The effect of macroeconomic news on beliefs and preferences: Evidence from the options market

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Abstract

We examine the effect of regularly scheduled macroeconomic announcements on the beliefs and preferences of participants in the U.S. Treasury market by comparing the option-implied state-price densities (SPDs) of bond prices shortly before and after the announcements. We find that the announcements reduce the uncertainty implicit in the second moment of the SPD regardless of the content of the news. The changes in the higher-order moments, in contrast, depend on whether the news is good or bad for economic prospects. We explore three alternative explanations for our empirical findings: relative mispricing, changes in beliefs, and changes in preferences. We find that our results are consistent with time-varying risk aversion.

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1. Introduction

The market for U.S. Treasury securities is one of the largest and most active financial markets in the world. Understanding the functioning of this market is therefore of primary importance to academics, policy makers, and practitioners alike. Financial theory predicts that asset prices reflect information about cash-flows and discount rates. In the case of riskfree government bonds, the cash-flows are fixed and the only relevant quantities for pricing are discount rates determined by the general macroeconomic environment. It follows logically that Treasury bond prices should vary with news about macroeconomic fundamentals. Motivated by this reasoning, a number of recent studies have investigated the response of U.S. Treasury bond prices to regularly scheduled U.S. macroeconomic information releases. The availability of high-frequency data has dramatically enhanced detection and estimation of announcement effects in bond prices (e.g., Ederington and Lee, 1993), return volatility (e.g., Bollerslev et al., 2000), and market liquidity (e.g., Fleming and Remolona, 1997, 1999). The results reveal a significant and extremely quick impact of certain announcement types on bond prices accompanied by substantial intra-daily fluctuations in volatility and liquidity. All of these studies share an ex post perspective by describing the realized market dynamics.

Our research takes an ex ante perspective. We examine the effect of the macroeconomic information releases on the forward-looking beliefs and preferences of participants in the U.S. Treasury market. Specifically, we compare the state-price densities (SPDs) of bond prices shortly before and after the announcements. The SPD, which can be recovered from option prices, is distinct from the objective probability density function (PDF) because it combines the beliefs of market participants about the likelihood of future states with their preferences toward these states. A high value of the SPD for a particular state indicates that market participants consider the state to be relatively likely to occur, that they dislike the state, or both. The changes in the SPD associated with the macroeconomic announcements can therefore be due to changes in beliefs and/or changes in preferences. The contribution of our paper is to document how the SPD of bond prices changes in response to the information contained in macroeconomic announcements, to illustrate that these changes are not due to relative mispricing in the options market, and then to disentangle the two components of the SPD to determine the extent to which changes in the SPD reflect changes in the beliefs or changes in the preferences of market participants.

The design of our analysis is straightforward. We extract SPDs for U.S. Treasury bond futures prices at several times during announcement and non-announcement days using transactions data on options traded on the Chicago Board of Trade (CBOT) over a five-year sample period.¹ We obtain the SPDs as Edgeworth expansions around log-normal densities, along the lines of Jarrow and Rudd (1982).² The results from comparing the SPDs shortly before and after the regularly scheduled information releases are intriguing. We find that the announcements reduce the uncertainty implicit in the second moment of the SPD, regardless of their content. The direction and magnitude of the changes in the

¹Vähämaa et al. (2005) and Vähämaa (2005) examine the impact of macroeconomic news and policy decisions of the European Central Bank on option-implied SPDs of German government bonds.

²This expansion approach is only one of several ways to estimate SPDs from option prices. One popular alternative is the non-parametric approach developed by Aït-Sahalia and Lo (1998, 2000) and its refinement for smaller samples by Aït-Sahalia and Duarte (2003). Another alternative is the implied binomial trees approach of Dupire (1994), Derman and Kani (1994), and Rubinstein (1994).
higher-order moments of the SPD, in contrast, depend on the information content. The SPD becomes less (more) negatively skewed and less (more) fat-tailed in response to bad (good) news for the bond market. Furthermore, the results are asymmetric, in that bad news have a greater impact on the higher-order moments of the SPD than do good news.

We explore three alternative interpretations for our empirical findings. Motivated by the evidence in Bollen and Whaley (2004) for the stock options market, we first investigate relative mispricing due to excess trading pressure in the presence of limits to arbitrage as a potential explanation for our results. Although we find some evidence that buying pressure responds to the content of macroeconomic news, we show that the extent of this effect is not sufficient to explain our results. Second, we use both a non-parametric and a parametric approach to interpret our empirical results in the context of changes in beliefs. We show that the changes in the higher-order moments of the SPD cannot be attributed to variation in the physical price process (changes in the higher-order moments of the PDF). In fact, the effect of the announcements on the higher-order moments of the PDF is often exactly opposite to the effect on the higher-order moments of the SPD. Finally, we show that the changes in the higher-order moments are consistent with counter-cyclically varying risk aversion. Combining our estimates of the SPD with estimates of the PDF obtained from a jump model for the underlying futures price, we recover estimates of the implied risk aversion before and after the announcements. We then relate the changes in the implied risk aversion directly to the content of macroeconomic news and find that good news for economic prospects leads market participants to become less risk averse. We hence conclude that macroeconomic announcements affect both preferences and beliefs.

The paper proceeds as follows. In Section 2 we describe the announcements and options data. Section 3 explains our econometric approach for estimating the options-implied SPDs. We present our empirical results in Section 4 and then interpret these results in Section 5. Section 6 concludes with a summary of our findings.

2. Data and preliminaries

2.1. Survey and announcement data

We obtain data on the dates, release times, actual released figures, and median forecasts for the 10 most important U.S. macroeconomic information releases from Money Market Services (MMS) covering the period from January 1995 through December 1999. MMS surveys about 40 money market managers on the Friday of the week before the release of each economic indicator.3 It reports the median forecast from the survey, which is made available to the market and the business press immediately after the survey is taken.4

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3The announcement of a given economic indicator typically occurs on the same day of the week and tends to be concentrated in the last two days of the week. Hence, the time between survey and announcement tends to be the same across announcements. In our sample, the average number of days between survey and announcement is 5.48 with a standard deviation of 1.46.

4Several studies have examined the accuracy of the MMS forecasts. Since the potential non-stationarity of forecasts and realized values could affect the validity of standard accuracy tests, we estimate a cointegration representation via the Engle-Granger two-step procedure for those series that proved to be integrated. We find strong evidence that the MMS median forecast has predictive ability for the actual release. We also find that the median forecast is usually an unbiased predictor.
The set of 10 announcements provides a comprehensive characterization of the macro economy, in that it describes: the inflationary process by the consumer price index (CPI) and producer price index (PPI); the situation in the labor market by the civilian unemployment rate (CUR) and non-farm payrolls (NFP); the dynamic of consumption by the retail sales (RS); the state of the production-side of the economy by the industrial production (IP); the perceived state of the economy by consumer confidence (CC) and the national association of purchasing managers index (NAPM); the conditions of the money market by the Federal Open Market Committee federal funds target rate (FOMC) and the situation in the real estate market by housing starts (HS). Most of these announcements are released widely and virtually instantaneously at a precise scheduled time. The statistical agencies impose lock-up conditions to ensure that the information is not released to the public before the scheduled time (see Fleming and Remolona, 1999). With a few exceptions, the announcements are timed as follows: 6 announcements are at 8:30 am ET (CUR, NFP, CPI, HS, PPI, and RS), two are at 10:00 am ET (CC and NAPM), and the remaining two announcements are at 09:15 am ET (IP) and at 2:15 pm ET (FOMC). All of the announcements are monthly, except for the eight FOMC meetings per year. A majority of the announcements occur on a Friday and the employment report (CUR and NFP) is normally the first government information release concerning economic activity in a given month. Table 1 describes in more detail the announcement timing in our sample.

2.2. Options and futures data

We collect tick-by-tick prices of options written on the U.S. Treasury bond futures. The options are American-style, which means they can be exercised at any time before expiration, and are traded alongside the underlying bond futures contracts at the Chicago Board of Trade (CBOT). The options data covers the same sample period as the announcements data (January 1995–December 1999). Each data record specifies the option type (call or put), the expiration year and month, the strike price, the date, the time to the nearest second, the exact price, and the type of price (actual trade, reported quote, or nominal price set by the CBOT). In order to have liquid option prices reflecting actual transactions, we exclude quotes and nominal prices. We also exclude transactions that occurred outside the open outcry time period (before 8:20 am or after 3:00 pm ET). Finally, we apply the usual data filters to reduce the influence of measurement errors and market microstructure problems (see Hentschel, 2003). The final sample consists of 1,004,068 observations.

We also obtain tick-by-tick prices of the underlying U.S. Treasury bond futures. The bond futures contracts require delivery of a U.S. Treasury bond with 15 or more years to maturity and are one of the most heavily traded long-term interest rate instruments in the world. The contracts mature in March, June, September, and December. Each data record specifies the time to the nearest second and the exact price of the futures transaction. Given

5For instance, in August 1999 the NAPM announcement was released one day before the scheduled date. Moreover, the release time was at 10:45 am instead of at 10:00 am.

6Specifically, we apply four filters to the options data. First, we exclude options with less than a week to maturity. Second, we eliminate options with moneyness greater than three standard deviations from the at-the-money level. Third, we exclude options trades at the minimum price of $\frac{1}{32}$. Finally, we eliminate options that violate the intrinsic value no-arbitrage bounds.
this data, we match every option price with the corresponding prevailing futures price (i.e., the most recent price of the futures contract for the appropriate maturity).

Finally, we use daily U.S. dollar LIBOR rates to proxy for the term structure of riskfree interest rates.\footnote{The use of LIBOR rates to proxy for riskfree interest rates in option pricing is an industry convention because market makers are typically financed at LIBOR. It is therefore a common assumption in the empirical option pricing literature (e.g., Bollen and Whaley, 2004).} We match every option price with the LIBOR rate reported the same trading day for the monthly maturity closest to the expiration date of the option.

### 2.3. Implied volatility patterns

It is common to describe the features of options data through the volatility of the underlying security implied by a standard option pricing model, such as that of Black and Scholes (1973). Since we are dealing with American-style options on futures contracts, we use a binomial tree version of the Black (1976) model to compute implied volatilities for

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**Table 1**

**Announcement timing**

<table>
<thead>
<tr>
<th>Announcement</th>
<th>Abbrev.</th>
<th>Units</th>
<th>Time</th>
<th>Concurrent announcements</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>(ET)</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td><strong>Panel A</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Consumer price index</td>
<td>CPI</td>
<td>% Change</td>
<td>8:30</td>
<td>60</td>
</tr>
<tr>
<td>Housing starts</td>
<td>HS</td>
<td>Millions of Units</td>
<td>8:30</td>
<td>59</td>
</tr>
<tr>
<td>Civilian unemployment</td>
<td>CUR</td>
<td>% Level</td>
<td>8:30</td>
<td>60</td>
</tr>
<tr>
<td>Nonfarm payrolls</td>
<td>NFP</td>
<td>Thousands</td>
<td>8:30</td>
<td>60</td>
</tr>
<tr>
<td>Producer price index</td>
<td>PPI</td>
<td>% Change</td>
<td>8:30</td>
<td>60</td>
</tr>
<tr>
<td>Retail sales</td>
<td>RS</td>
<td>% Change</td>
<td>8:30</td>
<td>60</td>
</tr>
<tr>
<td>Industrial production</td>
<td>IP</td>
<td>% Change</td>
<td>9:15</td>
<td>60</td>
</tr>
<tr>
<td>Consumer confidence</td>
<td>CC</td>
<td>% Level</td>
<td>10:00</td>
<td>60</td>
</tr>
<tr>
<td>NAPM index</td>
<td>NAPM</td>
<td>% Level</td>
<td>10:00</td>
<td>60</td>
</tr>
<tr>
<td>FOMC target</td>
<td>FOMC</td>
<td>% Rate</td>
<td>14:15</td>
<td>60</td>
</tr>
</tbody>
</table>

**Panel B**

<table>
<thead>
<tr>
<th>Announcement</th>
<th>Abbrev.</th>
<th>Time</th>
<th>Sequence</th>
</tr>
</thead>
<tbody>
<tr>
<td>CPI</td>
<td>0</td>
<td>22</td>
<td>14</td>
</tr>
<tr>
<td>HS</td>
<td>0</td>
<td>21</td>
<td>17</td>
</tr>
<tr>
<td>CUR</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>NFP</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>PPI</td>
<td>0</td>
<td>6</td>
<td>11</td>
</tr>
<tr>
<td>RS</td>
<td>0</td>
<td>17</td>
<td>8</td>
</tr>
<tr>
<td>IP</td>
<td>4</td>
<td>15</td>
<td>12</td>
</tr>
<tr>
<td>CC</td>
<td>0</td>
<td>58</td>
<td>2</td>
</tr>
<tr>
<td>NAPM</td>
<td>24</td>
<td>12</td>
<td>8</td>
</tr>
<tr>
<td>FOMC</td>
<td>0</td>
<td>28</td>
<td>11</td>
</tr>
</tbody>
</table>

Panel A shows the announcements, their abbreviations, the reported units of the variables, the times at which the announcements are normally released, and the number of times two announcements are concurrent (same date and time). Panel B shows the distribution of the announcements over the days of the week and the typical sequence of the announcements in a given month. The sample period is January 1995–December 1999.
each option price. We then sort the options into six moneyness categories (two groups of out-of-the-money options, two groups of in-the-money options, and two groups of at-the-money options) and four time to maturity categories (eight to 30 days, 30–60 days, 60–180 day, and more than 180 days). We define moneyness as

\[ m = \frac{\ln(K/F)}{\sigma_{atm} \sqrt{T - t}}, \]  

where \( K \) is the strike price, \( F \) is the futures price, \( \sigma_{atm} \) is the at-the-money implied volatility and \( T - t \) is the time to maturity. This measure of moneyness indicates how many standard deviations the option is in- or out-of-the-money.\(^8\)

Table 2 shows the means and standard deviations of the implied volatilities across the 24 moneyness and time to maturity categories. Comparing options with the same time to maturity but different levels of moneyness, we observe an implied volatility smile with some negative asymmetry. The average implied volatility is higher for far in- and out-of-the-money options than for the corresponding at-the-money options (the smile). Furthermore, the average implied volatility is slightly higher for out-of-the-money put options than for equally out-of-the-money call options (the negative asymmetry). Comparing at-the-money options with different times to maturity, we also observe a monotonically increasing term structure of average implied volatilities. Both of these patterns in the implied volatilities are well summarized in the smoothed implied volatility surface depicted in Fig. 1.

Table 2 also shows the number of observations in each category. Using this statistic as indication of liquidity, it is clear that short-dated out- or at-the-money put and call options are the most liquid. Long-dated or in-the-money options are traded much less frequently.

3. Econometric approach

3.1. Estimation of the SPD

We infer the SPD from the prices of options with the same time to maturity but different levels of moneyness using the Gram–Charlier expansion approach pioneered by Jarrow and Rudd (1982). However, rather than approximate the density of the price of the underlying security, as they do, we follow Backus et al. (1997) in approximating the density of the log price change. This latter approach leads to a simple characterization of the option prices in terms of the higher-order moments of the distribution of the log price change.

Let the one-period change in the log futures price be

\[ x_{t+1} = \ln F_{t+1} - \ln F_t, \]  

where \( F_t \) is the futures price at date \( t \). Over \( n \) periods, the log futures price is

\[ \ln F_{t+n} = \ln F_t + \sum_{j=1}^{n} x_{t+j} = \log F_t + x_{t+1,t+n}, \]  

\(^{8}\)Unlike a simple ratio of the strike price to the underlying price, this moneyness measure is designed to reflect the fact that the likelihood of an option being exercised also depends heavily on the volatility of the underlying and on the time remaining to expiration of the option. The same or similar moneyness measures are employed by Dumas et al. (1998), Carr and Wu (2003), and Bollen and Whaley (2004).
so that the distribution of $F_{t+n}$ conditional on $F_t$ depends on the distribution of the log price change $x_{t+1,t+n}$. The price of a European-style call option on the futures with expiration date $t+n$ and with strike price $K$ is

$$C_{t,n,K} = E_t[M_{t,t+n}(F_{t+n} - K)^+],$$

where $M_{t,t+n}$ denotes a stochastic discount factor and $x^+ = \max(0, x)$. Assuming markets are complete, we express, without loss of generality, the stochastic discount factor as a function of the futures prices $M_{t,t+n} = M(F_t, F_{t+n})$. The price of the call option is then:

$$C_{t,n,K} = \int_0^\infty M(F_t, F_{t+n})(F_{t+n} - K)^+ p(F_t, F_{t+n}) \, dF_{t+n}$$
$$= e^{-r_{tn}} \int_0^\infty (F_{t+n} - K)^+ q(F_t, F_{t+n}) \, dF_{t+n},$$

This table shows the mean of the annualized volatility (in percent) implied by a binomial tree version of the Black (1976) formula, the standard deviation of the implied volatility, and the number of observations for each moneyness and time to maturity category. Moneyness is defined as $m = \ln(K/F)/\sigma_{atm}\sqrt{T - t}$.

Table 2

<table>
<thead>
<tr>
<th>Days to maturity</th>
<th>Call Options</th>
<th>Put Options</th>
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<tbody>
<tr>
<td></td>
<td>$m &lt; -2$</td>
<td>$m [-2, -1]$</td>
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<td>$8$–$30$</td>
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If markets are incomplete, writing the stochastic discount factor as a function of the futures prices has the interpretation of a conditional, on $F_t$, projection of $M_{t,t+n}$ on $F_{t+n}$.
where \( p(F_t, F_{t+n}) \) denotes the conditional distribution of the futures price, \( q(F_t, F_{t+n}) \) denotes the corresponding risk-neutral distribution defined by the transformation:

\[
q(F_t, F_{t+n}) = e^{r_{nt} n} M(F_t, F_{t+n}) p(F_t, F_{t+n}),
\]

and \( r_{nt} \) is the continuously compounded \( n \)-period interest rate.\(^{10}\) Finally, we transform the risk-neutral distribution of the futures price to that of the \( n \)-period log price change and eliminate the max operator by limiting the range of integration:

\[
C_{t,n,K} = e^{-r_{nt} n} \int_{\ln(K/F_t)}^{\infty} (F_t e^{x_{t+1,t+n}} - K) q(x_{t+1,t+n}) \, dx_{t+1,t+n}.
\]

The risk-neutral distribution \( q(x) \) is the object which we referred to earlier as the SPD. Eq. (6) illustrates that the SPD combines the beliefs of market participants about the likelihood of future states, \( p(F_t, F_{t+n}) \) in our case, with the preferences of market participants toward these states, as measured by the stochastic discount factor \( M(F_t, F_{t+n}) \).

In the special case in which the SPD of the \( n \)-period log price change is conditionally Gaussian with mean \( \mu_n \) and standard deviation \( \sigma_n \), the risk-neutral distribution of \( F_{t+n} \) is conditionally log-normal and the solution to Eq. (7) is the Black (1976) formula:

\[
C_{t,n,K} = e^{-r_{nt} n} [F_t N(d) - KN(d - \sigma_n)],
\]

\(^{10}\)We implicitly assume that there exists a probability measure such that the futures price \( F_t \) follows a local martingale. This so-called forward measure is constructed by letting the numeraire be the \( n \)-period bond price instead of the money market account (see also Aït-Sahalia and Brandt, 2006).
where
\[
d = \frac{\ln(F_t/K) + \sigma_n^2/2}{\sigma_n}
\]  
(9)

and \(N(x)\) denotes the standard normal cumulative distribution function evaluated at \(x\).

In general, the SPD of the log price change can be non-Gaussian. Backus et al. (1997) show that an analytically convenient way to capture the non-normalities of the SPD is through a Gram–Charlier expansion of the SPD around a Gaussian density. Let \(X_{t+1,t+n}\) have mean \(\mu_n\) and standard deviation \(\sigma_n\) and define the standardized log price change:
\[
\omega_{t+1,t+n} = \frac{X_{t+1,t+n} - \mu_n}{\sigma_n}.
\]  
(10)

The Gram–Charlier expansion approach is based on the following fourth-order approximation of the distribution of \(\omega\):
\[
q(\omega) = \phi(\omega) - \gamma_{1n} \frac{1}{3!} D^3 \phi(\omega) + \gamma_{2n} \frac{1}{4!} D^4 \phi(\omega),
\]  
(11)

where \(\phi(x)\) is the standard normal density evaluated at \(x\) and \(D^j\) denotes the \(j\)th derivative operator. Eq. (11) serves as an approximation to an arbitrary density with non-zero higher-order moments in which the departures from normality are captured by measures of skewness and kurtosis. Specifically, the cumulant generating function of the Gram–Charlier expansion reveals that the parameters \(\gamma_{1n}\) and \(\gamma_{2n}\) correspond to the standard skewness and excess kurtosis statistics, respectively.

Applying the approximation (11) to the SPD in Eq. (7), we derive the following expression for the call option price (see Appendix A for details):
\[
C_{t,n,K} \approx e^{-rt} \left[ F_t \mathcal{N}(d) - KN(d - \sigma_n) \right] + F_t e^{-rt} \phi(d) \sigma_n \left[ \gamma_{1n} \frac{1}{3!} (2\sigma_n - d) - \gamma_{2n} \frac{1}{4!} (1 - d^2 + 3d\sigma_n - 3\sigma_n^2) \right],
\]  
(12)

where all of the variables are as defined above. Eq. (12) expresses the call option price as the Black (1976) formula plus terms involving the skewness and excess kurtosis of the \(n\)-period change in the log futures price.

The final step of our econometric approach is to estimate the parameters of the Gram–Charlier expansion of the SPD using prices of options with the same expiration date but with different strike prices. Consider a cross-section of \(N\) prices of call options that differ only in their strike prices, \(\{C_{t,n,K_1}, C_{t,n,K_2}, \ldots, C_{t,n,K_N}\}\). We estimate the three parameters \(\sigma_n, \gamma_{1n}, \) and \(\gamma_{2n}\) by numerically solving the non-linear least-squares (NLLS) problem:
\[
\min_{\sigma_n,\gamma_{1n},\gamma_{2n}} \sum_{i=1}^{N} \left[ C_{t,n,K_i} - C_{t,n,K_i}(\sigma_n, \gamma_{1n}, \gamma_{2n}) \right]^2,
\]  
(13)

where the first option price in the brackets represents the data and the second term is the corresponding theoretical price from Eq. (12). In the empirical analysis, we only use
out-of-the-money options to make sure that the numerical optimization does not overweight the less liquid in-the-money options.\textsuperscript{11}

3.2. Extensions

3.2.1. Non-negativity constraint

An obvious problem with using polynomial expansions to approximate probability densities is that unconstrained expansions can imply negative probabilities.\textsuperscript{12} In the context of Gram–Charlier expansions, Jondeau and Rockinger (2001) derive constraints on the skewness and kurtosis parameters in the NLLS problem (13) which guarantee positivity. In addition, they provide a computationally efficient algorithm for solving this constrained problem.

To get a sense for the importance of imposing this positivity constraint in our application, we present in Panel A of Table 3 unconstrained and constrained estimates of the SPD for a randomly selected sub-sample of 3,000 options with 30, 60, and 90 days to maturity. For all three maturities, the unconstrained and constrained estimates are identical, which means that the constraint is not binding. At least for this randomly selected sub-sample, the departures from normality implied by our options data are not severe enough to require a positivity constraint on the Gram–Charlier density approximation. Nonetheless, throughout our empirical work we check that the estimated moments of the SPD satisfy the constraints guaranteeing positivity and, in the few cases when they do not, impose the constraints using the algorithm described by Jondeau and Rockinger (2001).

3.2.2. Implied volatility-based estimates

Backus et al. (1997) suggest a further simplification of the NLLS estimation problem (13). Their approach is based on linearizing the call option price in Eq. (12) in terms of volatility, which leads to the following implied volatility function:

\[
v_n(d) \simeq \sigma_n \left[ 1 + \frac{\gamma_{1n}}{3!} (2\sigma_n - d) - \frac{\gamma_{2n}}{4!} (1 - d^2 + 3d\sigma_n - 3\sigma_n^2) \right],
\]

where \(v_n\) is the Black-implied volatility of the option which equates the theoretical price corresponding to the Black (1976) model to the observed price. Using this implied volatility function, Backus et al. estimate the parameters of the Gram–Charlier approximation using the following NLLS estimation problem based on implied volatilities:

\[
\min_{\sigma_n, \gamma_{1n}, \gamma_{2n}} \sum_{i=1}^{N} [v_{n,i} - v_n(d_i)]^2. \tag{15}
\]

This implied volatility-based estimator is computationally more efficient than our price-based counterpart (13) because it is easier to evaluate the expression (14) than (12).

\textsuperscript{11}We also implemented the NLLS problem using a percentage price error criterion. However, this alternative approach, which overweighs deep out-of-the-money options that are relatively more contaminated by microstructure noise, leads to numerical instabilities in solving for the parameters of the SPD.

\textsuperscript{12}Another problem with using polynomial expansions is to obtain probability densities that integrate to one. We address this issue empirically by scaling the probabilities by the inverse of the numerical integral of the density approximation. It turns out that this adjustment is practically irrelevant because for our skewness and kurtosis values the numerical integrals range from 0.999 to one.
Table 3
Econometric issues

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Panel A of Table 3 shows both price and implied volatility-based estimates of the SPD for the random sample of 3,000 option prices described above. The results illustrate clearly that the implied volatility-based estimates can be substantially different from the price-based estimates. For example, for the 60-day horizon the skewness of the SPD from the price-based estimates is \( \gamma_1 \) with a standard error of 0.017 while the volatility-based estimates give a skewness of 0.065 with a standard error of 0.050. Furthermore, judging by the standard errors in parentheses, the implied volatility-based estimates are all approximately half as precise as the corresponding price-based estimates. This observation is consistent with the finding of Christoffersen and Jacobs (2002) that implied volatility-based estimates of option pricing models are substantially more noisy than price-based estimates. Because of this greater imprecision of the implied volatility-based estimates and because it is unclear how accurate the linearization of the option price underlying Eq. (14) is in our context, we use price-based estimates of the SPD throughout our empirical work.

3.2.3. Early exercise of American-style options

Our econometric approach treats the options as if they are European-style although in actuality we are dealing with American-style options. Following Melick and Thomas (1997), we incorporate the early exercise feature by expressing the values of the American-style call and put options as convex combinations of upper and lower bounds:

\[
C^*_{t,n,K} \equiv \lambda^c_{t,n,K} C^u_{t,n,K} + (1 - \lambda^c_{t,n,K}) C^d_{t,n,K},
\]

\[
P^*_{t,n,K} \equiv \lambda^p_{t,n,K} P^u_{t,n,K} + (1 - \lambda^p_{t,n,K}) P^l_{t,n,K},
\]

(16)

with

\[
C^u_{t,n,K} = E_t[\max(0, (F_{t+n} - K))],
\]

\[
C^d_{t,n,K} = \max(E_t[F_{t+n}] - K, e^{-r_{t+n}} E_t[\max(0, (F_{t+n} - K))]),
\]

\[
P^u_{t,n,K} = E_t[\max(0, (K - F_{t+n})],
\]

\[
P^l_{t,n,K} = \max(K - E_t[F_{t+n}], e^{-r_{t+n}} E_t[\max(0, (K - F_{t+n}))]).
\]

(17)

The lower bound is the European-style option price and the upper bound is derived in Chaudhary and Wei (1994). Applying the Gram–Charlier approximation (11) to the SPDs
embedded in Eq. (17), we can derive analytic expressions for the upper and lower bounds (see Appendix A for details). Notice that for out-of-the-money options the upper and lower bounds differ only by the discount factor and their spread is therefore very tight, especially when interest rates are low and the maturity date is near. In fact, the maximum relative difference between the upper and lower bounds for our sample of options is only 0.59%, which suggests already that the early exercise feature is negligible.

To incorporate these bounds into our econometric approach, we assume that the parameters \( \lambda_{n,K}^c \) and \( \lambda_{n,K}^p \) are the same for all options with a given maturity. We then include this single parameter \( \lambda_n \) in the NLLS problem:

\[
\min_{\sigma, \gamma_1, \gamma_2, \lambda_n} \sum_{i=1}^{N} \sum_{j=1}^{M} ((C_{t,n,K_i} - C_{t,n,K_i}^*(\cdot))^2 + (P_{t,n,K_j} - P_{t,n,K_j}^*(\cdot))^2),
\]

where \( C_{t,n,K_i}^* \) and \( P_{t,n,K_j}^* \) are the American-style option prices in Eq. (16).

Panel B of Table 3 compares estimates of \( \sigma, \gamma_1, \text{ and } \gamma_2 \) obtained from the estimators (13), which treats the options as European-style, and (18), which explicitly incorporates the early exercise feature, for the random sample of 3,000 option prices described above. The results are strikingly similar. Even at the 60-day horizon, for which the differences in the estimates are most pronounced, the skewness and kurtosis of the SPD from the two estimators are well within two standard errors of each other. Furthermore, the estimates of the parameter \( \lambda_n \) are always less than \( \frac{1}{1000} \) in magnitude and are statistically indistinguishable from zero. This implies that the option price is essentially determined by the lower bound, the European-style price, which is consistent with the options normally being exercised at maturity. Indeed, the actual exercise data for our sample periods reveals that 83% the exercises occurred at the expiration date and more than 90% occurred in the week prior to the expiration date. Because of these findings and because the estimator (13) is easier to implement (it involves the computation of only one option price as opposed to two), we proceed as if the options are European-style throughout our empirical work.

4. Empirical results

4.1. Seasonality and time horizon

Before we can study the effects of the macroeconomic announcements on the SPD, we first need to address two issues which arise in this analysis: the possibility of intra-weekly and intra-daily seasonalities of the SPD and the dependence of the SPD on the time horizon.

We first compare the average at-the-money implied volatility and the moments of the option-implied SPD on announcement and non-announcement days for different days of the week and for different times of the day. We compute the at-the-money implied volatility by inverting a binomial tree version of the Black (1976) formula for options with moneyness \( m \) between \(-0.5\) and \(0.5\). We estimate the moments of the SPD through the

\[\]
NLLS estimator (13). In both cases, we use the most liquid cross-section of out-of-the-money options with eight to 44 days to maturity.

The first plot in the first row of Fig. 2 shows that if we consider only days during which at least one of the 10 announcements occurs, the at-the-money implied volatility and the second moment of the option-implied SPD exhibit a similar decreasing pattern, with Mondays displaying the highest value and Fridays the lowest. Mondays and Fridays are the days with the least and most announcements, respectively (28 versus 207 releases), suggesting that the announcements reduce the uncertainty implicit in both the at-the-money implied volatility and the second moment of the SPD.\footnote{Ederington and Lee (1996) document a similar day-of-the-week effect in the at-the-money implied volatility of options on Treasury bond futures for a different sample period (1988–1992).} In contrast, the higher-order moments of the SPD do not exhibit such a pattern. We conduct pairwise non-parametric tests for the equality of the medians for each parameter and each combination of days.\footnote{The detailed results of these tests are not tabulated to save space but are available on request.} The statistical tests confirm the graphical intuition: the at-the-money implied volatility and the second moment of the option-implied SPD on Mondays (Fridays) are significantly higher (lower) than on all other days of the week. In contrast, the higher-order

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Fig. 2. Day of the week and time of the day effects. This figure plots the average at-the-money implied volatility (circles) as well as the standard deviation (crosses), skewness (triangles), and excess kurtosis (squares) of the option-implied SPD for different days of the week and different times of the day.
moments of the SPD are never statistically different across the days of the week. The second plot in the first row demonstrates that the day-of-the-week effects in the at-the-money implied volatility and the second moment of the SPD are specific to the announcement days. If we consider only non-announcement days, these two uncertainty measures are virtually constant throughout the week. There is a slight increase in uncertainty on Thursdays, the most frequent pre-announcement day, which is consistent with uncertainty being greatest just prior to the announcements. The pairwise statistical tests confirm that the uncertainty measures and the higher-order moments of the SPD do not significantly change throughout the week.

The second row of Fig. 2 plots the at-the-money implied volatility and moments of the SPD at different times during the day. The first plot for announcement days shows that uncertainty is decreasing substantially throughout the day. The largest drop occurs after 8:30 am, which corresponds to the time at which most of the announcements occur. In contrast, the higher-order moments of the SPD are constant throughout the day. We conduct statistical tests for the equality of the median at-the-money implied volatility and the median moments of the SPD for each pair of daily intervals, confirming again the graphical intuition. The second plot of the second row shows that on non-announcement days there are two much smaller decreases in uncertainty at the beginning and at the end of the trading day, which may be attributable to the opening and closing of daily positions. Statistically, uncertainty is different only between the first and the last interval of the trading day.

We conclude from Fig. 2 that the SPD exhibits no apparent intra-weekly and intra-daily seasonality other than the ones associated with the announcements. This conclusion implies that there is no need to control for the day of the week and time of the day in our empirical work. Furthermore, the day-of-the-week and time-of-the-day effects observed on announcement days foreshadow some of our empirical results in the next section.

Another issue which arises in our empirical work is the varying time horizon of the SPD. Since we are using exchange-traded options with specific expiration dates, the horizon of the option-implied SPD varies in a sawtooth-like fashion throughout the sample. Due to the regularity of both the expiration and announcement calendars, certain announcements tend to be released just days before the next expiration date while others are typically released shortly after an expiration and hence about a month before the following expiration date. To the extent that the non-normalities of the SPD depend on the time horizon, this correlation between the announcement and expiration dates may lead to difficulties in comparing the results across the different announcement types.

We mitigate this problem in two ways. First, we concentrate on the cross-section of options with the shortest maturity between eight and 44 days. These short-term options are the most liquid. Furthermore, it is reasonable to expect that the effect of the announcements is most pronounced for short horizons that do not cover another information release of the same type. Second, we include the time to maturity as an explanatory variable in each of the following empirical specifications. If an announcement has a different effect at different horizons, this will be reflected in the time variable and the

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16It is common to ignore options with less than a week to expiration due to market microstructure issues.
17Consistent with this argument, the results for medium- and long-term options are qualitatively the same, but less pronounced than for short-term options. The results for longer horizons are available on request.
effect of an announcement release can therefore be disentangled from the effect of the time to maturity.

4.2. Unconditional response of the SPD

We first study the unconditional response of the SPD to the macroeconomic announcements without considering whether an announcement is “good” or “bad” news. We examine the changes in both the average at-the-money implied volatility and the moments of the fitted SPD at the daily and intra-daily frequency. For the daily analysis, we construct daily time-series of the average at-the-money implied volatility and moments of the fitted SPD using all transactions of the shortest maturity out-of-the-money options available each day. Given dummy variables $D_{kt}$, where $D_{kt} = 1$ if announcement $k$ is made on day $t$ and $D_{kt} = 0$ otherwise, we estimate the following regression:

$$(\mu_t - \mu_{t-1}) = \alpha_t + \sum_{k=1}^{9} \beta_{kt} D_{kt} + \gamma T_t + \epsilon_t,$$  \hspace{1cm} (19)$$

where $T_t$ is the time to maturity of the option used in the estimation of the implied volatility and SPD and $\mu_t - \mu_{t-1}$ represents the day-to-day change in either the average at-the-money implied volatility or in the standard deviation $\sigma_n$, absolute value of skewness $\text{abs}(\gamma_{1n})$, or excess kurtosis $\gamma_{2n}$ of the fitted SPD.\(^{19}\)

Although we include all 10 announcements in the regression, we only present and discuss here the results for the CPI, Employment Report (ER), and PPI announcements. Ederington and Lee (1993) and Bollerslev et al. (2000) document that these three announcement types are by far the most influential for Treasury bond returns and their volatility. Moreover, Balduzzi et al. (2001) and, for a more recent sample period, Andersen et al. (2004) show that these news releases have the largest impact on bond returns among an extensive set of more than 20 macroeconomic announcements. The findings for the other announcements, which we include in the regression mostly to disentangle the effects of concurrent announcements, are weaker but qualitatively similar. Furthermore, we do not report the coefficients on the time-to-maturity variable, because they are never statistically significant.\(^{20}\)

Panel A of Table 4 shows that almost one-third of the variance of the day-to-day changes in the average at-the-money implied volatility is attributable to the announcements. All coefficients are highly significant with negative signs, consistent with the intuition that the announcements reduce uncertainty. The strongest effect is registered for

\(^{18}\)Since most announcements take place at 8:30 am ET, we exclude the first 10 min of trading to sharpen the distinction between announcement and non-announcement days. The results are similar if we exclude the first 100 min to take into account that NAPM and CC are released at 10:00 am.

\(^{19}\)We take the absolute value of skewness in this specification for two reasons. First, we do not expect that the SPD becomes systematically more positively or more negatively skewed (as opposed to just become less skewed) in response to an announcement. Second, this specification with the absolute value of skewness fits better than alternative specifications with the signed level of skewness. We switch to examining the signed level of skewness when we condition the response of the SPD on the news content below.

\(^{20}\)Even non-linear transformations, such as the square or square-root, of the time to maturity are never significant. This finding is likely due to our focus on short-term options and the fact that we analyze first differences, as opposed to levels of the moments of the SPD.
The employment report with an average drop in the at-the-money implied volatility of 0.85%.

It is possible that the response of the at-the-money implied volatility masks changes in the higher-order moments of the SPD. However, Panel B of Table 4 shows that this is not the case in general. The skewness and excess kurtosis of the option-implied SPD are not systematically affected by the event of an announcement. Even considering the absolute value of skewness, a more uncertainty-related measure, we obtain just a 10% significance level for the employment report. We conclude from these results that the unconditional reduction in uncertainty is almost completely exerted on the second moment.

To further sharpen this analysis, we examine next the intra-day changes of the at-the-money implied volatility and moments of the fitted SPD surrounding the macroeconomic announcements. For this, we replace the daily changes $\mu_t - \mu_{t-1}$ in Eq. (19) with intra-daily changes $\mu_{post} - \mu_{pre}$, where the pre- and post-statistics are computed using all transaction during the 45 min preceding and following the typical release time, respectively. In the case of the early 8:30 am announcements, the pre-interval is 2:15–3:00 pm of the prior day since the market opens only at 8:20 am.

Panel A of Table 5 shows that the at-the-money implied volatility drops significantly during the 45 min after the CPI, ER, and PPI releases. This indicates a very quick reaction of the SPD to the announcements, consistent with the results of Fleming and Remolona (1999) and Bollerslev et al. (2000) for bond returns and their realized volatility, respectively. Moreover, comparing the intra-daily results to the corresponding daily results in Panel A of Table 4 reveals that the drop in implied volatility is not transitory. The 45-min change does not seem to revert over the remainder of the day. The differences between the daily and intra-daily coefficient are greatest for the PPI release. This is consistent with the PPI often being released the day before the CPI, so that the afternoon

<table>
<thead>
<tr>
<th>Panel A</th>
<th>( \alpha )</th>
<th>( \beta_{CPI} )</th>
<th>( \beta_{ER} )</th>
<th>( \beta_{PPI} )</th>
<th>( R^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>CPI</td>
<td>-0.004</td>
<td>-0.266***</td>
<td>-0.845***</td>
<td>-0.279***</td>
<td>0.265</td>
</tr>
<tr>
<td>ER</td>
<td>0.053</td>
<td>-0.398***</td>
<td>-0.997***</td>
<td>-0.283***</td>
<td>0.235</td>
</tr>
<tr>
<td>PPI</td>
<td>0.021</td>
<td>-0.000</td>
<td>-0.043*</td>
<td>0.036</td>
<td>0.026</td>
</tr>
<tr>
<td></td>
<td>0.030</td>
<td>0.039</td>
<td>0.065</td>
<td>0.103</td>
<td>0.019</td>
</tr>
</tbody>
</table>

This table shows selected parameter estimates for the following regression:

\[
\mu_t - \mu_{t-1} = \alpha + \sum_{k=1}^{9} \beta_k D_{k,t} + \gamma T_t + \epsilon_t.
\]

In Panel A, \( \mu_t \) is the average at-the-money implied volatility on day \( t \). In Panel B, it is the second moment \( \sigma_n \), absolute value of skewness \( abs(g_{1n}) \), or excess kurtosis \( g_{2n} \) of the SPD. \( D_{k,t} \) is a dummy variance indicating whether announcement \( k \) occurs on day \( t \) and \( T_t \) is the maturity of the options used to estimate the implied volatility and SPD.

***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Significance levels do not change if heteroscedasticity corrected standard errors are used.
of the PPI release is the pre-announcement period of the CPI release. Finally, Panel B of Table 5 shows that the results for the at-the-money implied volatility relates directly to the second moment of the SPD. The higher-order moments of the fitted SPD are again unaffected.

4.3. Conditional response of the SPD

We now turn to the conditional effect of the macroeconomic announcements on the SPD, where we condition our previous analysis on the content of the news. To gauge the extent to which an announcement contains new information, we follow Balduzzi et al. (2001) and construct the following standardized measure of surprise:

\[
S_{kt} = \frac{A_{kt} - X_{kt}}{\sigma_k},
\]

where \( A_{kt} \) is the value of the main statistic released in announcement \( k \) at time \( t \), \( X_{kt} \) denotes the corresponding median survey forecast, and \( \sigma_k \) is the (unconditional) empirical standard deviation of the innovations \( A_{kt} - X_{kt} \). Standardizing the surprise by \( \sigma_k \) allows us to compare the regression coefficients across different announcement types. We then estimate for each announcement type \( k \) the following regression:

\[
(\mu_t - \mu_{t-1}) = \alpha_k + \beta_k S_{kt} + \sum_{h=1, k \neq h}^{H} \delta_h S_{ht} + \gamma_k T_t + e_{kt},
\]

where \( \mu_t - \mu_{t-1} \) represents again the day-to-day change in either the average at-the-money implied volatility or in the standard deviation \( \sigma_n \), skewness \( \gamma_{1n} \) (signed here), or excess

This table shows selected parameter estimates for the following regression:

\[
\mu_{post} - \mu_{pre} = \beta_{CPI} \cdot \text{CPI}_k + \beta_{ER} \cdot \text{ER}_k + \beta_{PPI} \cdot \text{PPI}_k + \epsilon_t.
\]

In Panel A, \( \mu_{pre} \) and \( \mu_{post} \) are the average at-the-money implied volatility during the 45 min before and after the release, respectively. In Panel B, they are the second moment \( \sigma_n \), absolute value of skewness \( \text{abs}(\gamma_{1n}) \), or excess kurtosis \( \gamma_{2n} \) of the corresponding SPDs. \( D_{kt} \) is a dummy variance indicating whether announcement \( k \) occurs on day \( t \) and \( T_t \) is the maturity of the options used to estimate the implied volatility and SPD. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Significance levels do not change if heteroscedasticity corrected standard errors are used.

Table 5

<table>
<thead>
<tr>
<th></th>
<th>( \alpha )</th>
<th>( \beta_{CPI} )</th>
<th>( \beta_{ER} )</th>
<th>( \beta_{PPI} )</th>
<th>( R^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \text{CPI} )</td>
<td>0.024</td>
<td>-0.225***</td>
<td>-0.815***</td>
<td>-0.320***</td>
<td>0.326</td>
</tr>
<tr>
<td>( \text{ER} )</td>
<td>0.225***</td>
<td>-0.815***</td>
<td>-0.320***</td>
<td>0.326</td>
<td></td>
</tr>
<tr>
<td>( \text{PPI} )</td>
<td>0.815***</td>
<td>-0.320***</td>
<td>0.326</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Panel B</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \sigma_n )</td>
<td>0.036</td>
<td>-0.254***</td>
<td>-0.918***</td>
<td>-0.461***</td>
<td>0.184</td>
</tr>
<tr>
<td>( \text{abs}(\gamma_{1n}) )</td>
<td>-0.008</td>
<td>0.010</td>
<td>-0.017</td>
<td>-0.002</td>
<td>0.008</td>
</tr>
<tr>
<td>( \gamma_{2n} )</td>
<td>0.135</td>
<td>0.263</td>
<td>0.083</td>
<td>0.153</td>
<td>0.019</td>
</tr>
</tbody>
</table>

This table shows selected parameter estimates for the following regression:

21 The PPI is released the day before the CPI about 40% of the times in our five-year sample.
Table 6
Daily effect of the macroeconomic news

<table>
<thead>
<tr>
<th></th>
<th>( \beta_h )</th>
<th>( R^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CPI</td>
<td>-0.981***</td>
<td>0.057</td>
</tr>
<tr>
<td>NFP</td>
<td>-1.242***</td>
<td>0.063</td>
</tr>
<tr>
<td>PPI</td>
<td>-0.662***</td>
<td>0.023</td>
</tr>
</tbody>
</table>

\[ \sigma = z_k + \beta_k S_k + \gamma_1 S_h + \gamma_2 T_t + \epsilon. \]

In Panel A, \( \sigma \) is the average at-the-money implied volatility on day \( t \). In Panel B, it is the second moment \( \sigma_n \), skewness \( \gamma_1 n \), or excess kurtosis \( \gamma_2 n \) of the SPD. \( S \) denotes the standardized announcement surprise, \( h \) enumerates announcements which are released concurrently with announcement \( k \), and \( T_t \) is the maturity of the options used to estimate the implied volatility and SPD.

This table shows selected parameter estimates for the following regression:

\[
\mu_t = \mu_{t-1} \equiv z_k + \beta_k S_{kt} + \sum_{h=1}^{H} \delta_h S_{ht} + \gamma_k T_t + \epsilon_{kt}.
\]

In Panel A, \( \mu_t \) is the average at-the-money implied volatility on day \( t \). The intercepts of the regressions are all negative and statistically significant at the 1% level. However, the information content appears irrelevant for this drop in implied volatility. The slope coefficients are insignificant in all cases and the adjusted \( R^2 \) are substantially lower than in Panel A of Table 4.

The results for the standard deviation of the SPD in Panel B of Table 6 are qualitatively the same as for the implied volatility. The standard deviation drops after an announcement irrespective of the information content. However, the results for higher-order moments of the SPD are very different. A positive (negative) surprise in the CPI release does not affect the standard deviation of the SPD, but significantly increases (decreases) its skewness and

\[ kurtosis \gamma_2 n \] of the fitted SPD. The subscript \( h \) refers to announcements which are released concurrently with announcement \( k \) and \( H \) represents the total number of concurrent announcements for each release. Including the terms subscripted by \( h \) in the regression serves to isolate the marginal effect of each announcement type.

Table 6 presents the regression results for the CPI, NFP, and PPI announcements. Panel A shows again that the event of an announcement leads to a drop in the at-the-money implied volatility. The intercepts of the regressions are all negative and statistically significant at the 1% level. However, the information content appears irrelevant for this drop in implied volatility. The slope coefficients are insignificant in all cases and the adjusted \( R^2 \) are substantially lower than in Panel A of Table 4.

The results for the standard deviation of the SPD in Panel B of Table 6 are qualitatively the same as for the implied volatility. The standard deviation drops after an announcement irrespective of the information content. However, the results for higher-order moments of the SPD are very different. A positive (negative) surprise in the CPI release does not affect the standard deviation of the SPD, but significantly increases (decreases) its skewness and kurtosis \( \gamma_2 n \) of the fitted SPD. The subscript \( h \) refers to announcements which are released concurrently with announcement \( k \) and \( H \) represents the total number of concurrent announcements for each release. Including the terms subscripted by \( h \) in the regression serves to isolate the marginal effect of each announcement type.

This table shows selected parameter estimates for the following regression:

\[
\mu_t = \mu_{t-1} \equiv z_k + \beta_k S_{kt} + \sum_{h=1}^{H} \delta_h S_{ht} + \gamma_k T_t + \epsilon_{kt}.
\]

In Panel A, \( \mu_{t-1} \) is the average at-the-money implied volatility on day \( t \). The intercepts of the regressions are all negative and statistically significant at the 1% level. However, the information content appears irrelevant for this drop in implied volatility. The slope coefficients are insignificant in all cases and the adjusted \( R^2 \) are substantially lower than in Panel A of Table 4.

The results for the standard deviation of the SPD in Panel B of Table 6 are qualitatively the same as for the implied volatility. The standard deviation drops after an announcement irrespective of the information content. However, the results for higher-order moments of the SPD are very different. A positive (negative) surprise in the CPI release does not affect the standard deviation of the SPD, but significantly increases (decreases) its skewness and kurtosis \( \gamma_2 n \) of the fitted SPD. The subscript \( h \) refers to announcements which are released concurrently with announcement \( k \) and \( H \) represents the total number of concurrent announcements for each release. Including the terms subscripted by \( h \) in the regression serves to isolate the marginal effect of each announcement type.

For the announcements considered here, CUR and NFP are always released jointly in the Employment Report. The CPI and PPI are occasionally released together with RS. Table 1 summarizes the number of concurrent announcements in our sample.
decreases (increases) its excess kurtosis. This pattern in the coefficients is the same for the NFP announcement, although the significance levels are lower.

Given that the SPD is on average negatively skewed on both announcement and non-announcement days (see Fig. 2), we can interpret these findings as follows. A positive surprise results in a SPD which is closer to being Gaussian, with less negative skewness and less excess kurtosis. The opposite is true for a negative surprise. To better understand this pattern, we classify surprises as being good (bad) news for the Treasury market depending on whether the surprise is on average positively (negatively) correlated with bond returns over the 30 min following the announcement. For all of the announcements except the CUR, a positive (negative) surprise corresponds to bad (good) news, consistent with the literature (e.g., Edison, 1996). Therefore, bad news for Treasuries leads to a more Gaussian SPD. We will return to the broader economic significance of this finding below.

We further examine whether the announcement effects vary with the sign of the surprise. For this, we generalize Eq. (21) by allowing for different slope coefficients depending on whether the news is good or bad as follows:

\[
(\mu_t - \mu_{t-1}) = \alpha_k + \beta_{Gkt} S_{kt} G_{kt} + \beta_{Bkt} S_{kt} B_{kt} \\
+ \sum_{h=1}^{H} (\delta_{Ght} S_{ht} G_{ht} + \delta_{Bht} S_{ht} B_{ht}) + \gamma_k T_t + e_{kt},
\]

(22)

where \( G_{kt} = 1 \) and \( B_{kt} = 0 \) if the information released in announcement \( k \) at time \( t \) is good news (for the Treasury market) and \( G_{kt} = 0 \) and \( B_{kt} = 1 \) otherwise.

Table 7 presents the results for this specification. Panel A shows that the announcement related drop in the at-the-money implied volatility documented in the previous tables depends to some extent on the information content of the announcement. For both the CPI and NFP announcements, the slope coefficients are significantly positive, which, together with the negative intercepts, means that the at-the-money implied volatility drops comparatively less when these announcements contain bad news. However, Panel B of Table 7 reveals that this asymmetry in the at-the-money implied volatility response is actually an artifact of asymmetric responses of the higher-order moments of the SPD, rather than due to an asymmetric change in uncertainty. The slope coefficients for the standard deviation of the SPD are insignificant in almost all cases, while we observe a significant increase in the skewness of the SPD after CPI and NFP bad news and a significant reduction in the excess kurtosis of the SPD after CPI, NFP, and PPI bad news. We conclude from these results that the response of the SPD to the announcements is mostly driven by bad news.\footnote{We verified for all announcements that a dummy variable for good or bad news alone is never significant. The magnitude of the surprise is thus important in determining the change in the higher-order moments of the SPD. The results are qualitatively similar if we use the squared surprise instead of its absolute value.}

The asymmetry of our results is not due to a disproportionate number of bad news for the bond market (good news for the economy) relative to good news. Our sample period contains roughly the same number of good and bad news (recall that the MMS forecasts are unbiased) and the distribution of surprises is only slightly skewed toward bad news, with no significant excess kurtosis. It is the case, however, that our sample period covers only an economic expansion. Therefore, our results could potentially be explained by an asymmetric Fed reaction function by which, in an expansion, positive economic news raise
the likelihood of future increases in the target rate (bad news for the bond market) by more
than bad news raise the likelihood of future decreases in the target rate.

In Tables 8 and 9 we repeat the conditional analysis above for intra-day changes in the
at-the-money implied volatility and moments of the option-implied SPD. The results
confirm that the information content of the announcement plays a negligible role for
changes in the at-the-money implied volatility, with the exception of bad NFP news (Panel
A of Tables 8 and 9). The tables also support our previous finding that positive (negative)
CPI, NFP, and PPI surprises lead to a reduction (increase) in the negative skewness and
excess kurtosis of the SPD (Panel B of Table 8). Furthermore, the explanatory power is
again considerably enhanced by differentiating between the effects of good and bad news,
in which case only the effect of bad news remains highly significant (Panel B of Table 9).

It is possible that our findings are affected by the fact that, as we already mentioned
above, our sample period only covers an expansionary phase of the business cycle. However, there is some recent evidence on the effect of macroeconomic news on bond returns pointing to similar responses in different phases of the business cycle. Specifically, Andersen et al. (2004) show that the impact of NFP news on Treasury bond returns is negative and significant in both expansions and recessions, using a sample period from 1992 through 2002. Inflation, namely the release of CPI and PPI, also has a significantly negative impact on bond returns in expansions and still a negative impact, though not significant, in recessions.

Table 7
Daily effect of good and bad news

<table>
<thead>
<tr>
<th></th>
<th>$v_n$</th>
<th>$\gamma_{1n}$</th>
<th>$\gamma_{2n}$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\alpha_k$</td>
<td>$\beta_{Gk}$</td>
<td>$\beta_{Bk}$</td>
</tr>
<tr>
<td>CPI</td>
<td>-1.039***</td>
<td>0.029</td>
<td>0.171**</td>
</tr>
<tr>
<td>NFP</td>
<td>-1.531***</td>
<td>0.102</td>
<td>0.369***</td>
</tr>
<tr>
<td>PPI</td>
<td>-0.726***</td>
<td>-0.021</td>
<td>0.026</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>$\sigma_n$</th>
<th>$\gamma_{1n}$</th>
<th>$\gamma_{2n}$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\alpha_k$</td>
<td>$\beta_{Gk}$</td>
<td>$\beta_{Bk}$</td>
</tr>
<tr>
<td>CPI</td>
<td>-1.826***</td>
<td>-0.143</td>
<td>0.109</td>
</tr>
<tr>
<td>NFP</td>
<td>-1.487***</td>
<td>-0.191</td>
<td>0.224</td>
</tr>
<tr>
<td>PPI</td>
<td>-0.643**</td>
<td>0.309</td>
<td>-0.203</td>
</tr>
</tbody>
</table>

This table shows selected parameter estimates for the following regression:

$\ln(v_t) = \alpha_k + \beta_{Gk}S_kG_k + \beta_{Bk}S_kB_k + \sum_{h=1}^{H} (\delta_{Gh}S_{h}\alpha_hG_k + \delta_{Bh}S_{h}B_{h}) + \gamma_{1n}T_t + \gamma_{2n}T_t + \epsilon_{n}$.  

In Panel A, $\mu_t$ is the average at-the-money implied volatility on day $t$. In Panel B, it is the second moment $\sigma_n$, skewness $\gamma_{1n}$, or excess kurtosis $\gamma_{2n}$ of the SPD. $S$ denotes the standardized announcement surprise, $h$ enumerates announcements which are released concurrently with announcement $k$, and $T_t$ is the maturity of the options used to estimate the implied volatility and SPD.

***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Significance levels do not change if heteroscedasticity corrected standard errors are used.
Before turning to a more rigorous interpretation of our empirical results, we conclude this section by examining the time-series of the higher-order moments of the option-implied SPD. We plot in Fig. 3 the smoothed time-series of skewness and excess kurtosis along with the experimental coincident recession index (XRI-C) constructed by Stock and Watson (1989). The XRI-C is a monthly estimate of the probability that the economy is in a recession, constructed using four series of leading indicators such as IP, real personal income less transfer payments, real manufacturing and trade sales, and total employee-hours in non-agricultural establishments. An important feature of the XRI-C is that it establishes a real-time public forecasting record, i.e., it uses only information that is publicly available at a certain point in time. In contrast, the NBER business cycle dates for expansions and recessions make use of information that becomes available later.

The first plot shows a strong negative correlation between the option-implied skewness and the XRI-C index. This correlation is equal to $-0.48$. When economic conditions are relatively good and the probability of being in a recession is therefore lower, the option-implied skewness is less negative. The second plot of excess kurtosis and XRI-C shows a weaker relationship between these two series. The correlation is positive and equal to 0.20, suggesting that better economic conditions, meaning a lower probability of being in a recession, are associated with a lower level of kurtosis.

### Table 8

Intradaily effect of the macroeconomic news

<table>
<thead>
<tr>
<th>CPI</th>
<th>$\alpha_k$</th>
<th>$\beta_k$</th>
<th>$R^2$</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>-0.530**</td>
<td>0.063</td>
<td>0.158</td>
</tr>
<tr>
<td>NFP</td>
<td>-0.884***</td>
<td>0.075</td>
<td>0.128</td>
</tr>
<tr>
<td>PPI</td>
<td>-0.409**</td>
<td>0.042</td>
<td>0.136</td>
</tr>
</tbody>
</table>

Panel A

| Panel B
<table>
<thead>
<tr>
<th>CPI</th>
<th>$\alpha_k$</th>
<th>$\beta_k$</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-0.410**</td>
<td>-0.028</td>
<td>0.081</td>
</tr>
<tr>
<td>NFP</td>
<td>-0.912***</td>
<td>-0.076</td>
<td>0.124</td>
</tr>
<tr>
<td>PPI</td>
<td>-0.290**</td>
<td>-0.016</td>
<td>0.032</td>
</tr>
</tbody>
</table>

This table shows selected parameter estimates for the following regression:

$$\mu_{post} - \mu_{pre} = \alpha_k + \beta_k S_k + \sum_{h=1}^{H} \delta_h S_h + \gamma_k T + \epsilon_k.$$

In Panel A, $\mu_{pre}$ and $\mu_{post}$ are the average at-the-money implied volatility during the 45 min before and after the release, respectively. In Panel B, they are the second moment $\sigma_n$, skewness $\gamma_1n$, or excess kurtosis $\gamma_2n$ of the corresponding SPDs. $S$ denotes the standardized announcement surprise, $h$ enumerates announcements which are released concurrently with announcement $k$, and $T$ is the maturity of the options. **, ***, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Significance levels do not change if heteroscedasticity corrected standard errors are used.
5. Interpretation

Having documented systematic changes in the option-implied SPD in response to major macroeconomic announcements, we now turn to the economic interpretation of our empirical results. We first investigate whether relative mispricing due to trading pressure in the options market can explain our findings. After concluding that it cannot, we try to disentangle the effect on the SPD of changes in the beliefs and of changes in the preferences of market participants. We examine the effect of macroeconomic news on the PDF using a non-parametric approach, an event regression approach, and a jump model for the underlying futures price. Given our estimates of the SPD along with estimates of the PDF obtained from the jump model, we then recover the implied risk aversion and relate changes in risk aversion to the macroeconomic announcements. The results suggest that risk aversion varies counter-cyclically as predicted by a habit formation model, for example.

5.1. Relative mispricing due to trading pressure

There is considerable evidence in the empirical literature that implied volatilities and, as a result, the moments of option-implied SPDs, can be affected by buying pressure in the options market. Table 9 presents the intradaily effect of good and bad news. The table shows selected parameter estimates for the following regression:

\[
(m_{\text{post}} - m_{\text{pre}}) = \alpha_k + \beta_{G_k} S_k G_k + \beta_{B_k} S_k B_k + \sum_{h=1}^{H} (\delta_{G_h} S_h G_h + \delta_{B_h} S_h B_h) + \gamma_h T_t + e_{kt}.
\]

In Panel A, \(m_{\text{pre}}\) and \(m_{\text{post}}\) are the average at-the-money implied volatility during the 45 minutes before and after the release, respectively. In Panel B, they are the second moment \(\sigma_n\), skewness \(\gamma_{1n}\), or excess kurtosis \(\gamma_{2n}\) of the corresponding SPDs. \(S\) denotes the standardized announcement surprise, \(h\) enumerates announcements which are released concurrently with announcement \(k\), and \(T_t\) is the maturity of the options used to estimate the implied volatility and SPD.

***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Significance levels do not change if heteroscedasticity corrected standard errors are used.

Table 9
The intradaily effect of good and bad news

<table>
<thead>
<tr>
<th>Panel A</th>
<th></th>
<th></th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>(v_n)</td>
<td>(\alpha_k)</td>
<td>(\beta_{G_k})</td>
<td>(\beta_{B_k})</td>
</tr>
<tr>
<td>CPI</td>
<td>-0.556**</td>
<td>0.039</td>
<td>0.122*</td>
</tr>
<tr>
<td>NFP</td>
<td>-1.093***</td>
<td>-0.105</td>
<td>0.267**</td>
</tr>
<tr>
<td>PPI</td>
<td>-0.477**</td>
<td>0.042</td>
<td>0.038</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B</th>
<th></th>
<th></th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\sigma_n)</td>
<td>(\alpha_k)</td>
<td>(\beta_{G_k})</td>
<td>(\beta_{B_k})</td>
</tr>
<tr>
<td>CPI</td>
<td>-0.542**</td>
<td>0.008</td>
<td>-0.049</td>
</tr>
<tr>
<td>NFP</td>
<td>-1.167***</td>
<td>-0.035</td>
<td>0.007</td>
</tr>
<tr>
<td>PPI</td>
<td>-0.382**</td>
<td>0.112</td>
<td>-0.107</td>
</tr>
</tbody>
</table>

This table shows selected parameter estimates for the following regression:

\[
(m_{\text{post}} - m_{\text{pre}}) = \alpha_k + \beta_{G_k} S_k G_k + \beta_{B_k} S_k B_k + \sum_{h=1}^{H} (\delta_{G_h} S_h G_h + \delta_{B_h} S_h B_h) + \gamma_h T_t + e_{kt}.
\]
Fig. 3. Higher-order moments and probability of a recession. This figure plots smoothed time-series of skewness and excess kurtosis of the option-implied SPD, along with the Stock and Watson (1989) recession index XRI-C (dashed line) for our sample period.

options market when arbitrageurs are prevented, by the so-called limits to arbitrage, from instantaneously eliminating any differences between observed market prices and theoretical no-arbitrage values. Specifically, Bollen and Whaley (2004) show that

25Limits to arbitrage is a catch-all phrase for institutional and behavioral reasons for why arbitrageurs fail to equalize prices and for why apparent arbitrage opportunities persist, including importantly transaction costs, shorting restrictions, capital constraints, and risk aversion.
changes in implied volatilities of index and individual stock options are directly related to net buying pressure from public order flow. Excess demand for puts has the strongest effect on the implied volatilities of stock index options, while excess demand for calls has the strongest effect on the implied volatilities of individual stock options. Although there is no direct evidence of the same phenomenon in bond options markets, it is still reasonable to suspect that buying or selling pressure can also affect the implied volatilities of Treasury futures options. More specifically, in the context of our study, it is possible that the information content of macroeconomic news triggers trading behaviors which, due to market inefficiencies, lead to implied volatility changes that are unrelated to beliefs or preferences.26

It is difficult to formalize the effects of limits to arbitrage on asset prices in general and, in the context of our paper, on option-implied SPDs in particular. We therefore tackle this issue empirically. We collect daily data on traded volume and open interest for the same option contracts and sample period used in the estimation of the SPDs. We use this data to construct six proxies for trading pressure in the Treasury futures options market. Specifically, we compute the ratios of put to call options volume and put to call options open interest. Dennis and Mayhew (2002) use these measures as proxies of trading pressure. Following Bollen and Whaley (2004), we also differentiate options by moneyness and compute the daily percentage changes in out-of-the-money call options and out-of-the-money put options trading volume and open interest.27

To examine the relationship, if any, between trading pressure in the options market and the information content of the macroeconomic announcements we estimate the following regression:

\[
bpt = \alpha_k + \beta_k S_{kt} + \sum_{h=1}^{H} \delta_h S_{ht} + \epsilon_{kt},
\]  
(23)

where \(bpt\) represents one of the six proxies for trading pressure described above and \(S_{kt}\) denotes the standardized announcement surprise for announcement \(k\).

Panels A and B of Table 10 present the regression results for the volume-based proxies and for the open interest-based proxies, respectively. None of the volume-based proxies for trading pressure are significantly related to the information content of the macroeconomic announcements. However, changes in open interest and, in particular, in open interest of out-of-the-money put options are positively and statistically significantly related to CPI and NFP surprises. The positive slope coefficients imply that open interest of out-of-the-money puts increases in response to bad news for the bond market or good news about the economy. Assuming that an increase in open interest exerts price pressure on out-of-the-money puts and temporarily raises their prices above no-arbitrage values, the observed option-implied SPD would become more negatively skewed. However, this is exactly the

---

26Another possible explanation along the same lines is given by Buraschi and Jiltsov (2005), who argue that divergence in beliefs explains implied volatility dynamics in the stock market. In the context of our paper, while one could argue that divergence in beliefs decreases after the release of macroeconomic news, it is more difficult to argue that divergence in beliefs changes depending on the content of the news being good or bad. That is, for this explanation to explain our results, there needs to exist a correlation between the content of the news and the divergence in beliefs.

27We include in the category of out-of-the-money options all call (put) options with strike prices above (below) the price of the underlying. The empirical results do not change if we only consider call (put) options with strike prices that are at least 5% above (below) the price of the underlying.
opposite effect of what we find when we relate changes in the higher-order moments of the SPD to macroeconomic news. We observe that the option-implied SPD becomes less negatively skewed in response to good news about the economy. We hence conclude from this set of regressions that trading pressure in the options market is unlikely to explain our results.

As a more direct test of the trading pressure and limits to arbitrage explanation of our empirical results, we estimate a modified version of Eq. (21) in which we add as regressor a proxy for trading pressure:

$$b_{pt} = z_k + \beta_k S_{kt} + \sum_{h=1}^H \delta_h S_{ht} + e_{kt}. \tag{24}$$

In Panel A, $b_{pt}$ is the put/call volume ratio on the announcement day $p_{cvolu}$, the percentage change in out-of-the-money call volume $otm_{Cvolu}$, or the percentage change in out-of-the-money put volume $otm_{Pvolu}$. In Panel B, $b_{pt}$ is the put/call open interest ratio on the announcement day $p_{Olvu}$, the percentage change in out-of-the-money call open interest $otm_{Olvu}$, or the percentage change in out-of-the-money put open interest $otm_{Olvu}$. $S$ denotes the standardized announcement surprise and $h$ enumerates announcements which are released concurrently with announcement $k$.

***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Significance levels do not change if heteroscedasticity corrected standard errors are used.

This table shows parameter estimates for the following regression:

<table>
<thead>
<tr>
<th></th>
<th>$p_{cvolu}$</th>
<th>$otm_{Cvolu}$</th>
<th>$otm_{Pvolu}$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$z_k$</td>
<td>$\beta_k$</td>
<td>$R^2$</td>
</tr>
<tr>
<td><strong>Panel A</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CPI</td>
<td>1.080***</td>
<td>0.055</td>
<td>0.002</td>
</tr>
<tr>
<td>NFP</td>
<td>1.083***</td>
<td>0.109</td>
<td>0.042</td>
</tr>
<tr>
<td>PPI</td>
<td>1.095***</td>
<td>0.105</td>
<td>0.020</td>
</tr>
<tr>
<td>$p_{Olvu}$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CPI</td>
<td>1.228***</td>
<td>0.188</td>
<td>0.011</td>
</tr>
<tr>
<td>NFP</td>
<td>1.199***</td>
<td>-0.021</td>
<td>0.002</td>
</tr>
<tr>
<td>PPI</td>
<td>1.298***</td>
<td>0.221</td>
<td>0.026</td>
</tr>
</tbody>
</table>

opposite effect of what we find when we relate changes in the higher-order moments of the SPD to macroeconomic news. We observe that the option-implied SPD becomes less negatively skewed in response to good news about the economy. We hence conclude from this set of regressions that trading pressure in the options market is unlikely to explain our results.

As a more direct test of the trading pressure and limits to arbitrage explanation of our empirical results, we estimate a modified version of Eq. (21) in which we add as regressor a proxy for trading pressure:

$$\mu_t - \mu_{t-1} = z_k + \beta_k S_{kt} + \omega_t b_{pt} + \sum_{h=1}^H \delta_h S_{ht} + \gamma_k T_t + e_{kt}, \tag{24}$$

where, as before, $\mu_t - \mu_{t-1}$ represents the announcement day change in either the skewness $\gamma_{1n}$ or excess kurtosis $\gamma_{2n}$ of the option-implied SPD, and $b_{pt}$ represents one of the six proxies for trading pressure described above. Under the hypothesis that in Table 6 the macroeconomic surprises $S_{kt}$ enter the regression significantly because of a correlation with an omitted trading pressure variable, we expect the trading pressure proxy $b_{pt}$ to take on most of the explanatory power in this regression specification.
Table 11, which shows the results for this augmented regression specification, can and should be compared directly to Table 6. We focus on the put to call volume ratio (in Panel A) and the percentage change in open interest of out-of-the-money puts (in Panel B) because these two trading pressure proxies deliver the strongest results. Consider first the results in Panel B. For the skewness regressions on the left side of the panel, the coefficients for the percent change in open interest of out-of-the-money puts is negative and statistically insignificant. More importantly, the coefficients for the announcement surprises remain statistically significant with about the same magnitudes. The fact that the explanatory power of the regression for the CPI release increases suggests that trading activity may play some role but, consistent with the results in Table 10, the effect has the opposite sign of what the relative mispricing due to trading pressure explanation predicts. The SPD becomes less negatively skewed when the open interest of out-of-the-money puts increases. For the kurtosis regressions on the right side of the panel, we find a more significant effect of trading pressure. Specifically, an increase in open interest of out-of-the-money puts on CPI announcement days is associated with an increase in excess kurtosis. However, the coefficients on the announcement surprises are still statistically significant and the magnitude of the coefficients are not statistically different from those in Table 6. The results in Panel A of Table 11 are similar but statistically weaker.

The empirical analysis in this section reveals that relative mispricing due to trading pressure seems to be an unlikely explanation for our empirical results. Of course, we are only using proxies for trading pressure, albeit a number of them, and it may be the case that these measures do not properly capture excess option supply or demand. With this

### Table 11

Daily effect of the macroeconomic news and buying pressure

<table>
<thead>
<tr>
<th></th>
<th>$\gamma_{1n}$</th>
<th>$\gamma_{2n}$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$z_k$</td>
<td>$\beta_k$</td>
</tr>
<tr>
<td>Panel A</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CPI</td>
<td>0.283*</td>
<td>0.048**</td>
</tr>
<tr>
<td>NFP</td>
<td>0.091</td>
<td>0.044*</td>
</tr>
<tr>
<td>PPI</td>
<td>-0.157</td>
<td>-0.020</td>
</tr>
<tr>
<td>Panel B</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CPI</td>
<td>0.284*</td>
<td>0.054**</td>
</tr>
<tr>
<td>NFP</td>
<td>0.086</td>
<td>0.029*</td>
</tr>
<tr>
<td>PPI</td>
<td>-0.059</td>
<td>-0.007</td>
</tr>
</tbody>
</table>

This table shows parameter estimates for the following regression:

$$\mu_t - \mu_{t-1} = z_k + \beta_k S_{kt} + \omega_t b_{pt} + \sum_{h=1}^{H} \delta_h S_{ht} + \gamma_{kt} T_t + \epsilon_{kt}.$$  

In all panels, $\mu_t$ is the skewness $\gamma_{1n}$, or excess kurtosis $\gamma_{2n}$ of the SPD. $S$ denotes the standardized announcement surprise, $h$ enumerates announcements which are released concurrently with announcement $k$, and $T_t$ is the maturity of the options used to estimate the implied volatility and SPD. In Panel A, $b_{pt}$ is the put/call volume ratio on the announcement day. In Panel B, $b_{pt}$ is the percentage change in out-of-the-money put open interest. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Significance levels do not change if heteroscedasticity corrected standard errors are used.
caveat in mind, we proceed to explore alternative explanations of our empirical results, namely changes in beliefs or changes in preferences of market participants.

5.2. Change in beliefs

We now turn to the interpretation of our results in the context of the SPD being a convolution of beliefs and preferences. The most natural approach to disentangling changes in the beliefs from changes in the preferences of market participants is to complement the analysis of the risk-neutral SPD presented above with an analysis of the physical PDF (and noting that preferences make up the difference between the two). Unfortunately, doing so without a parametric model for the physical dynamics of the underlying futures price is challenging because estimating the changes in the higher-order moments of the PDF from historical data requires a considerable number of observations for each announcement type. In contrast, the moments of the SPD can be easily recovered using a cross-section of option prices traded on a single day. We try to resolve this issue by considering a variety of different econometric approaches, including a non-parametric approach in which we aggregate announcements according to whether they are good or bad news, an event regression approach, and a parametric jump model for the physical dynamics of the underlying futures price.

5.2.1. Non-parametric approach

We begin by aggregating all announcements into groups of influential good and influential bad announcements. The purpose of this aggregation is to increase the number of observations for estimating the higher-order moments of the physical return distribution before and after each announcement. Specifically, we first identify the days in our sample on which the largest positive and largest negative surprises in the macroeconomic data occurred. It is for these influential announcement days that we expect the changes in the SPD and PDF to be most pronounced, which implies that these influential announcement days are also the most informative about the link between the two distributions. We then compute the daily returns on the underlying asset before and after these announcement days for a time interval spanning the time to maturity of the options used to construct the SPD (in order to match the horizon of the SPD). Naturally, we exclude the announcement day return in order to separate the announcement effect on prices from the announcement effect on the shape of the return distribution. We then jointly estimate from the daily returns the skewness and excess kurtosis before and after influential positive and influential negative surprises. The estimation is conducted by standard GMM, which allows us to construct asymptotic standard errors for the changes in skewness and kurtosis from before to after the announcements. Finally, we compare the change in the physical skewness and kurtosis to the change in the corresponding moments of the SPD for the same announcement days.

Table 12 presents the results of this non-parametric comparison of sample moments for the 5–25 most influential negative and most influential positive announcement surprises. Negative (positive) surprises, which are good (bad) news for the Treasury market in our sample period, are consistently associated with a relatively less (more) negatively skewed PDF after the announcement. These changes in skewness are larger in magnitude and statistically more significant for positive surprises. The physical excess kurtosis decreases significantly after negative surprises (good news) and increases significantly after positive
surprises (bad news). This pattern for the higher moments of the physical PDF lies in stark contrast to the evidence presented in the previous section for the risk-neutral SPD. Positive surprises are associated with a more negatively skewed and also more fat-tailed PDF, but with a less negatively skewed and also less fat-tailed SPD.

5.2.2. Event regression approach

To obtain additional evidence on the evolution of the PDF surrounding macroeconomic announcements, we employ the same event regression approach as for relating the changes in the moments of the SPD to the macroeconomic surprises. Specifically, we compute the sample skewness and kurtosis of daily returns in-between subsequent monthly announcements (typically 20 observations) and then regress the changes in each moment on the announcement surprises using the same regression specification as above:

\[
\left( \hat{\mu}_{\text{post}} - \hat{\mu}_{\text{pre}} \right) = \alpha_k + \beta_k S_{kt} + \sum_{h=1, h \neq k}^{H} \delta_h S_{ht} + e_{kt},
\]  

(25)

where \( \hat{\mu}_{\text{pre}} \) and \( \hat{\mu}_{\text{post}} \) denote the sample skewness or excess kurtosis for the approximately 20 days before and after the release of announcement \( k \) on date \( t \), respectively.

Estimating this regression for our sample period, none of the slope coefficients turns out to be statistically significant. The obvious reasons for this lack of significance is that the regressions are based on only 60 observations (announcements per type) and that the sample skewness and kurtosis estimates are very noisy due to the short sample periods between announcements. To increase the power to detect a relationship between the higher-order moments of the PDF and macroeconomic news, we therefore increase the sample period by extending our initial sample of futures returns and announcement data back as far as possible. Limited by the availability of MMS forecasts, our extended sample period goes from January 1985 through December 2003. By extending the sample, we increase the number of observations for our event regression approach from 60 to 225.

Table 13 presents the regression results for this extended sample period. The coefficient on the surprise is always positive for the changes in skewness and negative for the changes in excess kurtosis. The signs of the coefficients imply that, consistent with the results above, the PDF becomes more negatively skewed and fat-tailed in response to good news, exactly opposite to the changes in the SPD. The coefficients are still insignificant except in the case

<table>
<thead>
<tr>
<th>Largest surprises</th>
<th>Top 25</th>
<th>Top 20</th>
<th>Top 15</th>
<th>Top 10</th>
<th>Top 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Negative surprises</td>
<td>( \Delta \gamma_{1} )</td>
<td>0.0717</td>
<td>0.0244</td>
<td>0.0896</td>
<td>0.1631</td>
</tr>
<tr>
<td>( \Delta \gamma_{2} )</td>
<td>-0.4741***</td>
<td>-0.4487***</td>
<td>-0.5017***</td>
<td>-0.2267</td>
<td>-1.8913***</td>
</tr>
<tr>
<td>Positive surprises</td>
<td>( \Delta \gamma_{1} )</td>
<td>-0.4411*</td>
<td>-0.4609*</td>
<td>-0.7005**</td>
<td>-0.5492***</td>
</tr>
<tr>
<td>( \Delta \gamma_{2} )</td>
<td>3.4176***</td>
<td>2.4000***</td>
<td>3.4376***</td>
<td>1.5753**</td>
<td>2.8167***</td>
</tr>
</tbody>
</table>

This table shows the estimated change in the skewness (\( \Delta \gamma_{1} \)) and in the extra-kurtosis (\( \Delta \gamma_{2} \)) of the physical density around the largest 25, 20, 15, 10, and 5 surprises in the scheduled macroeconomic releases. We use a GMM estimator on the bunch of daily returns of the underlying before and after the announcement day to compute the change in the higher moments of the physical distribution.

***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.
of changes in skewness after NFP releases. If we restrict our sample only to the expansion phases of the business cycle, as defined by the NBER business cycle dates, to reflect the fact that the sample period for our SPD analysis is part of an expansion phase, the results reported in Table 13 are stronger with the same signs. We therefore conclude that there is no evidence that the changes in the SPD are mirrored by changes in the PDF. If anything, the PDF appears to react in an opposite way to the economic news.

5.2.3. Parametric approach

As a third and final approach to measuring the effect of macroeconomic news on the higher-order moments of the PDF, we specify and estimate a parametric model for the underlying futures price. The model incorporates a time-varying risk premium, conditional heteroscedasticity, as well as jumps with an arrival process that depends on the pattern of scheduled macroeconomic announcements. We use this model to construct by simulation estimates of the physical PDF before and after each news release. We then relate the changes in the skewness and excess kurtosis of the simulated distribution to the announcement surprises using again event regressions. In the next section, we also use this model to obtain estimates of risk aversion toward each future state (a so-called risk aversion function) by comparing, state by state, the model-implied PDF to the option-implied SPD.

Following closely the model of Maheu and McCurdy (2004) for equities, we model the innovations to the daily log return as the sum of a heteroscedastic shock associated with diffusive information flow and a jump component capturing the effect of a sudden release of important news.\(^{28}\) Since the sharpest price changes in the U.S. Treasuries market tend to be associated with macroeconomic announcements (e.g., Fleming and Remolona, 1997), we explicitly allow the jump arrival rate to increase on announcement days. Furthermore, we let both the mean return on non-announcement days as well as the jump mean on announcement days depend on the announcement surprises.

---

\(^{28}\)Maheu and McCurdy (2004) use their model to study the impact of earnings news on stock prices.
We start by specifying the log futures return as the sum of a time-varying conditional mean, a normal innovation $\varepsilon_{1,t+1}$ representing diffusive information flow, and a jump innovation $\varepsilon_{2,t+1}$ representing the effect of sudden information arrival:

$$x_{t+1} = \ln F_{t+1} - \ln F_t = \mu_{t+1} + \varepsilon_{1,t+1} + \varepsilon_{2,t+1}. \quad (26)$$

We assume that both innovations have a conditional mean of zero and are contemporaneously independent. Furthermore, the first innovation is distributed:

$$\varepsilon_{1,t+1} = \sigma_{t+1} z_{t+1} \quad \text{where } z_{t+1} \sim \text{N}[0, 1]. \quad (27)$$

The second innovation is governed by a Poisson jump distribution with a time-varying conditional jump intensity $\lambda_t$. That is, the conditional probability of observing $n_{t+1} = j$ jumps between dates $t$ and $t + 1$ is

$$\text{Prob}[n_{t+1} = j|\Phi_t] = \frac{\exp(-\lambda_{t+1})\lambda_{t+1}^j}{j!} \quad \text{for } j = 1, 2, \ldots. \quad (28)$$

The jump innovation can then be expressed as

$$\varepsilon_{2,t+1} = \sum_{k=1}^{n_{t+1}} Y_{t+1,k} - \theta_{t+1}\lambda_{t+1}, \quad (29)$$

where $Y_{t+1,k}$ represents the size of the $k$th jump, if it occurs, drawn independently from a normal distribution with time-varying conditional mean $\theta_{t+1}$ and constant volatility $\delta$.

The conditional variance of returns is also divided into two components. First, we assume that the volatility of the normal innovation $\varepsilon_{1,t+1}$ follows a standard GARCH process:

$$\sigma_{t+1}^2 = \omega + \alpha \varepsilon_t^2 + \beta \sigma_t^2, \quad (30)$$

where $\varepsilon_t$ denotes the sum of the two return innovations $\varepsilon_{1,t} + \varepsilon_{2,t}$. This specification allows both return innovations to affect future volatility through the coefficient $\alpha$ and for volatility shocks to be persistent through the coefficient $\beta$.29 Second, the conditional volatility of the jump innovation $\varepsilon_{2,t+1}$ is governed by the jump process and is given by

$$\text{var}[\varepsilon_{2,t+1}|\Phi_t] = \lambda_{t+1}(\theta_{t+1}^2 + \delta^2). \quad (31)$$

The ultimate goal of our model is to capture changes in the physical distribution of futures returns in response to macroeconomic announcements. To accomplish this, we allow the macroeconomic announcements to affect the return dynamics in three distinct ways. Motivated by the observed counter-cyclical variation in the interest rate risk premium (e.g., Cochrane and Piazzesi, 2005), we let the mean log return $\mu_t$ change in response to news about economic prospects:

$$\mu_{t+1} = \mu_t + \mu_G S_{t+1} G_{t+1} + \mu_B S_{t+1} B_{t+1}, \quad (32)$$

where, following our notation above, $S_{t+1}$ is the standardized surprise of an announcement between dates $t$ and $t + 1$, $G_{t+1} = 1$ and $B_{t+1} = 0$ if the announcement is good news, and

---

29We examined several alternative specifications of the GARCH process, including ones with an asymmetric reaction of volatility to squared return innovations, with separate coefficients for the two squared return innovations, and with the expected number of jumps as a proxy for past jumps (as in Maheu and McCurdy, 2004). None of these richer specifications provides a statistical significant improvement in the fit of the model or qualitatively changes the results below.
$G_{t+1} = 0$ and $B_{t+1} = 1$ if the announcement is bad news for the Treasury market. This specification has two important features. The effect of the announcement surprise on the mean is made permanent through the random walk-like dependence of $\mu_{t+1}$ on $\mu_t$. Furthermore, the response of the conditional mean to economic news can be asymmetric depending on whether the news is good or bad.

The second and more prominent role of macroeconomic announcements is through the conditional jump intensity. Consistent with the empirical fact that the majority of extreme Treasury market moves have occurred on announcement days (e.g., Fleming and Remolona, 1999), we allow the jump intensity to increase on announcement days from $\lambda_0$ to $\lambda_0 + \lambda_1$. More concretely, we model the conditional jump intensity as

$$\lambda_{t+1} = \lambda_0 + \lambda_1 D_{t+1},$$

where $D_{t+1}$ is a dummy variable signaling whether an announcement is scheduled between dates $t$ and $t+1$. Notice that unless $\lambda_0 = 0$, which the model accommodates, jumps can occur on non-announcement days, as they do in the data.

Finally, we model the conditional mean of the jump size distribution on announcement days as a function of the realized announcement surprise:

$$y_{t+1} = y_G S_{t+1} G_{t+1} + y_B S_{t+1} B_{t+1}.$$  

(34)

The intuition underlying this specification is that the sign and magnitude of the immediate market reaction to the announcement depends on the news content. However, this link is far from deterministic in the data, which leads us to model the mean jump size, as opposed to the jump itself, as a function of the surprise. As for the mean log return $\mu_{t+1}$, we allow the effect of the announcement surprise on the mean jump size $\theta_{t+1}$ to be asymmetric. On non-announcement days, the mean jump size is zero.

We estimate this jump model by standard maximum likelihood using daily data on the underlying Treasury bond futures. The likelihood function of the model as well as the detailed results of the estimation are reported in Appendix B. To ensure that the model is reasonably well specified, we conduct a sequence of specification tests. Specifically, starting with the most restricted version of the model with constant mean log return and without jumps (i.e., $\mu_{t+1} = \mu$ and $\lambda_{t+1} = 0$), we use likelihood ratio tests to sequentially examine each restriction. We find that, for every model generalization, the statistical improvement is highly significant and thus the restrictions on the model are strongly rejected in favor of the most general version. Consistent with the likelihood ratio tests, each of the additional parameters is statistically different from zero and the coefficients $\mu_G$ and $\mu_B$ as well as $\theta_G$ and $\theta_B$ are statistically different from each other, respectively.

We conclude that our dynamic model provides a reasonable description of the data. More importantly, our results confirm that the macroeconomic announcements are important in shaping the physical distribution of log returns. The estimates of $\mu_G$ and $\mu_B$ are both significantly negative, confirming the interest rate risk premium drops (rises) in response to positive (negative) news about future economic prospects, leading to the observed counter-cyclical variation. Interestingly, the estimated $\mu_B$ is significantly more negative than $\mu_G$, both statistically and economically, which reveals that for our sample.

30The autoregressive coefficient in a mean-reverting specification is not significantly different than one.

31A mean jump size of zero on non-announcement days is consistent with the data. However, we also estimated a specification with an intercept $\theta_0$ to capture a non-zero mean jump size on non-announcement days. The intercept was not statistically significant and the estimates of $\theta_G$ and $\theta_B$ were very similar.
period the effect of good news for the economy, or bad news for the bond market, is stronger than for bad news for the economy, or good news for the bond market. In addition, the macroeconomic announcements play a leading role in determining the jump dynamics. We obtain a significantly positive estimate of $\lambda_1$, indicating that the jump intensity rises sharply on announcement days. Consistent with our intuition, the estimates of $\theta_G$ and $\theta_B$ are both significantly negative, suggesting that the size of the jump has a lower (higher) mean when the surprise in the release is positive (negative). As for the mean log return, the estimated $\theta_B$ is significantly more negative than $\theta_G$, indicating again asymmetries for bad versus good news.

The negative parameter estimates for $\theta$ are already an indication that positive surprises have a negative effect on the skewness of the PDF, in contrast to the opposite evidence for the SPD. However, as a more rigorous test, we simulate data from the estimated model to construct the model-implied PDF before and after each news release for horizons matching those of the option-implied SPD. The simulations involve 50,000 random paths of future returns that take into account the actual timing of macroeconomic releases as well as the standard normal distribution of the news surprises. We then compute the skewness and excess kurtosis of the simulated returns and regress the changes in these higher-order moments on the announcement surprises, using the same specification as in Eq. (25). Table 14 shows our results. We find that positive surprises in the CPI and NFP releases have a significantly negative effect on objective skewness. The magnitudes of the coefficients are remarkably similar to our findings in Table 13, but the explanatory power

<table>
<thead>
<tr>
<th>Table 14</th>
<th>Macroeconomic news and moments of the simulated PDF</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Skewness</td>
</tr>
<tr>
<td></td>
<td>$\alpha_k$</td>
</tr>
<tr>
<td>CPI</td>
<td>-0.004</td>
</tr>
<tr>
<td>NFP</td>
<td>-0.002</td>
</tr>
<tr>
<td>PPI</td>
<td>0.003</td>
</tr>
</tbody>
</table>

This table shows parameter estimates for the following regression:

$$
(s_{\text{post}} - s_{\text{pre}}) = \alpha_k + \beta_k S_{kt} + \sum_{h=1,k\neq h}^H \delta_h S_{ht} + \epsilon_{kt},
$$

$$
(ku_{\text{post}} - ku_{\text{pre}}) = \alpha_k + \beta_k S_{kt} + \sum_{h=1,k\neq h}^H \delta_h S_{ht} + \epsilon_{kt},
$$

where $s_{\text{post}}$ and $ku_{\text{post}}$ represent the skewness and kurtosis, respectively, of the distribution of returns simulated using the state-dependent jump model after the macroeconomic announcement released on day $t$. $s_{\text{pre}}$ and $ku_{\text{pre}}$ represent the skewness and kurtosis, respectively, of the distribution of returns simulated using the state-dependent jump model before the macroeconomic announcement released on day $t$.

***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Significance levels do not change if heteroscedasticity corrected standard errors are used.

32This intuition can be formally derived from the conditional moments implied by the model. Using the expression for the conditional skewness in Maheu and McCurdy (2004), their Eq. (20), it is easy to see that a lower jump size mean following positive surprises implies a more negative value for skewness.
is much higher. The coefficients on the surprises for the effect on the change in excess kurtosis are all positive, but none of them is significant and the explanatory power is very low.

The parametric model confirms the evidence obtained from the non-parametric and event regression approaches. The change in the higher-order moments of the physical PDF in response to the macroeconomic news is exactly opposite to the evidence presented for the risk-neutral SPD. The only way to reconcile these opposite changes of the physical and risk-neutral distributions is through a change in preferences in response to the macroeconomic news. We therefore turn to the task of estimating these changes in preferences.

5.3. Change in preferences

Comparing the changes in the sample moments of the PDF and in the option-implied moments of the SPD surrounding the most influential announcements allows us to draw indirect inferences about changes in preferences. However, with the help of the jump model for the physical dynamics of the underlying futures price specified and estimated above, we can actually recover an explicit estimate of risk-aversion for each date by comparing the model-implied PDF to the option-implied SPD, as in Aït-Sahalia and Lo (2000), Jackwerth (2000), and Rosenberg and Engle (2002), for example. Specifically, we obtain estimates of risk aversion toward each future state (a so-called risk aversion function) by comparing, state by state, the model-implied PDF to the option-implied SPD. We then relate the observed changes in estimated risk aversion from before to after each macroeconomic announcement to the content of the news release to document directly how preferences change in response to the macroeconomic announcements.

Aït-Sahalia and Lo (2000) and Jackwerth (2000) explain how to construct an estimate of the representative agent’s state-dependent relative risk aversion from estimates of the physical PDF and option-implied SPD. Specifically, an estimate of the Arrow–Pratt measure of relative risk aversion in state $x_T$ is given by

$$\hat{\Gamma}_i(x_T) = \frac{\hat{p}'_i(x_T)}{\hat{p}_i(x_T)} - \frac{\hat{q}'_i(x_T)}{\hat{q}_i(x_T)},$$

(35)

where $\hat{p}_i(x_T)$ and $\hat{p}'_i(x_T)$ are estimates of the physical PDF and its first derivative, $\hat{q}_i(x_T)$ and $\hat{q}'_i(x_T)$ are estimates of the option-implied SPD and its first derivative, and all terms are functions of the future terminal state $x_T$.

We implement this approach using the level and first-derivative of the Gram–Charlier estimates of the model-implied PDF (from the simulation approach described above) and option-implied SPD (from Section 4) before and after each macroeconomic announcement in our sample period. We then relate the estimated change in the risk aversion function to the information content of the news releases to understand how macroeconomic news alter the preferences of market participants. More specifically, we estimate for each announcement type and for a set of different future states the following regression:

$$\Gamma_i(x_T) - \Gamma_{i-1}(x_T) = \alpha_k + \beta_k S_k + \sum_{h=1}^{H} \delta_h S_h + e_k,$$

(36)
where $\Gamma_t(x_T) - \Gamma_{t-1}(x_T)$ represents the change in implied relative risk aversion for state $x_T$, $S_{kt}$ is again the standardized surprise of announcement $k$ at date $t$, and, as in previous regression specifications, the subscript $h$ refers to concurrent announcements.

Table 15 presents the regression results for the CPI, PPI, NFP, and CUR announcements. We estimate the relationship between changes in relative risk aversion and economic news for three future states: a left-tail state ($-1.5$ standard deviations), a central state (no change), and a right-tail state ($+1.5$ standard deviations). For all regressions, the intercepts are statistically insignificant and are thus not reported in the table. The slope coefficients are generally negative and slightly more significant for the tail states.

Consistent with our previous interpretation of the change in the option-implied SPD on announcement days, a positive (negative) surprise in the NFP release decreases (increases) implied risk aversion for all future states. For the central state, the information content of the announcement explains more than one-third of the variation in implied risk aversion on announcement days. Positive surprises in the CPI and CUR reduce risk aversion for future tail states, but leave it unchanged for future central states. The results for the PPI are somewhat weaker, which may be attributed to the relative timing of the CPI and PPI releases. Incidentally, the results for the PPI also provide indirect evidence that our findings are not a mechanical outcome of our methodology, but that the results depend on the observed pattern of announcements, released information, and asset prices.

The plots in Fig. 4 illustrate the regression results. For each announcement type, we plot the estimated change in implied risk aversion resulting from a one standard deviation positive news surprise. We also plot corresponding 95% confidence bands. Naturally, given the noisy estimates of the change in implied risk aversion obtained from the two density estimates, these confidence bands are relatively wide.

Overall, the results confirm the indirect evidence obtained from the changes in beliefs. Positive economic news is associated with a drop in risk aversion by jointly affecting the shapes of the SPD and PDF (often in opposite ways). This effect is qualitatively consistent

<table>
<thead>
<tr>
<th></th>
<th>$\Gamma(-1.5\sigma)$</th>
<th>$\Gamma(0)$</th>
<th>$\Gamma(+1.5\sigma)$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\beta$</td>
<td>$R^2$</td>
<td>$\beta$</td>
</tr>
<tr>
<td>CPI</td>
<td>$-0.065^{*}$</td>
<td>0.037</td>
<td>0.008</td>
</tr>
<tr>
<td>PPI</td>
<td>$-0.041$</td>
<td>0.111</td>
<td>$-0.019$</td>
</tr>
<tr>
<td>NFP</td>
<td>$-0.114^{***}$</td>
<td>0.128</td>
<td>$-0.109^{***}$</td>
</tr>
<tr>
<td>CUR</td>
<td>$-0.091^{*}$</td>
<td>0.128</td>
<td>$-0.012$</td>
</tr>
</tbody>
</table>

This table shows selected parameter estimates for the following regression:

$$
\Gamma_t(x_T) - \Gamma_{t-1}(x_T) = z_k + \beta_k S_k + \sum_{h=1}^H \delta_h S_h + e_k.
$$

$\Gamma_t(x_T)$ represents the implied risk aversion for a given future state $x_T$. $S$ denotes the standardized announcement surprise, $h$ enumerates announcements which are released concurrently with announcement $k$, $H$ is the total number of concurrent announcements, and $T$ is the maturity of the options.

$^{*}$, $^{**}$, and $^{***}$ denote statistical significance at the 1%, 5%, and 10% levels, respectively. $\sigma$ is the standard deviation implicit in the SPD for each announcement day.
with the intuition underlying habit formation models. The analysis also show that our conclusion is quantitatively plausible. The changes in risk aversion illustrated in Fig. 4 are far from extreme. For example, in order for risk aversion to change by 0.5, arguably a moderate change over the course of a business cycle, it requires a sequence of five one standard deviation surprises of the same sign.

We conclude that, at a minimum, the results in this section suggest that macroeconomic news not only affects beliefs about future economic states but also the preferences of market participants toward these states. The results point toward counter-cyclical variation in relative risk aversion, consistent with habit formation models.

6. Conclusion

We examined the effect of regularly scheduled macroeconomic announcements on the beliefs and preferences of participants in the U.S. Treasury market by comparing the
option-implied SPD of bond prices shortly before and after the announcements. At least two stylized facts emerged from our empirical analysis. First, the announcements reduce the uncertainty implicit in the second moment of the SPD, regardless of the content of the news. Second, the changes in higher-order moments of the SPD depend on whether the news is good or bad. Specifically, bad news for bonds, which tends to be good news for economic prospects, leads to a less negatively skewed and also less fat-tailed SPD.

We explore three alternative interpretations for our empirical results. We demonstrate that the changes in the higher-order moments of the SPD are unlikely to be explained by relative mispricing due to trading pressure in the options market. While there is some evidence of an effect of buying pressure on the shape of the SPD, this effect is not large enough to drive out or even to reduce the magnitude of our empirical findings. We then show that the changes in the higher-order moments of the SPD cannot be attributed to variation in the physical price process (changes in the higher-order moments of the PDF) either. In fact, the effect of the announcements on the higher-order moments of the PDF is often exactly opposite to the effect on the higher-order moments of the SPD. Instead, we show that the changes in the higher-order moments are consistent with time-varying risk aversion. Combining our estimates of the SPD with estimates of the PDF obtained from a jump model for the underlying futures price, we recover estimates of the implied risk aversion before and after the announcements. We then relate the changes in the implied risk aversion directly to the content of macroeconomic news and find that good news for economic prospects leads market participants to become less risk averse. We therefore conclude that macroeconomic announcements affect both preferences and beliefs.

We acknowledge that our interpretation of the empirical results hinges on the accurate measurement of trading pressure and on the proper modeling of the dynamics of the underlying returns. In fact, any mismeasurement in these respects would likely show up as a residual in what we interpret as a change in preferences. However, the consistency of our results across the various specifications and ways of examining the evidence gives us confidence that our interpretation is not completely ill-founded.

Appendix A. Option pricing formulas

A.1. Gram–Charlier density for futures options

Recall the Gram–Charlier density function (11) and its components:

$$f(\omega) = \phi(\omega) - \frac{\gamma_1 n}{3!} D^3 \phi(\omega) + \frac{\gamma_2 n}{4!} D^4 \phi(\omega),$$

(A.1)

with $\omega = (\chi_i - \mu_n)/\sigma_n$ and $\phi(\omega) = (2\pi)^{-1/2} \exp(-\omega^2/2)$. Under risk-neutrality, the call option price depends on the conditional distribution of the standardized log price change $\omega$:

$$\int_{\omega^*}^{\infty} (F_i e^{\mu_n + \sigma_n \omega} - K) f(\omega) d\omega = \int_{\omega^*}^{\infty} (F_i e^{\mu_n + \sigma_n \omega} - K) \phi(\omega) d\omega - \frac{\gamma_1 n}{3!} \int_{\omega^*}^{\infty} (F_i e^{\mu_n + \sigma_n \omega} - K) \phi''(\omega) d\omega$$
For the second term, we obtain by repeated integration by parts and using the fact that 
\[ \frac{\gamma_n}{3!} \int_{\omega}^{\infty} (F_t e^{\mu_n t + \gamma_n \omega} - K) \phi'''(\omega) \, d\omega \n = I_1 - \frac{\gamma_n}{3!} I_2 + \frac{\gamma_n}{4!} I_3, \] 
(A.2)

with \( \omega^* = (\log(K/F_t) - \mu_n)/\sigma_n \). The first term on the right side of this equality is the Black (1976) call option price capitalized to the end of the period:

\[ I_1 = F_t N(d) - KN(d - \sigma_n). \] 
(A.3)

For the second term, we obtain by repeated integration by parts and using the fact that \( \lim_{x \to -\infty} e^x \phi^{(n)}(x) = 0 \), the expression:

\[ I_2 = -\sigma_n K \phi(\omega^*)(\omega^* + \sigma_n) - \sigma_n^3 I_1 - \sigma_n^3 KN(-\omega^*). \] 
(A.4)

The third term is

\[ I_3 = \sigma_n K \phi(\omega^*)[(\omega^*)^2 - 1 + \omega^* \sigma_n + \sigma_n^2] + \sigma_n^4 I_1 + \sigma_n^4 KN(-\omega^*). \] 
(A.5)

The call option price is therefore:

\[ C_{nt} = e^{-rn} \left( I_1 - \frac{\gamma_n}{3!} I_2 + \frac{\gamma_n}{4!} I_3 \right) \]
\[ = e^{-rn} \left[ F_t N(d) - KN(d - \sigma_n) \right] \left( 1 + \frac{\gamma_n}{3!} \sigma_n^3 + \frac{\gamma_n}{4!} \sigma_n^4 \right) \]
\[ + \frac{\gamma_n}{3!} \left[ e^{-rn} \sigma_n K \phi(\omega^*)(\omega^* + \sigma_n) + e^{-rn} \sigma_n^3 KN(-\omega^*) \right] \]
\[ + \frac{\gamma_n}{4!} \left[ e^{-rn} \sigma_n K \phi(\omega^*)[(\omega^*)^2 - 1 + \omega^* \sigma_n + \sigma_n^2] + e^{-rn} \sigma_n^4 KN(-\omega^*) \right]. \] 
(A.6)

Finally, we obtain Eq. (12) from Eq. (A.6) by (i) substituting the identities \( \omega^* = \sigma_n - d \) and \( F_t \phi(d) = K \phi(d - \sigma_n) \) (which is equivalent to \( F_t \phi(d) = K \phi(\sigma_n - d) \)), (ii) applying the arbitrage condition \( \mu_n = -\sigma_n^2/2 - \sigma_n^3 \mu_n/3! - \sigma_n^4 \mu_n/2! \), and (iii) eliminating the terms involving \( \sigma_n^3 \) and \( \sigma_n^4 \), which are very small (see Backus et al., 1997).

Consider now a linear approximation of the Black (1976) formula as a function of implied volatility \( \nu_n \) around the point \( \nu_n = \sigma_n \):

\[ C_{nt} = e^{-rn} \left[ F_t N[d(\nu_n)] - KN[d(\nu_n) - \sigma_n] \right] \]
\[ \approx e^{-rn} \left[ F_t N[d(\sigma_n)] - KN[d(\sigma_n) - \sigma_n] \right] + F_t e^{-rn} \phi(d)(\nu - \sigma_n). \] 
(A.7)

If we equate the approximated call option price in Eq. (A.7) to the Gram–Charlier call option price in Eq. (12), we obtain the implied volatility function in Eq. (14).

We briefly repeat the same steps for a put option:

\[ \int_{-\infty}^{\omega^*} (K - F_t e^{\mu_n t + \sigma_n \omega}) \phi(\omega) \, d\omega = \int_{-\infty}^{\omega^*} (K - F_t e^{\mu_n t + \sigma_n \omega}) \phi(\omega) \, d\omega \]
\[ - \frac{\gamma_n}{3!} \int_{-\infty}^{\omega^*} (K - F_t e^{\mu_n t + \sigma_n \omega}) \phi''(\omega) \, d\omega \]
\[ + \frac{\gamma_n}{4!} \int_{-\infty}^{\omega^*} (K - F_t e^{\mu_n t + \sigma_n \omega}) \phi'''(\omega) \, d\omega \]
Gram–Charlier put option price in Eq. (A.11). The result is a linear approximation of the Black formula for the put option similar to Eq. (A.7), to the future terminal price and the strike price. Obtaining the intrinsic value for an option on a Eq. (12), and the intrinsic value of the option, that is the difference between the expected future terminal price and the strike price. Using the same logic as for the call option, we obtain:

\[ I_4 = KN(\sigma_n - d) - F_t N(-d), \]
\[ I_5 = \sigma_n K \phi(\omega^*)(-\omega^* - \sigma_n) + \sigma_n^3 KN(\omega^*), \]
\[ I_6 = -\sigma_n K \phi(\omega^*)(1 - (\omega^*)^2 - \sigma_n \omega^* - \sigma_n^2) - \sigma_n^4 KN(\omega^*). \]

(A.9)

The put price is then:

\[ P_{nt} = e^{-r_{nt}} I_4 - \frac{\gamma_{1n}}{3!} I_5 + \frac{\gamma_{2n}}{4!} I_6 \]
\[ = e^{-r_{nt}} [KN(\sigma_n - d) - F_t N(-d)] + \frac{\gamma_{1n}}{3!} [e^{-r_{nt}} \sigma_n K \phi(\omega^*)(-\omega^* - \sigma_n) + e^{-r_{nt}} \sigma_n^3 KN(\omega^*)] \]
\[ + \frac{\gamma_{2n}}{4!} [-e^{-r_{nt}} \sigma_n K \phi(\omega^*)(1 - (\omega^*)^2 - \sigma_n \omega^* - \sigma_n^2) - e^{-r_{nt}} \sigma_n^4 KN(\omega^*)]. \]

(A.10)

Applying the same substitutions as for the call option formula and observing again that \( \omega^* = \sigma_n - d \), we obtain the Gram–Charlier put option price:

\[ P_{nt} \approx e^{-r_{nt}} [KN(\sigma_n - d) - F_t N(-d)] + F_t e^{-r_{nt}} \phi(d) \sigma_n \frac{\gamma_{1n}}{3!} (-2\sigma_n + d) - \frac{\gamma_{2n}}{4!} (1 - d^2 + 3d\sigma_n - 3\sigma_n^2). \]

(A.11)

We obtain the put option-implied volatility function, analogous to Eq. (14), by equating a linear approximation of the Black formula for the put option similar to Eq. (A.7), to the Gram–Charlier put option price in Eq. (A.11). The result is

\[ \nu_n(d) \approx \sigma_n \left[ 1 + \frac{\gamma_{1n}}{3!} (-2\sigma_n + d) - \frac{\gamma_{2n}}{4!} (1 - d^2 + 3d\sigma_n - 3\sigma_n^2) \right]. \]

(A.12)

A.2. American-style option pricing with Gram–Charlier densities

We integrate the upper and lower bounds for the American-style call option price defined in Eq. (17) with respect to the risk neutral density function given by the Gram–Charlier expansion. The upper bound is just the undiscounted value of a European-style call option derived in Eq. (12):

\[ C_{nt}^u \approx F_t N(d) - KN(d - \sigma_n) \]
\[ + F_t \phi(d) \sigma_n \frac{\gamma_{1n}}{3!} (2\sigma_n - d) - \frac{\gamma_{2n}}{4!} (1 - d^2 + 2d\sigma_n - 2\sigma_n^2 - \sigma_n + d). \]

(A.13)

The lower bound is the maximum between the price of the European-style call option, Eq. (12), and the intrinsic value of the option, that is the difference between the expected future terminal price and the strike price. Obtaining the intrinsic value for an option on a
bond futures is straightforward:
\[
E_t[F_{t+n}] - K = \int_{-\infty}^{\infty} F_t f(\omega) \, d\omega - K
\]
\[
= \int_{-\infty}^{\infty} F_t(\phi(\omega)) - \frac{\gamma_{1n}}{3!} D^3 \phi(\omega) + \frac{\gamma_{2n}}{4!} D^4 \phi(\omega)) \, d\omega - K
\]
\[
= F_t - K,
\]
and hence we get
\[
C^d_{nt} = \max \left[ \begin{array}{c}
F_t - K, \
F_t e^{-rn_t} N(d) - Ke^{-rn_t} N(d - \sigma_n) \
+ F_t e^{-rn_t} \phi(d) \sigma_n \left[ \frac{\gamma_{1n}}{3!}(2\sigma_n - d) - \frac{\gamma_{2n}}{4!}(1 - d^2 + 2d\sigma_n - 2\sigma_n^2 - \sigma_n + d) \right] \\
- \frac{\gamma_{2n}}{4!}(1 - d^2 + 2d\sigma_n - 2\sigma_n^2 - \sigma_n + d)
\end{array} \right].
\]

The formula for the Gram–Charlier American-style call price is the weighted average of the upper and lower bound:
\[
C^n_{nt} \approx \lambda_n C^u_{nt}(F_t, K, r_{nt}, d; \sigma_n, \gamma_{1n}, \gamma_{2n})
\]
\[
+ (1 - \lambda_n) C^d_{nt}(F_t, K, r_{nt}, d; \sigma_n, \gamma_{1n}, \gamma_{2n})
\]
\[
= \lambda_n \left[F_t N(d) - KN(d - \sigma_n) + F_t e^{-rn_t} \phi(d) \sigma_n \left[ \frac{\gamma_{1n}}{3!}(2\sigma_n - d) - \frac{\gamma_{2n}}{4!}(1 - d^2 + 2d\sigma_n - 2\sigma_n^2 - \sigma_n + d) \right] \right]
\]
\[
+ (1 - \lambda_n) \max \left[ +F_t e^{-rn_t} \phi(d) \sigma_n \left[ \frac{\gamma_{1n}}{3!}(2\sigma_n - d) - \frac{\gamma_{2n}}{4!}(1 - d^2 + 2d\sigma_n - 2\sigma_n^2 - \sigma_n + d) \right], F_t - K \right].
\]

In the empirical implementation, we replace the max operator with a logistic approximation, to help in the non-linear optimization:
\[
\logit \max[x, y] = \frac{1}{1 + \exp[-8(x - y)]},
\]
\[
\max[x, y] \approx \logit \max[x, y] x + (1 - \logit \max[x, y]) y.
\]

Melick and Thomas (1997), use a similar technique.

The American-style Gram–Charlier put option price can be obtained by analogous steps.

Appendix B. State-dependent jump model estimates

Conditional on \( j \) jumps occurring, our model implies the following distribution of log returns:
\[
f(x_{t+1} | n_{t+1} = j, \Phi_t) = \frac{1}{\sqrt{2\pi(\sigma_{t+1}^2 + j\delta^2)}} \exp \left( -\frac{(x_{t+1} - \mu_{t+1} + \theta_{t+1} \lambda_{t+1} - \theta_{t+1} j)^2}{2(\sigma_{t+1}^2 + j\delta^2)} \right).
\]
The unconditional distribution is then obtained by forming an expectation over the number of jumps for each date:

\[
f(x_{t+1}|\Phi_t) = \sum_{j=0}^{\infty} f(x_{t+1}|n_{t+1} = j, \Phi_t) \text{Prob}(n_{t+1} = j|\Phi_t). \tag{B.2}
\]

Finally, the likelihood function is the product of the T unconditional log return distributions. Note that the likelihood function involves infinite summations over the number of possible jumps. In practice, we truncate the summations at 20. It turns out that, for our parameter estimates, the conditional Poisson distribution has zero probability for more than 10 jumps.

We maximize the likelihood function using daily log returns on the Treasury bond futures for our sample period 1995–1999. We begin with the most restricted version of the model and then sequentially relax the restrictions to ultimately obtain an estimate of the most general specification. In particular, we estimate (1) a model with a constant mean log return and without jumps; (2) a model with a constant mean log return and a constant jump intensity; (3) a model with a constant mean log return and a jump intensity that depends on macroeconomic releases; (4) a model with a constant mean log return and both the jump intensity and the jump size mean that depend on macroeconomic releases; (5) the most general model specification. For every model generalization, we test whether the restrictions are rejected in favor of the more general version using a likelihood ratio (LR) test.

The parameter estimates of the various model specifications and the corresponding LR tests are reported in the table below.

<table>
<thead>
<tr>
<th>Model (1) restrictions:</th>
<th>Model (2) restrictions:</th>
<th>Model (3) restrictions:</th>
<th>Model (4) restrictions:</th>
<th>Model (5)</th>
</tr>
</thead>
<tbody>
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<td>( \mu_t = \mu )</td>
<td>( \mu_t = \mu )</td>
<td>( \mu_t = \mu )</td>
<td></td>
</tr>
<tr>
<td>( \lambda_t = 0 )</td>
<td>( \lambda_t = \lambda_0 )</td>
<td>( \theta_t = 0 )</td>
<td>( \theta_t = 0 )</td>
<td></td>
</tr>
</tbody>
</table>

\[
\begin{array}{cccccc}
\omega & 0.0000*** & 0.0006*** & 0.0000*** & 0.0000*** & 0.0000*** \\
\alpha & 0.0214*** & 0.0131*** & 0.0134*** & 0.0135*** & 0.0149*** \\
\beta & 0.9570*** & 0.9786*** & 0.9761*** & 0.9580*** & 0.9576*** \\
\mu & 0.0000     & 0.0001     & 0.0001     & 0.0002     & –         \\
\mu_G & –1.00e−04*** &            &            &            &           \\
\mu_B & 1.36e−04*** &            &            &            &           \\
\lambda_0 & 0.2594*** & 0.2889*    & 0.3962*** & 0.4628*** &           \\
\lambda_1 & 0.8159**  & 0.2786***  & 0.2530*** &            &           \\
\theta_G & –0.0045*** & –0.0041*** &            &            &           \\
\theta_B & –0.0070*** & –0.0074*** &            &            &           \\
\delta & 0.0064*** & 0.0054***  & 0.0049*** & 0.0048*** &           \\
\log L & 4,741.84   & 4,773.78   & 4,787.19   & 4,801.02   & 4,804.43   \\
p-value & –         & 8.70e−14    & 2.23e−7    & 1.45e−7    & 0.009      \\
\end{array}
\]

***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.
References