.64	3.69	3.01	8.02
(d.f.)	5.00	5.00	5.00	5.00	5.00	5.00	5.00
Only BBD as additional instrument	0.31	0.86	1.63	0.35	2.68	0.22	1.69
(d.f.)	3.00	3.00	3.00	3.00	3.00	3.00	3.00
Only GJ as additional instrument	5.42	3.79	1.16	0.15	3.14	2.56	7.08
(d.f.)	3.00	3.00	3.00	3.00	3.00	3.00	3.00
Endogeneity test difference in J statistic							
BBD and GJ as additional instrument	0.13	1.25	0.87	2.04	0.15	1.66	0.04
(d.f.)	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Only BBD as additional instrument	4.28**	0.78	1.32	1.44	0.49	1.50	0.79
(d.f.)	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Only GJ as additional instrument	0.21	1.81	0.02	1.73	<0.01	1.41	<0.01
(d.f.)	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Panel B: Russel 3000							
Change in MPW							
BBD and GJ as additional instrument	-3.00	-2.36	1.82	2.48	0.13	2.34	-0.38
	-1.03	-0.99	0.75	1.00	0.06	1.29	-0.19
Only BBD as additional instrument	-6.38	-3.44	1.97	2.21	-0.47	3.14	2.26
	-1.39	-1.20	0.79	0.80	-0.21	1.12	0.86
Only GJ as additional instrument	1.93	-3.90	-1.68	2.72	1.92	2.33	0.14
	0.65	-1.42	-0.61	1.05	0.82	1.27	0.07
Control Variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sargan's test J statistic							
BBD and GJ as additional instrument	4.16	5.63	2.84	0.45	4.31	3.59	7.74
(d.f.)	5.00	5.00	5.00	5.00	5.00	5.00	5.00
Only BBD as additional instrument	0.36	0.87	1.58	0.36	3.10	0.17	1.80
(d.f.)	3.00	3.00	3.00	3.00	3.00	3.00	3.00
Only GJ as additional instrument	5.44	3.82	1.39	0.04	2.66	2.93	6.70*
(d.f.)	3.00	3.00	3.00	3.00	3.00	3.00	3.00
Endogeneity test difference in J statistic							
BBD and GJ as additional instrument	0.27	0.36	0.84	2.02	0.01	2.05	0.11
(d.f.)	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Only BBD as additional instrument	4.45**	0.97	1.32	1.54	0.22	2.07	0.59
(d.f.)	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Only GJ as additional instrument	0.23	1.98	0.01	1.98	0.03	1.86	<0.01
(d.f.)	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Note: The sample spans from October 2006 to April 2021. The dependent variables are the index returns of the S&P500 and the Russell 3000. The control variable includes VIX, changes in EPU and ADS, the current and the first 4 lags of the dependent variable. For all models, we employ lags of change in MPW from 1 to 2 periods and change in MPUs from 0 to 1 period as instruments to account for possible endogeneity. The reported t statistics of the estimates are evaluated by White's weighting matrix and robust standard errors. We use "<0.01" to identify positive values smaller than 0.01. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

TABLE 10
Sensitivity of MPW's impact on stock market returns given all additional instruments from MPUs

	R_d	R_{d+1}	R_{d+2}	R_{d+3}	R_{d+4}	R_{d+5}	R_{d+6}
Panel A: S&P 500							
Change in MPW							
BBD and GJ as additional instrument	-0.69	-2.09	1.77	2.42	-0.37	2.08	-0.34
	-0.32	-0.91	0.77	1.02	-0.18	1.23	-0.17
Only HRS as additional instrument	-8.02	-2.22	-0.70	1.66	-0.29	1.85	3.44
	-1.79*	-0.76	-0.27	0.65	-0.12	0.80	1.25
All MPUs as additional instrument	-6.53	-1.72	1.02	2.25	-0.05	0.91	0.26
	-1.78*	-0.90	0.51	1.00	-0.02	0.59	0.18
Control Variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sargan's test J statistic							
BBD and GJ as additional instrument	8.21	5.48	2.90	0.64	3.69	3.01	8.02
(d.f.)	5.00	5.00	5.00	5.00	5.00	5.00	5.00
Only HRS as additional instrument	0.54	4.16	2.72	0.21	5.31	1.79	1.77
(d.f.)	3.00	3.00	3.00	3.00	3.00	3.00	3.00
All MPUs as additional instrument	5.32	7.27	4.26	0.77	7.00	6.86	10.12
(d.f.)	7.00	7.00	7.00	7.00	7.00	7.00	7.00
Endogeneity test difference in J statistic							
BBD and GJ as additional instrument	0.13	1.25	0.87	2.04	0.15	1.66	0.04
(d.f.)	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Only HRS as additional instrument	5.74**	0.23	<0.01	0.91	0.07	1.15	1.81
(d.f.)	1.00	1.00	1.00	1.00	1.00	1.00	1.00
All MPUs as additional instrument	1.03	0.14	0.44	1.95	0.01	0.51	0.01
(d.f.)	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Panel B: Russel 3000							
Change in MPW							
BBD and GJ as additional instrument	-3.00	-2.36	1.82	2.48	0.13	2.34	-0.38
	-1.03	-0.99	0.75	1.00	0.06	1.29	-0.19
Only HRS as additional instrument	-8.45	-2.61	-0.47	2.01	0.05	2.39	3.42
	-1.76*	-0.85	-0.17	0.72	0.02	0.94	1.21
All MPUs as additional instrument	-7.40	-1.96	1.08	2.37	2.86	1.19	0.11
	-1.83*	-0.99	0.51	0.99	1.30	0.74	0.08
Control Variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sargan's test J statistic							
BBD and GJ as additional instrument	4.16	5.63	2.84	0.45	4.31	3.59	7.74
(d.f.)	5.00	5.00	5.00	5.00	5.00	5.00	5.00
Only HRS as additional instrument	0.58	3.97	2.62	0.17	5.22	1.69	1.70
(d.f.)	3.00	3.00	3.00	3.00	3.00	3.00	3.00
All MPUs as additional instrument	5.23	7.19	4.01	0.53	7.58	7.28	9.39
(d.f.)	7.00	7.00	7.00	7.00	7.00	7.00	7.00
Endogeneity test difference in J statistic							
BBD and GJ as additional instrument	0.27	0.36	0.84	2.02	0.01	2.05	0.11
(d.f.)	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Only HRS as additional instrument	5.51**	0.36	0.02	1.15	0.01	1.65	1.48
(d.f.)	1.00	1.00	1.00	1.00	1.00	1.00	1.00
All MPUs as additional instrument	1.38	0.24	0.45	1.95	<0.01	0.74	<0.01
(d.f.)	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Note: The sample spans from October 2006 to April 2021. The dependent variables are the index returns of the S&P500 and the Russell 3000. The control variable includes VIX, changes in EPU and ADS, the current and the first 4 lags of the dependent variable. For all models, we employ lags of change in MPW from 1 to 2 periods and change in MPUs from 0 to 1 period as instruments to account for possible endogeneity. The reported t statistics of the estimates are evaluated by White's weighting matrix and robust standard errors. We use "<0.01" to identify positive values smaller than 0.01. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

TABLE 11

Sensitivity of MPW's impact on stock price returns

	rp_d or ar_d	rp_{d+1} or ar_{d+1}	rp_{d+2} or ar_{d+2}	rp_{d+3} or ar_{d+3}	rp_{d+4} or ar_{d+4}	rp_{d+5} or ar_{d+5}	rp_{d+6} or ar_{d+6}
Panel A: Simple risk premiums							
Change in MPW							
BBD and GJ as additional IVs	-1.05	3.00	-0.94	-1.15	0.62	-0.11	-2.75
	-3.36***	9.55***	-3.11***	-3.69***	2.56**	-0.32	-4.26***
Only BBD as additional IVs	-1.28	2.74	-0.34	-1.65	0.53	-0.32	-2.22
	-3.60***	7.72***	-0.97	-3.95***	2.54**	-0.97	-3.21***
Only GJ as additional IVs	-0.88	2.74	-1.00	-1.11	0.86	-0.32	-2.77
	-3.22***	7.20***	-3.12***	-3.24***	3.84***	-1.03	-4.50***
Only HRS as additional IVs	-1.08	2.84	-0.48	-1.97	0.92	-0.74	-1.62
	-3.68***	5.79***	-0.92	-3.23***	3.76***	-2.78***	-2.70***
All MPUs as additional IVs	-0.96	3.08	-0.98	-1.25	0.62	-0.29	-2.26
	-3.41***	8.60***	-2.65***	-3.30***	2.66***	-0.81	-3.70***
Sargan's test J statistic							
BBD and GJ as additional IVs	67.86***	393.86***	71.68***	71.52***	46.06***	107.11***	65.11***
(d.f.)	5.00	5.00	5.00	5.00	5.00	5.00	5.00
Only BBD as additional IVs	10.53**	21.49***	10.44**	8.54**	35.23***	28.10***	47.13***
(d.f.)	3.00	3.00	3.00	3.00	3.00	3.00	3.00
Only GJ as additional IVs	31.76***	261.23***	69.43***	59.02***	24.09***	45.47***	12.62***
(d.f.)	3.00	3.00	3.00	3.00	3.00	3.00	3.00
Only HRS as additional IVs	2.58	40.62***	7.39*	3.94	43.48***	20.27***	28.27***
(d.f.)	3.00	3.00	3.00	3.00	3.00	3.00	3.00
All MPUs as additional IVs	73.30***	396.26***	72.47***	86.88***	101.92***	122.59***	108.67***
(d.f.)	7.00	7.00	7.00	7.00	7.00	7.00	7.00
Panel B: Abnormal returns based on five factors							
Change in MPW							
BBD and GJ as additional IVs	-0.55	0.48	-0.24	-0.20	0.43	0.13	-0.92
	-2.74***	2.01**	-0.98	-0.90	2.40**	0.44	-1.67*
Only BBD as additional IVs	-0.71	0.48	-0.05	-0.38	0.40	0.05	-0.89
	-3.03***	1.89*	-0.18	-1.29	2.17**	0.22	-1.51
Only GJ as additional IVs	-0.51	0.36	-0.19	-0.19	0.44	<0.01	-0.91
	-2.74***	1.31	-0.75	-0.86	2.45**	0.03	-1.74*
Only HRS as additional IVs	-0.58	0.30	0.11	-0.56	0.45	-0.14	-0.77
	-2.95***	0.91	0.24	-1.16	2.37**	-0.73	-1.60
All MPUs as additional IVs	-0.48	0.41	-0.17	-0.23	0.48	0.06	-0.87
	-2.62***	1.61	-0.55	-0.83	2.71***	0.20	-1.73*
Sargan's test J statistic							
BBD and GJ as additional IVs	5.05	10.80*	11.31**	15.81***	5.40	12.44**	1.06
(d.f.)	5.00	5.00	5.00	5.00	5.00	5.00	5.00
Only BBD as additional IVs	0.61	5.33	7.21*	7.79*	3.16	9.28**	0.39
(d.f.)	3.00	3.00	3.00	3.00	3.00	3.00	3.00
Only GJ as additional IVs	3.36	4.96	8.66**	9.02**	4.30	3.69	1.01
(d.f.)	3.00	3.00	3.00	3.00	3.00	3.00	3.00
Only HRS as additional IVs	2.76	1.89	1.72	1.22	3.16	1.74	0.36
(d.f.)	3.00	3.00	3.00	3.00	3.00	3.00	3.00
All MPUs as additional IVs	9.72	13.49*	12.94*	17.07**	10.02	14.70**	1.51
(d.f.)	7.00	7.00	7.00	7.00	7.00	7.00	7.00

Note: The sample spans a period from October 2006 to April 2021 and it contains 239 stocks that remain S&P 500 component stocks during the period. The dependent variables include simple risk premiums and abnormal returns. The former is excess returns of raw returns (adjusted for dividends and splits) more than the risk-free rate and the latter refer to abnormal returns adjusted for the five factors of Fama and French (2015). The explanatory variables include changes in MPW and control variables, and control variables include VIX, changes in EPU and ADS, monthly dummy variables, and lags of the dependent variable from 1 to 4 periods. For each regression, we employ White's period correcttion for residual serial correlation and heteroscedasticity for difference GMM estimation, and we employ lags of change in MPW from 1 to 2 periods and change in MPU from 0 to −1 periods as instruments to account for possible endogeneity. We use "<0.01" and "<|0.01|" to identify positive values smaller than 0.01 and negative values between 0 and −0.01, respectively. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

TABLE 12
MPW's impact on stock market returns given different downside risk for measuring MPW

	R_d	R_{d+1}	R_{d+2}	R_{d+3}	R_{d+4}	R_{d+5}	R_{d+6}
Panel A: S&P 500							
Change in MPW							
BBD and GJ as additional IVs							
MPW from 1% value at risk	-0.69	-2.09	1.77	2.42	-0.37	2.08	-0.34
	-0.32	-0.91	0.77	1.02	-0.18	1.23	-0.17
MPW from 5% value at risk	-0.73	-1.76	-0.01	2.76	0.84	2.21	0.64
	-0.34	-0.72	<|0.01|	0.75	0.42	0.98	0.32
MPW from 10% value at risk	<0.01	-2.03	-0.15	2.41	-1.44	1.61	-0.65
	<0.01	-0.67	-0.05	0.67	-0.56	0.68	-0.30
HRS as additional IVs							
MPW from 1% value at risk	-8.02	-2.22	-0.70	1.66	-0.29	1.85	3.44
	-1.79*	-0.76	-0.27	0.65	-0.12	0.80	1.25
MPW from 5% value at risk	-6.93	-1.81	-0.35	1.61	0.57	1.85	4.83
	-1.37	-0.67	-0.15	0.52	0.28	0.79	1.00
MPW from 10% value at risk	-6.33	-2.65	-0.81	0.58	-2.34	1.63	8.28
	-0.99	-0.58	-0.24	0.19	-0.59	0.52	0.83
Sargan's test J statistic							
BBD and GJ as additional IVs							
MPW from 1% value at risk	8.21	5.48	2.90	0.64	3.69	3.01	8.02
(d.f.)	5.00	5.00	5.00	5.00	5.00	5.00	5.00
MPW from 5% value at risk	5.53	5.40	5.64	0.69	4.97	3.24	6.97
(d.f.)	5.00	5.00	5.00	5.00	5.00	5.00	5.00
MPW from 10% value at risk	5.63	5.55	4.99	0.69	3.36	3.38	5.99
(d.f.)	5.00	5.00	5.00	5.00	5.00	5.00	5.00
HRS as additional IVs							
MPW from 1% value at risk	0.54	4.16	2.72	0.21	5.31	1.79	1.77
(d.f.)	3.00	3.00	3.00	3.00	3.00	3.00	3.00
MPW from 5% value at risk	1.15	3.75	4.58	0.42	6.18	1.34	0.87
(d.f.)	3.00	3.00	3.00	3.00	3.00	3.00	3.00
MPW from 10% value at risk	1.25	4.05	3.02	0.38	3.75	1.28	0.42
(d.f.)	3.00	3.00	3.00	3.00	3.00	3.00	3.00
Panel B: Russel 3000							
Change in MPW							
BBD and GJ as additional IVs							
MPW from 1% value at risk	-3.00	-2.36	1.82	2.48	0.13	2.34	-0.38
	-1.03	-0.99	0.75	1.00	0.06	1.29	-0.19
MPW from 5% value at risk	-0.89	-1.84	-0.09	2.62	1.03	2.09	0.49
	-0.38	-0.74	-0.04	0.72	0.50	0.96	0.25
MPW from 10% value at risk	-0.13	-2.17	-0.43	2.08	-0.77	1.45	-1.64
	-0.06	-0.70	-0.16	0.60	-0.33	0.62	-0.69
HRS as additional IVs							
MPW from 1% value at risk	-8.45	-2.61	-0.47	2.01	0.05	2.39	3.42
	-1.76*	-0.85	-0.17	0.72	0.02	0.94	1.21
MPW from 5% value at risk	-6.63	-2.03	-0.36	1.80	0.50	1.78	4.37
	-1.29	-0.72	-0.16	0.55	0.24	0.80	0.96
MPW from 10% value at risk	-5.65	-3.00	-0.95	0.74	-2.02	1.55	7.29
	-0.90	-0.61	-0.28	0.23	-0.54	0.50	0.80
Sargan's test J statistic							
BBD and GJ as additional IVs	4.16	5.63	2.84	0.45	4.31	3.59	7.74
MPW from 1% value at risk	5.00	5.00	5.00	5.00	5.00	5.00	5.00
(d.f.)	5.99	5.51	5.67	0.55	4.71	3.80	6.69
MPW from 5% value at risk	5.00	5.00	5.00	5.00	5.00	5.00	5.00
(d.f.)	6.14	5.75	5.15	0.56	3.41	3.90	4.57
MPW from 10% value at risk	5.00	5.00	5.00	5.00	5.00	5.00	5.00
(d.f.)	4.16	5.63	2.84	0.45	4.31	3.59	7.74
HRS as additional IVs							
MPW from 1% value at risk	0.58	3.97	2.62	0.17	5.22	1.69	1.70
(d.f.)	3.00	3.00	3.00	3.00	3.00	3.00	3.00
MPW from 5% value at risk	1.32	3.54	4.57	0.35	5.36	1.23	0.83
(d.f.)	3.00	3.00	3.00	3.00	3.00	3.00	3.00
MPW from 10% value at risk	1.52	3.87	3.01	0.31	3.29	1.22	0.44
(d.f.)	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Note: The sample, dependent variables, control variables, and instrumental variables are the same as illustrated in Table 4 and Table 5. The reported t statistics of the estimates are evaluated by White's weighting matrix and robust standard errors. We use "<0.01" and "<|0.01|" to identify positive values smaller than 0.01 and negative values between 0 and −0.01, respectively. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

TABLE 13

MPW's impact on stock market volatility given different downside risk for measuring MPW

	VIX	S&P 500	Russel 3000
Change in MPW			
20% quantile of volatility			
MPW from 1% value at risk	0.01	0.04	-0.06
	0.34	0.08	-0.22
MPW from 5% value at risk	0.01	-0.02	0.22
	0.39	-0.06	1.17
MPW from 10% value at risk	0.01	-0.01	0.25
	0.43	-0.05	2.08^{**}
50% quantile of volatility			
MPW from 1% value at risk	<|0.01|	0.10	0.16
	-0.18	0.78	0.83
MPW from 5% value at risk	0.03	0.08	0.08
	0.59	0.79	0.75
MPW from 10% value at risk	0.03	0.14	0.11
	0.82	1.39	1.07
80% quantile of volatility			
MPW from 1% value at risk	0.01	0.33	0.36
	0.33	1.95^{*}	2.31^{**}
MPW from 5% value at risk	0.03	0.16	0.22
	0.66	0.69	1.17
MPW from 10% value at risk	0.02	0.13	0.20
	0.65	0.69	1.28
Adjusted R^2			
20% quantile of volatility			
MPW from 1% value at risk	0.44	0.25	0.26
MPW from 5% value at risk	0.44	0.25	0.30
MPW from 10% value at risk	0.44	0.25	0.26
50% quantile of volatility			
MPW from 1% value at risk	0.46	0.28	0.30
MPW from 5% value at risk	0.46	0.28	0.30
MPW from 10% value at risk	0.46	0.29	0.30
80% quantile of volatility			
MPW from 1% value at risk	0.48	0.30	0.31
MPW from 5% value at risk	0.48	0.29	0.30
MPW from 10% value at risk	0.49	0.30	0.30

Note: The sample spans from October 2006 to April 2021. The dependent variables are log of VIX and the realized volatility of S&P 500 and Russel 3000. The independent variables are changes in MPW, and control variables include changes in EPU and ADS, monthly dummy variables, and lags of the dependent variable from 1 to 2 periods. The reported *t* statistics are evaluated by covariance using Huber sandwich estimators. We use "<0.01" and "<|0.01|" to identify positive values smaller than 0.01 and negative values between 0 and −0.01. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

TABLE 14

MPW's impact on stock price returns given different downside risk for measuring MPW

	rp_d or ar_d	rp_{d+1} or ar_{d+1}	rp_{d+2} or ar_{d+2}	rp_{d+3} or ar_{d+3}	rp_{d+4} or ar_{d+4}	rp_{d+5} or ar_{d+5}	rp_{d+6} or ar_{d+6}
Panel A: Simple risk premiums							
Change in MPW							
MPW from 1% value at risk	-1.08	2.84	-0.48	-1.97	0.92	-0.74	-1.62
	-3.68***	5.79***	-0.92	-3.23***	3.76***	-2.78***	-2.70***
MPW from 5% value at risk	-0.63	2.10	1.18	-3.52	0.66	0.43	-1.53
	-1.81*	4.79***	1.30	-3.68***	1.76*	1.67*	-3.72***
MPW from 10% value at risk	-0.55	1.98	0.79	-2.17	0.04	0.48	-0.80
	-1.99**	6.83***	1.36	-3.33***	0.10	2.32**	-1.66*
Sargan's test J statistic							
MPW from 1% value at risk	2.58	40.62***	7.39*	3.94	43.48***	20.27***	28.27***
(d.f.)	3.00	3.00	3.00	3.00	3.00	3.00	3.00
MPW from 5% value at risk	5.35	66.66***	18.61***	2.38	45.69***	23.15***	27.31***
(d.f.)	3.00	3.00	3.00	3.00	3.00	3.00	3.00
MPW from 10% value at risk	3.55	58.12***	8.63**	4.66	45.30***	22.78***	19.34***
(d.f.)	3.00	3.00	3.00	3.00	3.00	3.00	3.00
Panel B: Abnormal returns (five factors)							
Change in MPW							
Only HRS as additional IVs	-0.58	0.30	0.11	-0.56	0.45	-0.14	-0.77
	-2.95***	0.91	0.24	-1.16	2.37**	-0.73	-1.60
MPW from 5% value at risk	-0.36	0.30	0.47	-0.93	0.56	-0.07	-0.65
	-1.05	0.94	0.54	-1.07	2.09**	-0.35	-1.86*
MPW from 10% value at risk	-0.29	0.27	0.43	-0.57	0.39	-0.17	-0.48
	-1.25	1.17	0.76	-0.97	1.49	-0.91	-1.11
Sargan's test J statistic							
MPW from 1% value at risk	2.76	1.89	1.72	1.22	3.16	1.74	0.36
(d.f.)	3.00	3.00	3.00	3.00	3.00	3.00	3.00
MPW from 5% value at risk	3.16	3.93	1.58	0.53	5.27	1.75	0.29
(d.f.)	3.00	3.00	3.00	3.00	3.00	3.00	3.00
MPW from 10% value at risk	3.13	3.70	0.89	0.60	3.55	1.63	0.15
(d.f.)	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Note: The sample spans a period from October 2006 to April 2021 and it contains 239 stocks that remained S&P 500 component stocks during the period. The dependent variables include simple risk premiums and abnormal returns. The former is excess returns of raw returns (adjusted for dividends and splits) more than the risk-free rate, and the latter refer to abnormal returns adjusted for the five factors of Fama and French (2015). The explanatory variables include changes in MPW and control variables, and control variables include VIX, changes in EPU and ADS, monthly dummy variables, and lags of dependent variable from 1 to 4 periods. For each regression, we employ White's period correction for residual serial correlation and heteroscedasticity for difference GMM estimation, and we employ lags of change in MPW from 1 to 2 periods and change in MPU from 0 to −1 period as instruments to account for possible endogeneity. We use "<0.01" and "<|0.01|" to identify positive values smaller than 0.01 and negative values between 0 and −0.01, respectively. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

TABLE 15

Cross-sectional pricing tests given different downside risk for measuring MPW

	Full sample	Trading volume		Liquidity ratio		ILLIQ index	
		Small	Large	Small	Large	Small	Large
Panel A: Not control the effect of 1st lag of dependent variable							
Change in MPW							
MPW from 1% value at risk	0.01	0.02	<0.01	0.04	<|0.01|	<0.01	<0.01
	1.56	1.83*	0.49	2.67***	-0.16	0.27	0.53
MPW from 5% value at risk	0.02	0.03	0.01	0.03	0.02	0.01	0.01
	1.67*	1.71*	0.74	1.93*	1.37	0.80	0.80
MPW from 10% value at risk	0.01	0.04	0.02	0.01	0.07	0.01	-0.01
	1.12	1.95*	1.03	1.00	2.56**	0.96	-0.44
Monthly dummy variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes
1st lag of dependent variable	No	No	No	No	No	No	No
Adjusted R^2							
MPW from 1% value at risk	0.87	0.87	0.89	0.87	0.83	0.69	0.93
MPW from 5% value at risk	0.87	0.87	0.89	0.86	0.84	0.69	0.93
MPW from 10% value at risk	0.83	0.78	0.89	0.86	0.74	0.69	0.87
Panel B: Control the effect of 1st lag of dependent variable							
Change in MPW							
MPW from 1% value at risk	0.01	0.02	<0.01	0.03	<|0.01|	<0.01	<0.01
	1.18	2.03**	0.45	1.54	-0.10	0.15	0.41
MPW from 5% value at risk	<|0.01|	0.02	-0.04	<|0.01|	0.01	<0.01	-0.01
	-0.21	1.74*	-1.33	-0.18	1.26	0.29	-0.56
MPW from 10% value at risk	<0.01	0.02	0.01	<0.01	0.02	0.01	<|0.01|
	0.31	1.64	0.59	0.07	1.45	0.55	-0.33
Monthly dummy variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes
1st lag of dependent variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2							
MPW from 1% value at risk	0.86	0.86	0.88	0.86	0.83	0.72	0.93
MPW from 5% value at risk	0.73	0.86	0.73	0.71	0.84	0.72	0.71
MPW from 10% value at risk	0.86	0.86	0.88	0.85	0.84	0.72	0.93

Note: The cross-sectional sample contains 239 stocks that that remained S&P 500 component stocks during the period from October 2006 to April 2021. The dependent variable is the average of simple risk premiums, and simple risk premiums refer to excess returns more than the risk-free rate. The independent variables are regression coefficients from the stock-specific time-series regression of each stock's simple risk premiums on MPW, VIX, changes in EPU and ADS, and monthly dummy variables. The reported t statistics of the estimates are evaluated by White's robust standard errors. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.