Recovering the FOMC Risk Premium

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Abstract

The Federal Open Market Committee (FOMC) meetings are among the most important economic events. We propose a novel method to recover the FOMC risk premium and the drift sizes. Empirically, we find that the FOMC risk premium varies from 3 to 326 basis points (bps) for the 192 meetings from 1996 to 2019, with an average of 45 bps. We obtain an out-of-sample $R^2$ of 7.51% when using the recovered FOMC premium to predict the meeting return around the announcement. The average predicted upward drift size is 101 bps, and the average predicted downward drift size is 129 bps, matching well with the realized ones.

$JEL \text{ Classification}: \text{G11, G14}$

$Keywords: \text{Options, FOMC Meeting, Risk Premium, Drift, Recovery}$
1 Introduction

The Federal Open Market Committee (FOMC) meetings announce key decisions about interest rates and the growth of the United States money supply. It is generally recognized that an FOMC announcement has a significant influence on the market (see, e.g., Bernanke and Kuttner (2005)). In particular, Savor and Wilson (2013) and Lucca and Moench (2015) find that investors require a much greater risk compensation during a time interval of 24 to 48 hours before a meeting. Studies so far have only computed the average realized pre-FOMC market returns, which can be a good estimate of the FOMC unconditional risk premium. However, if the FOMC risk premium, like many other types of risk premia, also changes with economic conditions, then the average realized excess return would not be a good estimate of the risk premia of the meetings. The key economic questions of interest are whether the FOMC risk premium is time-varying, and if so, how we can estimate it.

In this paper, we propose a novel method to recover the FOMC risk premium associated with each FOMC meeting using options written on the S&P 500 index that expire soon after the meeting based on an equilibrium asset pricing model. The main idea is as follows. If there are options that expire soon after the announcement of an FOMC meeting, then in an efficient option market, the option prices prior and close to the announcement should correctly capture almost exclusively the risk from the imminent FOMC decision. This is because it is almost certain that the only major information of interest to investors at that time is the meeting, and the probability that the release of another important economic information (about other risk factors) coincides exactly with the FOMC announcement is virtually zero. As a result, the implied risk premium from these option prices should be equal to the FOMC risk premium almost without any contamination from other risk factors.

While using option data to recover risk premia is not new, it is a novel idea of this paper to focus on options that expire soon after an event (e.g., an FOMC meeting, an earnings announcement) and use their prices just before the event to recover the risk premia. As
explained above, the advantage of this approach is that the estimated risk premia are less
affected by other potential factors, and hence have a cleaner economic interpretation.

The S&P 500 options are the most liquid options written on the broad market index
and are the most widely-studied derivatives for the U.S. financial market. Given the short
time frame (24 to 48 hours), we assume that immediately after an FOMC announcement,
the S&P 500 index can take only two possible values: either drifts up or drifts down from
the measurement time point.\(^1\) Accordingly, we consider a simple one-period binomial tree
model for the S&P 500 index and use the close-to-announcement prices of options that expire
soon after the announcement to estimate the drift sizes. Then, using a representative agent
framework with a recursive utility as in Ai and Bansal (2018), we can recover the FOMC
risk premium for a given FOMC meeting.

In our empirical analysis, we first estimate the drift sizes around the FOMC meetings.
Our sample includes all the 192 FOMC meetings between 1996 and 2019. There are 83 FOMC
meetings in our sample that have options with short maturity soon after the meeting. We
fill in the rest of data via a machine learning method.\(^2\) The estimated average upward and
downward drift sizes are 101 and 129 bps, respectively. Comparing their values with the
realized drifts shows that our estimates are quite precise.

We find that the FOMC risk premium is time-varying. Our estimated FOMC risk pre-
mium varies from 3 to 326 bps over the period from 1996 to 2019, assuming typical levels
of parameters in an Epstein-Zin utility model.\(^3\) Its long-term average is 45 bps, matching
well with the average of the realized returns around the meetings. It also matches
well with the average pre-announcement return documented in the literature. This is be-

\(^1\) For a robustness check, we also consider a three-state model, which allows for the possibility of no drift,
and obtain similar results. See Section 4 for details.

\(^2\) The method estimates the implied volatility surface to extrapolate option prices. The results are con-
sistent with the 83 available sample (Section 3.2).

\(^3\) The results are based on intertemporal elasticity of substitution $\psi = 1.5$, and relative risk aversion
$\gamma = 10$. We also present results with $\gamma = 7.5$ in Section 3.4.
the post-announcement return as commonly used in the literature, and the average post-announcement return is close to zero (e.g., Lucca and Moench (2015), Hu et al. (2019)). Since the FOMC risk premium is shown to be time-varying, our estimate provides a better benchmark for hedging and speculation at each meeting, contributing to the literature in a substantial way, because the existing literature assumes a constant FOMC risk premium.

Our FOMC risk premium estimates can also be used to forecast out-of-sample future market returns around the meetings. The out-of-sample R-squared, a measure of predictability, is 7.51%. This level of predictability is regarded as high and economically significant according to the predictability literature (see, e.g., Campbell and Thompson (2008)).

With our estimates of the FOMC time-varying risk premium, we are able to examine how it responds to various macroeconomic conditions. We find that the FOMC risk premium is high when the consumption growth rate, the GDP growth rate, or the inflation rate are low, when the VIX index is high, and when the market is more pessimistic. These patterns of the FOMC risk premium are consistent with the economic intuition that investors require a higher risk compensation when the economy is in a bad state.

Our paper is the first to recover the time-varying FOMC risk premium. Our empirical results show that the investors’ demand of risk compensation before the FOMC meetings is well reflected by the option market. This, in turn, allows us to extract forward-looking information, and to estimate the time-dependent conditional FOMC risk premium from option prices regarding each meeting. The large time-variation in the estimated FOMC risk premium suggests that it is important to understand the risks associated with each meeting for its asset pricing implications on investments and corporate planning, instead of using only the average of the realized return as the FOMC risk premium.

Our paper is closely related to the literature that shows the existence of the FOMC risk premium. Savor and Wilson (2013), Lucca and Moench (2015), and Neuhierl and Weber (2020) present empirical evidence of the premium. Ai and Bansal (2018) introduce the idea
of macro-announcement premium with a theoretical model and explain the high average return over this time period with uncertainty resolution around the announcement. Hu et al. (2019) propose a two-risk model to explain the premium with heightened uncertainty. Savor and Wilson (2014) and Ai et al. (2020) show that the cross-section of stocks also behaves differently around macroeconomic announcements. Moreover, Zhang and Zhao (2018) and Boguth et al. (2019) explore the predictability of the FOMC premium. We contribute to the literature by finding evidence of time-varying risk premium from the option market.

Our paper also contributes to the recovery literature. Ross (2015) proposes a theory to recover the entire physical distribution of market returns from options written on the S&P 500 index. Subsequent papers focus on recovering the expected return of assets from option prices under normal market conditions and over a relatively long time interval (e.g., Martin (2017), Kadan and Manela (2019), Tang (2018), Jensen et al. (2019), Martin and Wagner (2019), and Kadan and Tang (2020)). Our paper introduces a methodology to recover expected returns and drift sizes within a short time horizon around important events while minimizing the impact of other potential risk factors.

Our paper also adds to the literature that explores the relation between the FOMC meetings and the derivatives market behavior. Vähämaa and Äijö (2011) and Amengual and Xiu (2018) find that the FOMC meeting significantly influences the behavior of implied volatility of index options through an uncertainty channel. Neuhierl and Weber (2019) construct a slope factor based on implied fed funds rates of different maturities to predict future market returns. Ai et al. (2019) show that S&P 500 index option prices around the FOMC announcements identify investors’ preference for the timing of resolution of uncertainty. Our paper shows that option prices can be used directly to measure and predict stock price drifts around the FOMC meetings.

The rest of the paper proceeds as follows. Section 2 introduces our theoretical framework and estimation methodology. Section 3 conducts estimation using option prices of the S&P 500 index. Section 4 presents further analysis and Section 5 concludes.
2 Theoretical Framework

In this section, we consider an asset whose price will experience either an upward or a downward drift right at an imminent event (for example, an FOMC meeting, earnings announcement, important economic news release). We begin with a one-period binomial tree model to estimate the drift sizes from observed option prices. Then, we employ a representative agent equilibrium model to recover physical probabilities of the upward drift and the downward drift, as well as the implied risk premium for the asset associated with the event. This method can be applied to any asset that will likely experience a drift in its price before an imminent event, as long as its liquid options that mature shortly after the event are available.

2.1 The Model

We consider a discrete time model with \( t = 0, 1 \). To capture the meeting drift within a short time interval, we assume an event occurs between \( t = 0^- \) and \( t = 0^+ \) and asset price jumps at \( t = 0^+ \). There exists a representative firm which produces one consumption good at time 0 and time 1. The consumption good produced at time 0 is \( \bar{c}_0 \) and at time 1 is \( \bar{c}_H \) or \( \bar{c}_L \), where \( \bar{c}_H > \bar{c}_L > 0 \). The representative agent owns the firm which issues one share of stock. The firm pays the stock holder the consumption good produced as dividend at time 0 and time 1.

The event occurring between \( t = 0^- \) and \( t = 0^+ \) fully determines the consumption good production state \( (\bar{c}_H \text{ or } \bar{c}_L) \) at \( t = 1 \). Let \( S_0 \) denote the price of the asset at time \( t = 0^- \). The price of this asset at time \( t = 0^+ \) jumps up by \( uS_0 \), or jumps down by \( dS_0 \), with \( u > 0 \) and \( d > 0 \). Thus, the binomial tree for the asset price starts at time \( t = 0^- \) and ends at \( t = 0^+ \), while the consumption changes at time \( t = 1 \). This is the same set up as in the simplest case of Ai and Bansal (2018).\(^4\) With this set up, the gross return on the asset around the

\(^4\)Our model can be extended to a multi-period one with dynamic consumption choice, but the results
Figure 1: Consumption and Asset Prices
Notes: This figure plots the consumption (top panel) and asset price (bottom panel) as well as the
time line in our model.

event takes two possible values: $1 + u$ and $1 - d$, corresponding to the two states. Denote
the probabilities of the two states as $p(u)$ and $p(d)$, the risk premium associated with this
event is then given by$^5$

$$E(r) = p(u)u - p(d)d.$$  \hspace{1cm} (1)

Figure 1 illustrates our assumptions for this one-period and two-state model. The corres-
dpondence between states ($up, down$) and ($H, L$) (i.e., whether blue arrows or red arrows
apply between time 0 and time 1 in the bottom panel) is determined in equilibrium, as
explained in details in Section 2.3. From Figure 1, one can clearly see that, consistent with
facts documented in the literature, the asset prices will change immediately upon the arrival
remain the same. This is because all future consumptions can be summarized by the end of period con-
sumption and the utility at $t = 1$ can be viewed as the continuation utility from all the future consumptions. Thus the impact of an event on asset prices can be captured by our one-period model.$^5$

Because the time between $t = 0^-$ and $t = 0^+$ is zero, the risk free rate is absent in the premium expression.
of the event. However, as in Ai and Bansal (2018), neither the firm’s dividend nor the agent’s consumption jumps. As a result, the agent only changes the investment between time $t = 0$ and $t = 1$.\(^6\)

### 2.2 Jump Sizes and State Prices

As a first step, we recover the jump sizes and corresponding state prices using option prices. Assume that there are two call options and two put options written on this asset, all maturing at time $t = 0^+$. At time $t = 0^-$, let the prices of these options be $C_1$, $C_2$, $P_1$, and $P_2$ with respective strike prices of $K_1^C$, $K_2^C$, $K_1^P$, and $K_2^P$ such that $(1 - d)S_0 < K_1^C$, $K_2^C < (1 + u)S_0$ and $(1 - d)S_0 < K_1^P$, $K_2^P < (1 + u)S_0$. Thus, at time $t = 0^+$, the call options will be exercised only when the realized state is $u$, with payoff $(1 + u)S_0 - K_i^C$, and the put options will be exercised only when the realized state is $d$, with payoff $(1 - d)S_0 - K_i^P$, for $i = 1, 2$.

Let $q_0(u)$ denote the time $t = 0^-$ state price of the up state at $t = 0^+$ (i.e., the time $t = 0^-$ price of an Arrow-Debreu security that pays $1$ in the up state and $0$ otherwise at $t = 0^+$). Then the call options are priced as

$$C_i = q_0(u)\left((1 + u)S_0 - K_i^C\right), \quad i = 1, 2,$$

which implies the following equalities:

$$q_0(u) = \frac{(1 + u)S_0 - K_1^C}{C_1} = \frac{(1 + u)S_0 - K_2^C}{C_2}. \quad (2)$$

Therefore, the implied upward jump size $u$ is equal to

$$u = \frac{K_1^CC_2 - K_2^CC_1}{S_0(C_2 - C_1)} - 1. \quad (3)$$

\(^6\)We have also analyzed a problem where the consumption can change around the event. The results are similar and available from the authors.
and the implied state price of the up state is equal to

\[ q_0(u) = \frac{C_1 - C_2}{K^C_2 - K^C_1}. \]  (4)

In summary, with the information contained in a pair of call options, we can estimate the future upward jump size of an asset, as well as the corresponding state price.

Similarly, we can compute the size of the downward jump and the corresponding state price \( q_0(d) \) by a pair of put options. Following the same steps as above, we have that the implied downward jump size \( d \) is equal to

\[ d = 1 - \frac{K^P_1 P_2 - K^P_2 P_1}{S_0 (P_2 - P_1)}, \]  (5)

and the implied state price of the down state is equal to

\[ q_0(d) = \frac{P_1 - P_2}{K^P_1 - K^P_2}. \]  (6)

Therefore, using a pair of calls and a pair of puts, we can infer both the jump sizes and states prices, which will be used below to estimate the risk premium due to the event.

For the choice of these options in our empirical analysis, we use those close to the money (CTM). This is because CTM options are more liquid and thus their prices are less distorted by illiquidity. We use call options to estimate the upward jump size and the up state price because call options are likely to better reflect information about an upward jump.\(^7\) Similarly, we use put options to estimate the downward jump size and the down state price.\(^8\)

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\(^7\)For example, as shown in An et al. (2014), informed traders with positive news trade mostly by buying call options.

\(^8\)Since the asset itself can be viewed as an option with zero strike price, it can also be used to help estimate the state prices and jump sizes. In an efficient financial market, this would result in the same estimates. In our empirical analysis later, we find that the difference is smaller than 0.1%, implying a high degree of market efficiency.
2.3 Risk Premium

To estimate the risk premium, we use the Epstein-Zin preference as in Ai and Bansal (2018). More specifically, we assume that the instantaneous utility of the representative agent is

$$u(c) = c^{1-\frac{1}{\psi}} \cdot \frac{1}{1-\frac{1}{\psi}},$$

where $\psi$ is the intertemporal elasticity of substitution parameter. Let $\phi(x) = \frac{x^{1+\alpha}}{1+\alpha}$, where $\alpha = \frac{1-\gamma}{1-\psi}$ and $\gamma$ is the relative risk aversion coefficient. For state $s$, define

$$V(s) = u(c_0(s)) + \beta u(c_1(s))$$

as the aggregated intertemporal utility in state $s$. We then specify the Epstein-Zin preference by its certainty equivalent function: $I(V) = \phi^{-1}(E[\phi(V)])$. The representative agent faces the following optimal consumption problem at $t = 0$:

$$\max_{c_0, c_1(s)} I(V)$$

subject to

$$\sum_{s=\text{u,d}} (q_0(s)(c_0(s) - \bar{c_0}) + q_1(s)(c_1(s) - \bar{c_1})) = 0.$$ 

State prices $q_t(s)$ ($t = 0, 1$) are time $t = 0$—prices of contingent claims that pay off $\$ 1$ at time $t$ if the revealed state at $t = 0+$ is $s$. They satisfy $\sum_{s=\text{u,d}} q_0(s) = 1$. Let $\lambda$ denote the Lagrange multiplier, then the first order condition (FOC) of the optimization problem with respect to $c_0$ is

$$\frac{\partial I(V)}{\partial V(s)} u'(c_0) = \lambda q_0(s),$$

(7)

9One of the advantages of the Epstein-Zin preferences over the expected utility preferences is that it allows the separation of consumption and investment decisions.
and the FOC with respect to $c_1(s)$ is

$$\frac{\partial I(V)}{\partial V(s)} u'(c_1(s)) = \lambda q_1(s). \quad (8)$$

Summing (7) over $s$, we have that

$$\lambda = \sum_{s=u,d} \frac{\partial I(V)}{\partial V(s)} u'(c_0). \quad (9)$$

Plugging (9) back into (8), we obtain

$$q_1(s) = \frac{\frac{\partial I(V)}{\partial V(s)} \beta u'(c_1(s))}{\sum_{s=u,d} \frac{\partial I(V)}{\partial V(s)} u'(c_0)}.$$

Notice that

$$\frac{\partial I(V)}{\partial V(s)} = p(s)(c_0^{1-\frac{1}{\varphi}} + \beta c_1(s)^{1-\frac{1}{\varphi}})^{\alpha}.$$

The stochastic discount factor is thus given by

$$m^*(s) = \frac{(c_0^{1-\frac{1}{\varphi}} + \beta c_1(s)^{1-\frac{1}{\varphi}})^{\alpha}}{\sum_{s=u,d} p(s)(c_0^{1-\frac{1}{\varphi}} + \beta c_1(s)^{1-\frac{1}{\varphi}})^{\alpha}}. \quad (10)$$

Then the state prices $q_1(s)$ can be rewritten as:

$$q_1(s) = m^*(s)p(s)\frac{\beta u'(c_1(s))}{u'(c_0)}.$$

So for the stock price, we have that

$$S_{0-} = \sum_{s=u,d} (g_0(s)\bar{c}_0 + q_1(s)\bar{c}_1(s)) = \bar{c}_0 + \sum_{s=u,d} q_1(s)\bar{c}_1(s) = \bar{c}_0 + \sum_{s=u,d} m^*(s)p(s)\frac{\beta u'(c_1(s))}{u'(c_0)}\bar{c}_1(s). \quad (11)$$

After the announcement, the state $s$ at $t = 1$ is fully revealed. The representative agent
faces the following problem

$$\max_{c_0, c_1(s)} u(c_0) + \beta u(c_1(s))$$

s.t. $$c_0 + \hat{q}_1(s)c_1(s) \leq \bar{c}_0 + \hat{q}_1(s)\bar{c}_1(s),$$

where $\hat{q}_1(s)$ are time $t = 1$ prices of the contingent claims that pays off $\$1$ at time $t = 2$ and state $s$. Following the standard procedure, the FOC is given by

$$\hat{q}_1(s) = \beta \frac{u'(c_1(s))}{u'(c_0)}.$$

Thus, at $t = 0+$, the price of the stock is equal to

$$S_{0+}(s) = c_0 + \hat{q}_1(s)\bar{c}_1(s) = c_0 + \beta \frac{u'(c_1(s))}{u'(c_0)}\bar{c}_1(s).$$

Comparing (12) with (11), we obtain

$$S_{0-} = \sum_{s=u, d} m^*(s)S_{0+}(s).$$

Define $W(s) = V(s)^\alpha = (u(c_0(s)) + \beta u(c_1(s)))^\alpha$, the stochastic factor can be expressed as

$$m^*(s) = \frac{W(s)}{\sum_{s=u,d} p(s)W(s)}.$$ 

Relation (13) then reduces to

$$S_{0-} = m^*(u)S_{0+}(u) + m^*(d)S_{0+}(d).$$
Then by (14), we obtain that

$$\frac{p(u)W_u(1 + u) + p(d)W_d(1 - d)}{p(u)W_u + p(d)W_d} = 1,$$

(15)

based on our assumptions that $S_1(u) = (1 + u)S_0$, and $S_1(d) = (1 - d)S_0$. Equation (15) together with the fact that $p(u) + p(d) = 1$ imply

$$p(u) = \frac{dW_d}{dW_d + uW_u},$$

$$p(d) = \frac{uW_u}{dW_d + uW_u}.

(16)

To fully recover these physical probabilities, consider the risk premium (1). We have

$$p(u)u - p(d)d = \frac{ud(W_d - W_u)}{dW_d + uW_u},$$

and so there is a positive risk premium if and only if $W_d > W_u$. Define $f(x) = (1 + \beta x^{1-\frac{1}{\psi}})^\alpha$, then we need $f(d) > f(u)$ for a positive risk premium. Consider the first order derivative

$$f'(x) = (1 + \beta x^{1-\frac{1}{\psi}})^{\alpha-1} \alpha \beta (1 - \frac{1}{\psi}) x^{-\frac{1}{\psi}}.$$

We have that $f'(x) < 0$ if and only if $\alpha (1 - \frac{1}{\psi}) < 0$, which is equivalent to $\gamma > \frac{1}{\psi}$. When $f'(x) < 0$ holds, we have that $W_d > W_u$ because $u > d$. Thus, in the following analysis, we work with the assumption that $\gamma > \frac{1}{\psi}$, consistent with the literature.

Letting

$$\hat{u} = \frac{c_H}{c_0},$$

$$\hat{d} = \frac{c_L}{c_0},$$

we have $\hat{u} > \hat{d}$.

We first consider the case where $\frac{1}{\psi} > 1$, which combined with $\gamma > \frac{1}{\psi}$ implies $\alpha > 0$. In addition, with $\frac{1}{\psi} > 1$, we have $\hat{u}^{1-\frac{1}{\psi}} < \hat{d}^{1-\frac{1}{\psi}}$. This implies that the marginal utility of a
dollar of payment in the low state of the consumption is so high that although the stock
pays less in the low state, the stock is more valuable in the low state than in the high state.
Therefore, in Figure 1, the blue arrows apply when \( \frac{1}{\psi} > 1 \) and

\[
S_{0+}(d) = \bar{c}_0 + \beta \bar{u}^{1-\frac{1}{\psi}} \bar{c}_0, \\
S_{0+}(u) = \bar{c}_0 + \beta \bar{d}^{1-\frac{1}{\psi}} \bar{c}_0.
\]

This leads to

\[
\frac{S_{0+}(u)}{S_{0+}(d)} = \frac{1 + u}{1 - d} = \frac{W_u^{\frac{1}{\psi}}}{W_d^{\frac{1}{\psi}}},
\]

which is equivalent to

\[
\frac{W_u}{W_d} = \left(\frac{1 - d}{1 + u}\right)^\alpha.
\]

Thus the physical probabilities are recovered by

\[
p(u) = \frac{d}{d + u(\frac{1+d}{1+u})^\alpha}, \quad \text{(17)}
\]

\[
p(d) = 1 - p(u).
\]

Now let us consider the case where \( \frac{1}{\psi} < 1 \). In this case, because \( \bar{u}^{1-\frac{1}{\psi}} > \bar{d}^{1-\frac{1}{\psi}} \), we have that

\[
S_{0+}(d) = \bar{c}_0 + \beta \bar{u}^{1-\frac{1}{\psi}} \bar{c}_0, \\
S_{0+}(u) = \bar{c}_0 + \beta \bar{u}^{1-\frac{1}{\psi}} \bar{c}_0.
\]

Similar arguments lead to

\[
p(u) = \frac{d}{d + u(\frac{1+u}{1+d})^\alpha}, \quad \text{(18)}
\]

\[
p(d) = 1 - p(u).
\]

Therefore, in Figure 1, the red arrows apply when \( \frac{1}{\psi} < 1 \).

The above discussions imply that whether (17) applies or (18) applies depends on the
preferences of the representative agent (e.g., \( \psi \)). According to the estimates of the parameter
values by Bansal and Yaron (2004), we have $\frac{1}{\psi} < 1$. Thus, our empirical studies rely on (18) for the recovery of the risk premium. Under such specification, the risk premium is given by

$$E(r) = p(u)u - p(d)d = \frac{d((\frac{1+u}{1-d})^\alpha - 1)}{\frac{d}{u} + (\frac{1+u}{1-d})^\alpha}. \quad (19)$$

### 2.4 Discussions

The proposed methodology is general enough for estimating the ex post returns and risk premia for any assets with liquid options around an event date. In this paper, we consider the 24- to 48-hour time window before the FOMC meeting as a candidate time interval during which a significant drift in the market price is likely to appear. Indeed, during this time window, significant amount of news about the monetary policy is expected to be released, bringing potential shocks to the market. Savor and Wilson (2013) and Lucca and Moench (2015) find that market excess returns over this time interval account for 60% to 80% of the market annual returns. As the dates of regular FOMC meetings are pre-specified and publicly known, the drifts are expected by the investors. Therefore, it is reasonable to assume that in an efficient option market, such drifts in the market index are reflected by option prices.

Under our framework, if we view $t = 0-$ as 24 or 48 hours before the FOMC meeting, and use $t = 0+$ to approximate the FOMC post-meeting announcement time, then the upward and downward drift sizes in this short time interval corresponds respectively to the upward and downward jump sizes in the model, and can thus be estimated using the above methodology. Such estimations are using information at that particular time, and are forward-looking. More importantly, for any given utility function of the representative agent, we can use this method to recover the FOMC risk premium (in most cases, the expected excess return from 24-48 hours before the FOMC meeting to the market close on the announcement day).
Notably, the FOMC risk premium estimated in this paper is forward-looking, and incorporates real-time information. In contrast, most of the current literature that examines the FOMC risk premium relies on realized market returns, which only contain information about the realized states of the drifts. For example, there is no way to obtain information about the downward drift state when the realization is an upward drift, and vice versa. Consequently, the premium estimated based on the realized returns is the unconditional one, and thus it cannot be utilized to examine the time-series variation of the FOMC risk premium. In contrast, we show that, with our methodology, we are able to recover the dynamics of the FOMC risk premium.

3 Empirical Results

3.1 Data

The main aim of our empirical analysis is to recover the FOMC risk premium from option prices. We obtain S&P 500 option pricing data from OptionMetrics with a sample period spanning January 1996 to December 2019. For each year in our sample, there are 8 regular FOMC meetings, with a total of 192 meetings. We choose options with life span covering the 24-hour time interval right before the FOMC meetings. To identify better the FOMC risk premium, we only consider options that mature within three days.\(^\text{(10)}\) For each meeting in our sample, we retain two calls and two puts that have strike prices closest to the pre-announcement S&P 500 index level and with the shortest available maturity horizon. In addition, we obtain S&P 500 index levels from the CRSP.

However, there are available data for only 83 out of 112 FOMC meetings over the recent 14 years from 2006 to 2019 that satisfy the above three-day expiration window. Prior to 2006, there are substantially fewer options available. In particular, there are no options that

\(^{10}\)As a robustness check, we relax this condition to four and five days. See Section 4.2 for details.
have maturity shorter than three days and cover the pre-announcement time window right before and to the end of the FOMC meetings. The data availability is, however, not an issue going forward, as in the current market, there are options written on the S&P 500 index maturing on every Monday, Wednesday, and Friday (except for days that the market is closed). This promises that we almost always have available options to estimate drifts and other related variables for any FOMC meeting in the future.

The available options from 2006 to 2019 on the 83 meetings are all liquidly traded. Indeed, the average trading volume is 2538.02, with the smallest trading volume being 52 contracts. Thus, the options prices are reliable. Following the option pricing literature, we use the midpoint of their highest closing bid and lowest closing ask prices for our estimation. For each pair of call and put options, we follow the methodology presented in Section 2 to recover information about the upward and downward drift states, respectively.

To have more samples and to make our study comparable to those using realized returns covering the full 192 meetings from 1996 to 2019, we also apply a machine learning technique to back out the rest of the data. The desired outputs are the implied volatilities of options that are available 48 hours before the FOMC meetings and that expire on the meeting announcement day. This requires us to extrapolate the volatility relation between relatively short- and relatively long-term options. We use a recently developed machine learning method, the smoothing-embedded matrix completion, to fit the implied volatility surface. Details are provided in the Appendix.

### 3.2 Drift Size Estimates

Consider first the case with the actual option data for the recent 82 meetings. Panel A of Table 1 reports summary statistics of the variables used in the estimation. The mean prices of $C_1, C_2, P_1,$ and $P_2$ are $9.09, 10.87, 9.68,$ and $9.24$, respectively. These options are all very close to at-the-money (ATM), with moneyness ranging from 0.9569 to 1.0232. Thus
their strike prices are quite likely to fall between the downward and upward drifts. There are 36.14% of the options mature in one day, 7.23% mature in two days and the rest of them mature in three days.

Panel B reports the summary statistics of the estimated drift sizes. The upward drift sizes range from 30 basis points (bps) to 3.47%, with a mean of 107 bps. The downward drift sizes are from 26 bps to 7.56%. The mean downward drift size is 139 bps. While the mean in either case seems quite reasonable, the lowest and highest drifts deserve some analysis and explanation.

The top panel of Figure 2 plots the time series of the drift estimates along with the corresponding S&P 500 returns around the meetings. The drift sizes are associated with volatility. The extreme low level downside drift, 7.56%, occurs during the financial crisis period. Other than this one outlier, the estimated downside drifts are in fact quite close to the realized values when the market indeed goes down. In contrast, the extreme upward drift, 3.47%, does not seem high as compared with the actual returns when the market indeed goes up. Overall, the magnitudes of the estimates are consistent with the realized drifts.

To better illustrate the precision of the drift estimates, we consider a pseudo prediction. Let

\[
\hat{r} = \begin{cases} 
  u & \text{if } \tilde{r} > 0, \\
  -d & \text{if } \tilde{r} < 0,
\end{cases}
\]

(20)

where \(\tilde{r}\) is the realized FOMC meeting return of the S&P 500 index. Then \(\tilde{r}\) is the predicted drift by the option market conditional on \(\tilde{r}\) being up or down. This is a pseudo prediction because we combine the estimated drift sizes, \(u\) and \(d\), with the directions of future realized drifts, and so we do not compute \(\tilde{r}\) before the drift realizations.

Nevertheless, our model-based pseudo forecast \(\hat{r}\) contains information on how well the market anticipates the size of the drift. Consider the out-of-sample R-squared, a widely used
measure of predictability,
\[ R_{OOS}^2 = 1 - \frac{\sum_{t=1}^{T}(\tilde{r}_t - \hat{r}_t)^2}{\sum_{t=1}^{T}(\tilde{r}_t - \bar{r}_t)^2}, \]  
(21)

where \( \tilde{r}_t \) is the historical average of realized meeting returns up to time \( t \), a common benchmark. It compares the forecast accuracy of \( \hat{r} \) with the benchmark. Under the model assumptions, the option implied drift sizes should be the same as the realized ones. As a result, ideally, the out-of-sample R-squared of the pseudo prediction should be 100%, i.e., the pseudo prediction \( \hat{r} \) has zero prediction error. The purpose of the pseudo prediction is to examine how close this is true. Due to imperfect matching of option maturity horizons to meeting time windows and potential noise in real data, we do not expect a 100% out-of-sample R-squared. However, a sufficiently high out-of-sample R-squared indicates that our drift size estimates are accurate. The bottom panel of Figure 2 plots \( \hat{r} \) and \( \tilde{r} \) over time. It is clear that there is a strong link between pseudo predictions and realized meeting returns, indicating that our estimation of the drift size is quite precise. Indeed, the correlation between the pseudo prediction and the realized return is as high as 85%. Predicting \( \tilde{r} \) with \( \hat{r} \) yields a pseudo out-of-sample R-squared of 75.6%, indicating a high accuracy of the drift size recovery.

Consider now the full sample results. Figure 3 includes plots parallel to Figure 2 for the extended sample period with the extrapolated data. The top panel plots the estimated upward and downward drifts together with the realized meeting returns. We can see that for the first few years (before 2003), the drift estimates based on the extrapolated data do not capture some of the high levels of realized meeting drifts. This seems reasonable, as the option trading before year 2003 is rather thin, leading to the loss of data or price accuracy. Moreover, the machine learning model is trained only based on a few observations, resulting in also less accuracy for the backed out data. Similarly, during the financial crisis, the estimates based on extrapolation are not able to capture the spike in October 2008, where the one-day return of the S&P 500 index is 9.6%. Perhaps this is also because, when the volatility is
too high, the estimation becomes less accurate, and hence the gap widens between what is estimated and what is realized in the presence of extreme events. Nevertheless, overall, the extrapolated data appear work well as shown below.

The bottom panel in Figure 3 presents the time-series of the realized meeting returns with the pseudo prediction estimated from (20). The comparison shows that except for the early years and the extreme cases during financial crisis, the estimates match the realized return pattern closely. Even for the two periods that are lack of information, the estimates are still able to match the trend of the drifts. This demonstrates that the matrix completion methodology applies well here to interpolate the option data.

Panel C of Table 1 reports summary statistics of the drift estimates with the extrapolated data. The average estimated upward and downward drift sizes are 101 and 129 bps, respectively. Both are slightly below the average estimated drift sizes with real data. The reason might be due to the financial crisis. During the crisis, extreme events are more likely to happen, and so there are quite a few greater drift sizes that make the average slightly higher. Now, on the pseudo prediction, the out-of-sample R-squared for the entire sample is 66.2%, which is still impressive as it is usually difficult to get predictors with such a high $R^2$. However, this value is about 10% lower than 75.6% for the subsample. It is likely caused by using the augmented data rather than the true but unavailable ones.

### 3.3 State Price Estimates

We next estimate the state prices following (4) and (6). As the time interval of interest is as short as only a few days, we assume that $r_f = 0$ as mentioned before. To compare information from puts and calls, we estimate two pairs of the state prices. In particular, we estimate $(\pi_u, 1 - \pi_u)$ following (4) with two call options, and estimate $(1 - \pi_d, \pi_d)$ following (6) with two put options.

Panel A of Table 2 reports the summary statistics for the subsample of 83 meetings.
There are two interesting facts. First, the two pairs of estimates are quite close to each other, which means that $\pi_u + \pi_d = 1$ roughly holds. Indeed, the average of $\pi_u + \pi_d$ is 0.9964, with a standard deviation of 0.0215. This is interesting because we use two different pairs of options, and there is no guarantee that $\pi_u + \pi_d = 1$ holds empirically. Furthermore, across all the quantiles, the two pairs of estimates are very close too. Figure 4 plots their values over time and their time-series patterns are very close as well. Therefore, in what follows, we continue to use both pairs of estimates to recover physical probabilities and combine the physical ones to recover the FOMC risk premium.

The second interesting fact is that, in general, the upward drift state has a higher state price than the downward state. This compensates the larger average downward drift size. The time-series plot in Figure 4 shows that the upward (downward) state prices are countercyclical (procyclical), which implies that good news is more desired during financial crisis than normal times.

Panel B of Table 2 presents summary statistics of the estimated state prices for the full sample. Again, we can see that the estimates based on call and put prices are quite close. The average of $\pi_u + \pi_d$ is 0.9909, with a standard deviation of 0.0475. Time series plot of the state prices for the full sample in Figure 5 further confirms this.

### 3.4 Recovery of the FOMC Risk Premium

With the estimated drift sizes $u$ and $d$, we are able to follow (19) to estimate the FOMC risk premium. Following Bansal and Yaron (2004), we consider $\psi = 1.5$, and $\gamma = 7.5$ or 10, implying $\alpha = -20.5$ and $-28$, respectively.

Panel A of Table 3 presents summary statistics of the estimated FOMC risk premium based on different risk aversion levels for the entire sample. The average risk premium is 41 bps for $\gamma = 7.5$, and 45 bps for $\gamma = 10$, with corresponding time-series volatility of 46 and 55 bps, respectively. This shows that there are substantial fluctuations of the FOMC risk.
premium over time. For example, when $\gamma = 10$, the FOMC risk premium ranges from 3 bps to 326 bps over the 192 FOMC meetings considered in our sample.\(^{11}\)

Figure 6 presents time-series plots of the estimated FOMC risk premiums. The estimates fluctuate significantly over time, consistent with large time-series volatility reported in Table 3. The estimated risk premium is always positive. While during the crisis, the FOMC risk premium is substantially higher, which indicates that investors demand higher compensation for monetary policy uncertainty during the market distress time. Under normal market conditions, the risk premium level is moderate, and is sometimes very close to zero.

We also report summary statistics of the realized meeting returns. Notice that the realizations only reflect information of the realized drift states. Thus it is expected to see that the realized returns are much more volatile than the estimated risk premium. Indeed, the time-series volatility of the realized returns is 156 bps and they range from -309 to 537 bps. The average realized return is 43 bps, which can be considered as an ex-post estimate of the unconditional FOMC risk premium for the 192 FOMC meetings of interest. This estimate falls between the option-implied FOMC risk premium estimates in cases when $\gamma = 7.5$ and when $\gamma = 10$, validating our estimation procedure.

To further evaluate the predictive value of our FOMC risk premium estimates based on options, we calculate the out-of-sample R-squared,

$$R^2_{OOS} = 1 - \frac{\sum_{t=1}^{T}(\hat{E}_t(r) - \hat{\tilde{r}}_t)^2}{\sum_{t=1}^{T} (\tilde{r}_t - \bar{r}_t)^2}, \quad (22)$$

for $\hat{E}_t(r)$, the estimated FOMC risk premium, which is our forecast of $\hat{\tilde{r}}_t$. Note that the estimated FOMC risk premium only uses information of the option prices prior to the pre-announcement period, that is, unlike the “pseudo” prediction in (21), this prediction is

\(^{11}\)For comparison, we have also estimated the risk premiums using two other approaches, Breeden and Litzenberger (1978) with CRRA utility and Martin (2017), respectively, and found that the estimates are too small (no greater than 3.5 bps), due to their use of noisy out-of-the-money option prices. In contrast, our methodology relies only on at-the-money or nearby options whose prices are much more reliable.
out-of-sample, and does not suffer a look-ahead bias. In this case, $R^2_{OOS}$ is a true measure of predictability. It is 0.0679 and 0.0751, for $\gamma = 7.5$ and $\gamma = 10$, respectively. This indicates that there is a 6.79% to 7.51% reduction in the mean-squared forecasting error based on our forward-looking estimates compared to the historical average benchmark. This level of $R^2_{OOS}$ is quite large, and it is economically significant compared to the typical R-squared values documented in Campbell and Thompson (2008), Welch and Goyal (2008), and the predictability literature in general.

For completeness, we report the summary statistics of the FOMC risk premium as well as the corresponding realized returns for the 83 subsample in Panel B of Table 3. The average FOMC risk premium is 32 bps and 36 bps, in cases $\gamma = 7.5$ and $\gamma = 10$, respectively. The average realized meeting returns is 35 bps, again falling between the estimates based on our model. Note that the average risk premium for the subsample, which contains the crisis, is lower than that of the entire sample. This appears counter-intuitive, but can be explained with two reasons. First, the subsample (the 83 meetings) do not cover every meeting in the recent 12 years. In particular, there are 4 missing observations for the year 2008 and 2 missing observations for the year 2009. It happens that the subsample does not cover the FOMC associated with the huge upward drift in 2008, and so it does not fully capture the volatility during the crisis. Hence, the associated risk premium is lower than what it truly might be. Second, excluding the financial crisis (year 2008 and 2009), we find that the realized return volatility before 2006 is 1.54%, much greater than 1.12%, the return volatility after year 2006. This indicates that we can expect a greater risk premium for the first half of the sample than the second half under normal economic conditions. Empirically, the data reveal this relatively sizable difference. In contrast to the earlier drift size estimation whose average seems to be driven more by the large values during the crisis, the average of the risk premium is less affected because the numerical values of the risk premium are smaller than those of the drifts.
3.5 Relation to Macroeconomic Variables

We next examine the relation between our estimated FOMC risk premium and macroeconomic conditions. Here we consider the CBOE Volatility Index (VIX) and four economic measures: consumption growth, GDP growth, inflation rate, and market sentiment.\textsuperscript{12}

VIX is often considered as a popular measure of the option market’s expectation of uncertainty. Similar to our FOMC risk premium, the VIX is also estimated from options written on the S&P 500 index. Therefore, the VIX also contains time-conditional information and can be estimated with high frequency (daily or even intra-daily) and in a forward-looking manner. Consumption growth, GDP growth, and inflation rates are important indicators of the overall economy state. The sentiment index is taken from Huang et al. (2015). This is an aligned investor sentiment index which reflects an overall level of investors’ sentiment across the market.

To examine the relation between our estimated FOMC risk premium with these macroeconomic variables, we run the following time-series regression:

\[
\hat{E}(r) = \beta_0 + \beta_1 \text{MacroVar}_{t-1} + \epsilon_t, \quad (23)
\]

where \(\hat{E}(r)\) is the FOMC risk premium evaluated at time \(t\), and \(\text{MacroVar}_{t-1}\) is the lagged value of a macroeconomic variable at time \(t-1\).\textsuperscript{13} We work with the estimated FOMC risk premiums with \(\gamma = 7.5, 10\), and consider both the full sample and the sample based on real data (83 meetings during 2006 to 2019), respectively.

Table 4 reports the regression results. Panel A includes the coefficient estimates for the full sample. We can see that for all levels of \(\gamma\), a higher FOMC risk premium is associated with a higher VIX index, a lower consumption growth rate, a lower GDP growth rate, a lower inflation rate, and more pessimistic investors. For example, a one-percentage increase

\textsuperscript{12}We obtain VIX index values from CBOE, consumption growth and GDP growth from the Federal Reserve Economic Data, inflation rate from CRSP, and the market sentiment index from Guofu Zhou’s webpage.

\textsuperscript{13}We also perform the regression with contemporary levels of these variables and all the results hold.
in the VIX relates to a 218-basis-point increase in the FOMC risk premium given $\gamma = 7.5$; a one-percentage-point increase in the GDP growth relates to a 30-basis-point decrease in the FOMC risk premium given $\gamma = 10$. These results are consistent with the standard economic intuition that the investors require a higher risk compensation when the economy is in a relatively “bad” state. The results with subsample period (Panel B) exhibit similar patterns.

4 Further Analysis

In this section, we present some further analysis to complement our main results. First, we generalize our model to three states. Then we investigate the sensitivity of our estimates to the maximum maturity horizon allowed. We also evaluate the importance of the moneyness of the options used in recovering the drift sizes. Finally, we present results excluding years 2008 and 2009 to learn the behavior of the FOMC risk premium during normal times.

4.1 Three States

We consider an alternative model in which we allow for an additional state in which the price does not jump during the FOMC meeting. In particular, assume that there are three possible states at $t = 0+$: up, normal, and down, realized upon the arrival of the FOMC announcements. These states correspond to state prices of $q_0(u)$, $q_0(m)$, and $q_0(d)$, and stock prices of $S_0(1 + u)$, $S_0$, and $S_0(1 - d)$, respectively. We choose three CTM call options. In particular, one ATM, one out of the money (OTM) and one in the money (ITM). Then their prices at $t = 0+$ are

$$C_i = q_0(u)((1 + u)S_0 - K_1^C) + q_0(m)(S_0 - K_1^C),$$
where $i \in \{I, A, O\}$, representing ITM, ATM, and OTM options. Specifically,

$$C_I = q_0(u)((1 + u)S_0 - K_I^C) + q_0(m)(S_0 - K_I^C),$$

$$C_A = q_0(u)((1 + u)S_0 - K_A^C),$$

$$C_O = q_0(u)((1 + u)S_0 - K_O^C).$$

Together with $q_0(u) + q_0(m) + q_0(d) = 1$, we obtain

$$q_0(u) = \frac{-C_O + C_A}{-K_A^C + K_O^C},$$

$$q_0(m) = \frac{C_O(K_A^C - K_I^C) + C_A(K_I^C - K_O^C) + C_I(K_O^C - K_A^C)}{(K_A^C - K_O^C)(K_I^C - S_0)},$$

$$q_0(d) = 1 - q_0(u) - q_0(m).$$

The upward jump size is thus given by

$$u = \frac{C_A(K_O^C - S_0) + C_O(S_0 - K_A^C)}{(C_A - C_O)S_0}.$$

Similarly, we can choose three CTM put options and solve for the state prices:

$$q_0(d) = \frac{-P_O + P_A}{-K_A^P + K_O^P},$$

$$q_0(m) = \frac{P_O(K_A^P - K_I^P) + P_A(K_I^P - K_O^P) + P_I(K_O^P - K_A^P)}{(K_O^P - K_A^P)(K_I^P - S_0)},$$

$$q_0(u) = 1 - q_0(d) - q_0(m)$$

as well as the downward jump size:

$$d = \frac{P_A(S_0 - K_O^P) + P_O(K_A^P - S_0)}{(P_A - P_O)S_0}.$$
Because of the assumption that the market price does not jump in state \( m \ (S_{0+}(m) = S_0) \),
the price states are fully recovered with above estimates.

Table 5 reports the summary statistics of the estimates in (25) – (28) by choosing three
closest to the money call and put options for the 83 FOMC meetings in our subsample. The
average upward drift size is 147 bps and the average downward drift size is 185 bps. We
obtain somewhat more extreme values of drift estimates when we introduce possibilities of
no jumps around the FOMC meetings. Panel B shows that state prices of the normal state
is around 20%. Similar to our baseline model, state prices of upward drifts are consistently
higher than downward drifts. Again, the estimates from calls and puts are quite consistent.

The top panel of Figure 7 plots the realized meeting returns of the S&P 500 index for
each FOMC meeting with our estimates of drifts. We can see that the magnitude of the drift
size estimates is still quite reasonable compared to the realized returns. The middle panel
compares the realized returns with the pseudo prediction in (20) based on the upward and
downward drift sizes under this three-state model. The out-of-sample R-squared is as high
as 71.5%, reflecting precise estimates of drift sizes. To incorporate the information about
the normal states where the jump does not arrive, we consider also the following pseudo
prediction:

\[
\hat{r} = \begin{cases} 
    u & \text{if } \tilde{r} > 0.01, \\
    0 & \text{if } -0.01 < \tilde{r} < 0.01, \\
    -d & \text{if } \tilde{r} < -0.01, 
\end{cases}
\]  

and plot it with the realized return in the bottom panel.14 Incorporating more future in-
formation into the pseudo prediction naturally leads to a higher out-of-sample R-squared of
80.2%. Overall, the results show that our estimation methodology is quite robust to allowing
for a state of no jump.

\footnote{We also apply other thresholds of realized returns to define the normal state, and the results are similar.}
4.2 Maximum Maturity Horizon

We next check the robustness of our results over different maximum maturities allowed. In the results provided in Sections 3.2 and 3.3, we require the maturity of options to be less than or equal to three days, which leads to only 83 observations with real data. In this robustness check, we relax the maximum maturity to four or five days. Notice that the relaxation does not change the estimates for the 83 FOMC meetings, as the shortest option horizons on these days are already shorter than four or five days. This only allows us to include more observations with real data.

Table 6 reports the summary statistics of the estimated drift sizes under these specifications. When relaxing the maximum maturity horizon to four days, the number of days in our sample increases to 105. It increases further to 130 when the maturity horizons up to five days are allowed. The summary statistics are comparable to those in the main analysis.

Figure 8 plots the time-series of the pseudo prediction (estimated by (20)) along with the realized returns. From the plots we can see that allowing more options in the calculation extends our sample back to year 1996. When the maximum maturity is relaxed to four or five days, the pseudo predictions still agree with the realizations quite well. The corresponding out-of-sample R-squared are 72.9% and 72.5%, respectively, just slightly lower compared to the results when we restrict the option maturity to be less or equal to three days. These informative predictions indicate that the meeting drift in the market index level dominates other fluctuations within the neighborhood of the meeting. However, to cleanly identify the drift sizes during the FOMC meeting, we need to focus on a short-time window. A bias in drift size estimation could potentially happen if more days are allowed before the announcement. Thus, all the conclusions in this paper only apply to options with short-term maturity horizons.
4.3 Alternative Pair of Options

Under our baseline model that the stock return follows a two-state jump distribution, the size of the drift and the corresponding Arrow-Debreu price can be inferred from two options with different strike prices. In theory, any two options with strike prices lying between the two drifts can also be used for this estimation. In addition, the put-call parity relation implies that the estimates of the up and down drifts should not be sensitive to the exact calls and puts used. To this end, we provide drift estimates that use alternative pairs of calls and puts. In particular, we choose options with the second and third or the third and fourth (instead of the first and second as in the main result) closest strike price to the closing price to estimate upward and downward drift sizes.

Table 7 reports summary statistics of the estimated drifts with an alternative pair of options without data augmentation. The average upward drift size is 122 (138) bsp and the downward drift size is 155 (185) bsp, with options that are the second and third (third and forth) CTM. Compared to the results with those reported in Panel B of Table 1, the drift sizes of both directions become larger as the strike prices of the chosen options lie farther away from the closing price. To assess the accuracy of the drift size estimates with alternative pairs of options, Figure 9 plots the time-series of pseudo predictions along with the realized meeting returns. The patterns agree well with the early ones. However, the matching is less satisfactory compared to Figure 2. In fact, the out-of-sample R-squared for these two cases decreases sharply to 34.8% and 21.7%. The results suggest that the choice of option pairs is very important in accurately recovering the meeting drift sizes. Notice that the estimation methodology described in Section 2.2 requires that the two chosen options should have strike prices lie between the two drifts.\textsuperscript{15} In practice, since we do not know the realized drift sizes ex ante, we choose the two options that are closest to ATM to make sure the requirement holds with the highest probability. Indeed, there are more than 95% cases in our main analysis that the strike prices of both chosen options are less extreme when

\textsuperscript{15} We require that \((1 - d) S_0 < K_1^C, K_2^C < (1 + u) S_0\) and \((1 - d) S_0 < K_1^P, K_2^P < (1 + u) S_0\).
compared to the realized meeting returns. This ratio decreases to 77% and 71% if we choose options with the second and third, or third and fourth closest strike prices, respectively. Therefore, it is crucial to use options that are the closest to ATM for the drift estimation, not only because that these options are potentially more liquid, but also they are the most valid pairs for our recovery methodology.

### 4.4 Excluding Financial Crisis Period

Results in Section 3 show that the estimates, as well as the market itself, behave differently during the financial crisis compared to normal times. In this subsection, we examine the results by excluding years 2008 and 2009 that cover the crisis. Note that removing the two years drops the number of FOMC meetings to 176.

Panel A of Table 8 reports the summary statistics of the estimated drift sizes. The average upward drift size is 94 bps and the average downward drift size is 96 bps. The average upward drift sizes are comparable to the results in Table 1, while average downward drift sizes are 30 bps smaller. Also note that the standard deviations of the drift estimates drop by 9 to 24 bps, which is consistent with the notion that market is more volatile during financial crisis (See Roll (1988), Schwert (1990), and Hong et al. (2007)).

Panel B of Table 8 reports summary statistics of the FOMC risk premium for these 176 meetings. After excluding years 2008 and 2009, the average FOMC risk premium drops to 28 (when $\gamma = 7.5$) or to 34 (when $\gamma = 10$) bps, with the average realized return still falls between these two estimates. There is a decrement of 11 to 13 bps compared to the whole sample, which is consistent with the observations in Section 3.4 that investors require higher risk compensation for news announcement during financial crisis, and in Section 3.5 that the FOMC risk premium is countercyclical. Overall, the results are qualitatively similar even if we remove the crisis period.
5 Conclusion

The Federal Open Market Committee (FOMC) meetings are major events that significantly impact the stock market and the macroeconomy. In this paper, we propose a simple model to estimate the risk premia of the FOMC meetings based on the close-to-announcement prices of options that expire soon after the meetings. Our results indicate that the risk premium is time varying, ranging from 3 to 326 basis points (bps). The average is 45 bps, consistent with the related findings in the existing literature. Predicting the meeting returns with our FOMC risk premium yields an out-of-sample R-squared of 7.51%. Modeling the price move as a two-state jump process, we find that around the meetings, the average upward drift size is 101 bps, and the average downward drift size is 129 bps.

Our methodology applies not only to FOMC meetings, but also to any events around which asset prices are likely to experience significant changes if there are available options traded on these assets. In particular, for future research, it will be of interest to apply our approach to study the risk premium associated with earnings announcements for individual stocks in order to provide new insights on the findings of the vast literature on the effect of earnings announcement.

Appendices

I. Data Augmentation

In this appendix, we introduce a machine learning method, the smoothing-embedded matrix completion (Dai et al., 2019), to extrapolate the implied volatility surface. This allows us to fill in the option data with expirations right after the FOMC meeting announcements.

The method uses low-rank matrix factorization to complete a sparse matrix based on
its underlying structure. Specifically for our problem, the implied volatility surface has a well known matrix structure. Each row in the matrix represents a moneyness level, and each column corresponds to a specific maturity. The observed data fill certain matrix entries, while leaving others blank. The matrix completion method is capable of filling the empty entries based on a penalized low-rank matrix decomposition.\textsuperscript{16} We then use these extrapolated implied volatilities to obtain synthetic option prices.

Specifically, we consider the implied volatility data with moneyness levels from 0.5 to 1.5 and maturity values (day) from 1 to 100. Since the moneyness level is essentially a continuous variable, we divide the considered interval into 200 segments evenly, each with a range of 0.005. Consequently, this results in a 200-by-100 matrix in which the implied volatility values fill the entries with corresponding moneyness levels and maturity values. Given the selected segments, most of the observations have unique row and column indexes. If there are multiple observations sharing the same indexes (no more than two in our data sample), we just fill the matrix entry with the average value. The matrices for call and put options are constructed separately.

The low-rank matrix factorization model is a prevalent tool for matrix completion (Hastie et al., 2015), which enables us to complete the sparse matrix based on a small number of latent factors. Let $V$ denote the target matrix of implied volatilities, and let $W$ denote the observation indicator matrix with the entries to be one if the corresponding implied volatility in $V$ is observed and to be zero otherwise. Analogous to the singular value decomposition of an arbitrary matrix, the low-rank matrix factorization model considers approximating the target matrix with a few latent factors, $a_r$’s and $b_r$’s, through optimizing the following penalized loss function:

$$\min_{a_r, b_r} \left\| W \odot \left( V - \sum_{r=1}^{K} a_r \otimes b_r \right) \right\|_F^2 + \lambda \sum_{r=1}^{K} (\|a_r\|_2^2 + \|b_r\|_2^2),$$

\textsuperscript{16}See Jain et al. (2013) and Hastie et al. (2015) for details.
where “◦” denotes the point-wise Hadamard product, “⊗” denotes the outer product, and \( \| \cdot \|_F \) denotes the Frobenius norm and \( \| \cdot \|_2 \) denotes the \( L_2 \) norm. Note that the vectors \( \mathbf{a}_r = (a_{r1}, \ldots, a_{r200})' \) and \( \mathbf{b}_r = (b_{r1}, \ldots, b_{r100})' \) are essentially the latent row- and column-factors corresponding to moneyness level and maturity, respectively. Any missing entry of \( \mathbf{V} \) can be imputed as \( \hat{V}_{ij} = \sum_{r=1}^{K} \hat{a}_{ri} \hat{b}_{rj} \), for the \( i \)th row, the \( j \)th column. The rank \( K \) and the tuning parameter \( \lambda \) can be pre-selected based on the cross-validation method. Dai et al. (2019) discuss extensively on the implementation. Following their analysis, we choose \( K = 1 \) in our context.

We assume that the implied volatility surface is smooth, and further incorporate smoothing into the matrix completion by posing a spline structure onto the latent factors. In particular, we consider the cubic spline model as

\[
\begin{align*}
    a_{ri} &\approx \sum_{m=1}^{M} \beta_{rm} h_m(x_i), \\
    b_{rj} &\approx \sum_{m=1}^{M} \bar{\beta}_{rm} h_m(t_j),
\end{align*}
\]  

(31)

where \( h_m(\cdot) \)'s are spline basis functions, \( x_i \) and \( t_j \) are corresponding moneyness level and maturity value, respectively. By combing (30) and (31), we carry out a smoothing-embedded matrix completion which yields an extrapolation of implied volatility surface to certain moneyness level and maturity value. We then use these extrapolated implied volatilities to obtain synthetic option prices, and estimate drifts as well as state prices. With the above procedure, we are able to recover information for all of the 192 meetings during 1996 to 2019.
References


Figure 2: Drift size Estimates with Real Data

Notes: The top panel presents the time-series of the drift size estimations as well as the realized meeting returns. The bottom panel presents the time-series of pseudo prediction in (20) and the realized meeting returns. The sample includes options written on the S&P 500 index with a life span shorter than three days and those cover the 24-hour time window before the FOMC meeting between January 1996 and December 2017. Realized returns are the net S&P 500 returns over the life span of the corresponding options.
Figure 3: Drift sizes Over Extended Sample Period

Notes: The top panel presents the time-series of the drift size estimations as well as the realized meeting returns. The bottom panel presents the time-series of pseudo prediction in (20) and the realized meeting returns. The sample includes all FOMC meetings between January 1996 and December 2017. Realized returns are returns of the S&P 500 index over the 48-hour time window before the FOMC meeting.
Figure 4: State Price Estimates with Real Data
Notes: This figure presents the time-series of the state price estimations for upward and downward drift states. The sample includes options written on the S&P 500 index with a life span shorter than three days and that covers the 24-hour time window before the FOMC meeting between January 1996 and December 2017. There are two sets of estimations based on a pair of calls and a pair of puts, respectively.
Figure 5: State Prices Over Extended Sample Period
Notes: This figure presents the time-series of the state price estimations for upward and downward drift states. The sample includes all FOMC meetings between January 1996 and December 2017. There are two sets of estimations by a pair of calls and a pair of puts, respectively.
Figure 6: The FOMC Risk Premium
Notes: This figure presents the time-series of estimation of the FOMC risk premium following (19). We choose the relative risk aversion levels of 7.5 and 10. The sample includes all FOMC meetings between January 1996 and December 2017.
Figure 7: Robustness Check – Three States

Notes: The top panel presents the time-series of the drift size estimations as well as the realized meeting returns. The middle and bottom panels present the time-series of pseudo prediction and the realized meeting returns. The pseudo predictions are calculated by (20) in the middle panel and (29) in the bottom panel. The sample includes options written on the S&P 500 index with a life span shorter than three days and those cover the 24-hour time window before the FOMC meeting between January 1996 and December 2019. Realized returns are the net S&P 500 returns over the life span of the corresponding options.
Figure 8: Robustness Check – Maximum Maturity

Notes: This figure presents the time-series of pseudo prediction in (20) and the realized meeting returns. The sample includes options written on the S&P 500 index with a life span shorter than four (top panel) or five (bottom panel) days and that covers the 24-hour time window before the FOMC meeting between January 1996 and December 2017. Realized returns are the net S&P 500 returns over the life span of the corresponding options.
Figure 9: Robustness Check – Alternative Pair of Options

Notes: This figure presents the time-series of pseudo prediction in (20) and the realized meeting returns. The sample includes options written on the S&P 500 index with a life span shorter than three days and that covers the 24-hour time window before the FOMC meeting between January 1996 and December 2017. On each day in our sample, we select two call and two put options with the second and third (top panel) or the third and forth (bottom panel) closest strike prices to the S&P 500 index level for the estimation of the pseudo prediction. Realized returns are the net S&P 500 returns over the life span of the corresponding options.
Table 1: Summary Statistics of Drift Estimation

This table reports summary statistics of the variables associated with drift estimation (Panel A) and the estimated drift sizes (Panel B and Panel C). The sample in Panels A and B includes options written on the S&P 500 index with a life span shorter than three days and that covers the 24-hour time window before the Federal Open Market Committee meeting between January 1996 and December 2017. The sample in Panel C includes all Federal Open Market Committee meetings from January 1996 to December 2017. On each day in our sample, we use or estimate the synthetic prices of two call and two put options that have strike prices closest to the S&P 500 index level, and follow (3) and (5) to estimate the index drift sizes.

Panel A: Summary Statistics of Related Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs</th>
<th>Mean</th>
<th>Std.Dev</th>
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Panel B: Summary Statistics of $u$ and $d$

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Panel C: Summary Statistics of $u$ and $d$ for the full sample

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Table 2: Summary Statistics of State Price Estimation

This table reports summary statistics of estimated state prices. The sample in Panel A includes options written on the S&P 500 index with a life span shorter than three days and that covers the 24-hour time window before the Federal Open Market Committee meeting between January 1996 and December 2017. The sample in Panel B includes all Federal Open Market Committee meetings from January 1996 to December 2017. On each day in our sample, we use or estimate the synthetic prices of two call and two put options that have strike prices closest to the S&P 500 index level, and follow (4) and (6) to estimate the state prices of index drifts. The table reports summary statistics of two pairs of estimates: $(\pi_u, 1 - \pi_u)$ based on call options, and $(1 - \pi_d, \pi_d)$ based on put options.

<table>
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<table>
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</table>
This table reports summary statistics of the recovered FOMC risk premium. The sample in Panel A includes all Federal Open Market Committee meetings from January 1996 to December 2019. The sample in Panel B includes options written on the S&P 500 index with a life span shorter than three days and that covers the 24-hour time window before the Federal Open Market Committee meeting between January 1996 and December 2019. On each day in our sample, we use the observed prices (if available) or estimate the synthetic prices of two call and two put options that have strike prices closest to the S&P 500 index level, and follow (19) to estimate the FOMC risk premium. We set levels of $\gamma$ to 7.5 and 10. We also report summary statistics of realized meeting returns in the last row of each panel.

### Panel A: Full Sample with Extrapolated Data

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Realized Returns: 192 0.0043 0.0156 -0.0309 -0.0193 -0.0151 -0.0038 0.0035 0.0119 0.0201 0.0305 0.0537

### Panel B: Subsample with Real Data

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Realized Returns: 83 0.0035 0.0152 -0.0310 -0.0171 -0.0123 -0.0031 0.0029 0.0081 0.0174 0.0198 0.0956
Table 4: Relation to Macroeconomic Variables

This table reports the coefficient estimates of regression in (23). The FOMC risk premiums are based on $\gamma$ values of 7.5 and 10. We consider both the whole sample (Panel A) during 1996 to 2019 and the 83 meetings estimated with real option data (Panel B). The macroeconomic variables in (23) we consider include the VIX index, consumption growth, GDP growth, inflation rate, and sentiment index. The consumption growth is the monthly real personal consumption expenditure percent change from the preceding period seasonally adjusted. The GDP growth is the quarterly gross domestic product by expenditure in constant prices seasonally adjusted. The sentiment index is based on Huang et al. (2015).

| VIX     | 0.0218 (0.0025)*** | 0.0257 (0.0030)*** |
| Cons Growth | -0.0023 (0.0006)*** | -0.0027 (0.0008)*** |
| GDP Growth  | -0.0025 (0.0004)*** | -0.0030 (0.0004)*** |
| Inflation   | -0.1338 (0.0665)** | -0.1603 (0.0797)** |
| Sentiment   | -0.0062 (0.0033)*** |

Panel A: Full-Sample Results

| Adj R-Squared | 0.2930 | 0.2833 | 0.0581 | 0.0573 | 0.1923 | 0.207 | 0.0157 | 0.0157 | 0.1039 | 0.1042 |
| # Obs         | 192    | 192    | 192    | 192    | 192    | 192   | 192    | 192    | 192    | 192    |

Panel B: Subsample Results

| VIX     | 0.0517 (0.0019)*** | 0.0605 (0.0025)*** |
| Cons Growth | -0.0058 (0.0017)*** | -0.0068 (0.0020)*** |
| GDP Growth  | -0.0040 (0.0008)*** | -0.0047 (0.0010)*** |
| Inflation   | -0.3303 (0.1382)** | -0.3905 (0.1635)** |
| Sentiment   | -0.0068 (0.0014)*** |

| Adj R-Squared | 0.8995 | 0.8812 | 0.1195 | 0.1141 | 0.2205 | 0.2236 | 0.0544 | 0.0542 | 0.2240 | 0.2128 |
| # Obs         | 83     | 83     | 83     | 83     | 83     | 83    | 83     | 83     | 83     | 83     |
Table 5: Robustness Test – Three States

This table reports summary statistics of estimated drifts and corresponding state prices for a three-state model. The sample includes options written on the S&P 500 index with a life span shorter than three days and that covers the 24-hour time window before the Federal Open Market Committee meeting between January 1996 and December 2017. On each day in our sample, we use three call and three put options that have strike prices closest to the S&P 500 index level, and follow (25) – (28) to estimate the index drift sizes (reported in Panel A) and corresponding state prices (reported in Panel B).

Panel A: drift sizes

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<th>Std.Dev</th>
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<th>10%</th>
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<th>99%</th>
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<tbody>
<tr>
<td>$u$</td>
<td>83</td>
<td>0.0147</td>
<td>0.0093</td>
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<td>0.0040</td>
<td>0.0058</td>
<td>0.0089</td>
<td>0.0118</td>
<td>0.0182</td>
<td>0.0311</td>
<td>0.0346</td>
<td>0.0441</td>
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<tr>
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<td>83</td>
<td>0.0185</td>
<td>0.0159</td>
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<td>0.0053</td>
<td>0.0078</td>
<td>0.0109</td>
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</table>

Panel B: State Prices

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<th>5%</th>
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<th>75%</th>
<th>90%</th>
<th>95%</th>
<th>99%</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\pi_u(Call)$</td>
<td>83</td>
<td>0.4514</td>
<td>0.1226</td>
<td>0.1517</td>
<td>0.202</td>
<td>0.241</td>
<td>0.415</td>
<td>0.49</td>
<td>0.54</td>
<td>0.56</td>
<td>0.602</td>
<td>0.69</td>
</tr>
<tr>
<td>$\pi_m(Call)$</td>
<td>83</td>
<td>0.2106</td>
<td>0.1846</td>
<td>0.0305</td>
<td>0.0282</td>
<td>0.0495</td>
<td>0.0795</td>
<td>0.1475</td>
<td>0.2777</td>
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<td>0.7481</td>
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<tr>
<td>$\pi_d(Call)$</td>
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<td>0.3380</td>
<td>0.0853</td>
<td>0.1003</td>
<td>0.1861</td>
<td>0.2077</td>
<td>0.2715</td>
<td>0.3664</td>
<td>0.4051</td>
<td>0.4252</td>
<td>0.4390</td>
<td>0.4705</td>
</tr>
<tr>
<td>$\pi_u(Put)$</td>
<td>83</td>
<td>0.4556</td>
<td>0.1213</td>
<td>0.1599</td>
<td>0.2543</td>
<td>0.2904</td>
<td>0.3735</td>
<td>0.4732</td>
<td>0.5065</td>
<td>0.5463</td>
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<tr>
<td>$\pi_m(Put)$</td>
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<td>0.1823</td>
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<td>0.0235</td>
<td>0.0508</td>
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<tr>
<td>$\pi_d(Put)$</td>
<td>83</td>
<td>0.3482</td>
<td>0.0838</td>
<td>0.0883</td>
<td>0.16</td>
<td>0.253</td>
<td>0.35</td>
<td>0.38</td>
<td>0.42</td>
<td>0.45</td>
<td>0.474</td>
<td>0.49</td>
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</table>
Table 6: Robustness Test – Maximum Maturity

This table reports summary statistics of estimated drifts. The sample includes options written on the S&P 500 index with a life span shorter than four (Panel A) or five (Panel B) days and that covers the 24-hour time window before the FOMC meeting between January 1996 and December 2017. On each day in our sample, we select two call and two put options that have strike prices closest to the S&P 500 index level, and follow (3) and (5) to estimate the index drift sizes.

Panel A: Maximum Maturity: 4 Days

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs</th>
<th>Mean</th>
<th>Std.Dev</th>
<th>1%</th>
<th>5%</th>
<th>10%</th>
<th>25%</th>
<th>50%</th>
<th>75%</th>
<th>90%</th>
<th>95%</th>
<th>99%</th>
</tr>
</thead>
<tbody>
<tr>
<td>$u$</td>
<td>105</td>
<td>0.0117</td>
<td>0.0077</td>
<td>0.0030</td>
<td>0.0036</td>
<td>0.0047</td>
<td>0.0069</td>
<td>0.0096</td>
<td>0.0141</td>
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<td>$d$</td>
<td>105</td>
<td>0.0149</td>
<td>0.0110</td>
<td>0.0030</td>
<td>0.0045</td>
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<td>0.0086</td>
<td>0.0124</td>
<td>0.0176</td>
<td>0.0265</td>
<td>0.0317</td>
<td>0.0703</td>
</tr>
</tbody>
</table>

Panel B: Maximum Maturity: 5 Days

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs</th>
<th>Mean</th>
<th>Std.Dev</th>
<th>1%</th>
<th>5%</th>
<th>10%</th>
<th>25%</th>
<th>50%</th>
<th>75%</th>
<th>90%</th>
<th>95%</th>
<th>99%</th>
</tr>
</thead>
<tbody>
<tr>
<td>$u$</td>
<td>130</td>
<td>0.0133</td>
<td>0.0087</td>
<td>0.0030</td>
<td>0.0040</td>
<td>0.0049</td>
<td>0.0078</td>
<td>0.0109</td>
<td>0.0166</td>
<td>0.0258</td>
<td>0.0325</td>
<td>0.0437</td>
</tr>
<tr>
<td>$d$</td>
<td>130</td>
<td>0.0165</td>
<td>0.0117</td>
<td>0.0030</td>
<td>0.0047</td>
<td>0.0058</td>
<td>0.0095</td>
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<td>0.0204</td>
<td>0.0282</td>
<td>0.0348</td>
<td>0.0703</td>
</tr>
</tbody>
</table>
Table 7: Robustness Test – Alternative Pair of Options

This table reports summary statistics of estimated drifts. The sample includes options written on the S&P 500 index with a life span shorter than three days and that covers the 24-hour time window before the FOMC meeting between January 1996 and December 2017. On each day in our sample, we select two call and two put options with the second and third (Panel A) or the third and forth (Panel B) closest strike prices to the S&P 500 index level, and follow (3) and (5) to estimate the index drift sizes.

Panel A: Using the Second and Third Closest to ATM Options

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs</th>
<th>Mean</th>
<th>Std.Dev</th>
<th>1%</th>
<th>5%</th>
<th>10%</th>
<th>25%</th>
<th>50%</th>
<th>75%</th>
<th>90%</th>
<th>95%</th>
<th>99%</th>
</tr>
</thead>
<tbody>
<tr>
<td>u</td>
<td>83</td>
<td>0.0122</td>
<td>0.0086</td>
<td>0.0027</td>
<td>0.0035</td>
<td>0.0043</td>
<td>0.0063</td>
<td>0.0096</td>
<td>0.0154</td>
<td>0.0289</td>
<td>0.0309</td>
<td>0.0400</td>
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<tr>
<td>d</td>
<td>83</td>
<td>0.0155</td>
<td>0.0151</td>
<td>0.0039</td>
<td>0.0044</td>
<td>0.0053</td>
<td>0.0080</td>
<td>0.0119</td>
<td>0.0182</td>
<td>0.0285</td>
<td>0.0330</td>
<td>0.1280</td>
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</table>

Panel B: Using the Third and Forth Closest to ATM Options

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs</th>
<th>Mean</th>
<th>Std.Dev</th>
<th>1%</th>
<th>5%</th>
<th>10%</th>
<th>25%</th>
<th>50%</th>
<th>75%</th>
<th>90%</th>
<th>95%</th>
<th>99%</th>
</tr>
</thead>
<tbody>
<tr>
<td>u</td>
<td>83</td>
<td>0.0138</td>
<td>0.0106</td>
<td>0.0038</td>
<td>0.0044</td>
<td>0.0048</td>
<td>0.0066</td>
<td>0.0105</td>
<td>0.0162</td>
<td>0.0307</td>
<td>0.0353</td>
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<tr>
<td>d</td>
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<td>0.0185</td>
<td>0.0243</td>
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<td>0.0042</td>
<td>0.0051</td>
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<td>0.0193</td>
<td>0.0412</td>
<td>0.0446</td>
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</table>
Table 8: Robustness Test – Excluding Financial Crisis

This table reports summary statistics of estimated drifts and the FOMC risk premium excluding years 2008 and 2009. The sample includes all Federal Open Market Committee meetings from January 1996 to December 2017. On each day in our sample, we estimate the synthetic prices of two call and two put options that have strike prices closest to the S&P 500 index level, and follow (3) and (5) to estimate the index drift sizes (reported in Panel A). We follow (19) to estimate the FOMC risk premium (reported in Panel B). We set levels of relative risk aversion ($\gamma$) to 5, 8 and 10. We also report summary statistics of realized meeting returns in the last row.

Panel A: Drift Sizes

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs</th>
<th>Mean</th>
<th>Std.Dev</th>
<th>1%</th>
<th>5%</th>
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<th>25%</th>
<th>50%</th>
<th>75%</th>
<th>90%</th>
<th>95%</th>
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</tr>
</thead>
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<tr>
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<td>0.0044</td>
<td>0.0014</td>
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<td>0.0242</td>
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<tr>
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<td>176</td>
<td>0.0096</td>
<td>0.0063</td>
<td>0.0003</td>
<td>0.0012</td>
<td>0.0020</td>
<td>0.0049</td>
<td>0.0086</td>
<td>0.0126</td>
<td>0.0181</td>
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<td>0.0284</td>
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Panel B: FOMC Risk Premium

<table>
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<th>Obs</th>
<th>Mean</th>
<th>Std.Dev</th>
<th>1%</th>
<th>5%</th>
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<th>75%</th>
<th>90%</th>
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<th>99%</th>
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<tbody>
<tr>
<td>7.5</td>
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<td>0.0028</td>
<td>0.0021</td>
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<td>0.0004</td>
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<td>0.0002</td>
<td>0.0005</td>
<td>0.0011</td>
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<td>-0.0153</td>
<td>-0.0041</td>
<td>0.0034</td>
<td>0.0111</td>
<td>0.0189</td>
<td>0.0272</td>
<td>0.0362</td>
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