A Market Measure of Dispersion in Inflation Expectations

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Abstract

An issue of interest for financial market participants and policy institutions such as central banks is the degree to which movements in inflation options markets reflect investor sentiment. This paper examines how the dispersion of options-implied densities for consumer price inflation in the U.S. interacts with economic uncertainty across the history of the inflation cap and floor markets. We adapt the nonparametric estimation method of Stutzer (1996) to derive forward probabilities from the empirical distribution of historical U.S. inflation. We estimate a regime-switching model for dispersion in the forward distribution, and link the transitions in regime to perceived changes in monetary policy and sources of major economic uncertainty. We connect the dispersion in inflation expectations to newly developed measures of uncertainty [Jurado, Ludvigson, and Ng (2015), Baker, Bloom, and Davis (2016)]. Our analysis demonstrates substantial asymmetry in the behavior of inflation expectations: dispersion in the forward measure derived from inflation caps is associated with statements by the Board of Governors of the Federal Reserve or its Chair, while changes in dispersion due to inflation floors are typically attributable to structural economic performance (e.g., labor markets, oil prices). Innovations to financial and macroeconomic uncertainty increase the dispersion in inflation floors, while decreasing the dispersion in inflation caps.

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1 Introduction

The market for direct hedges of the inflation rate has matured since its inception, with $1.2 trillion worth of treasury inflation protected securities (TIPS) issued in 2017\(^1\) and over $2 billion of notional principle cleared daily in the inflation swap market.\(^2\) Alongside the TIPS and swap markets, cap and floor contracts have been written over-the-counter since late 2009. A question of continuing interest to financial market participants and central banks is the extent to which activity in the market for inflation options provides information with respect to investor beliefs about future changes in the price level.

This paper examines the dynamics of market uncertainty about future inflation implicit in inflation caps and floors. Methods for extracting forward probability densities from option prices have been established at least since Ross (1976) and Breeden and Litzenberger (1978). While it is well known that these densities are estimated under an assumption of risk neutrality and do not reflect market participants’ beliefs about the odds of future outcomes, we adopt the stance that useful information about investor uncertainty may be contained in the dispersion of the distribution; our object of interest is the time variation in the dispersion of the forward inflation distributions, where we measure dispersion as the difference between the 25th and 75th percentiles.\(^3\) While we will not be able to answer questions about the magnitude of inflation expectations (e.g., What is the market-perceived probability that inflation will be higher than 2% in one year?), we will be able to identify time variation in uncertainty (e.g., Relative to yesterday or last week or last year, is the market more or less certain that inflation will be higher than 2% in one year?). We show that this dispersion measure is well grounded in theory (Section 4), displays substantial time variation, and is strongly correlated with economic events and policy announcements.

We analyze daily Bloomberg composite prices for zero-coupon caps and floors over the period starting in January 2012 until May 2017. We argue the substantial increase in volume over the initial years of our sample period is sufficient for identifying changes in investor sentiment (Section 2). To back out implied probability densities, we use the “canonical valuation” method introduced by Buchen and Kelly (1996) and Stutzer (1996). This approach finds the forward densities that correctly price the inflation option (no arbitrage) and are the closest to the empirical distribution of inflation, where “closest” is measured according to the Kullback-Leibler Information Criterion (KLIC). The advantage of the canonical method for our purposes here is that we can isolate the density associated with specific options; that is, we do not need the entire set of option prices to form a forward distribution. This allows us to examine dispersion measures associated with inflation caps and floors separately. Section 3 also compares the canonical approach to the more common “derivative method” using the procedure of Aït-Sahalia and Duarte (2003).

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\(^1\)See Kowara (2017).
\(^2\)Daily volume reported by LCH: [https://www.lch.com/services/swapclear/volumes](https://www.lch.com/services/swapclear/volumes)
\(^3\)We also adopt the stance that the stringent restrictions necessary for forward and risk-neutral distributions to be unique (e.g., complete markets) do not hold. However, we contend and we show that forward densities contain information and react to news about changes in inflation expectations in statistically significant ways, and are therefore interesting objects worthy of study.
Section 4 contains our main results. We find that dispersion in the forward inflation distribution exhibits clear breaks between regimes following major economic developments. Transitions in dispersion typically take place over a period of one day up to a week, and display high inertia. The high stability and rapid transitions allow us to sidestep the critique of Fair (2002), and we find that breaks are typically accompanied by either statements from the Federal Reserve and its Chairperson, or a shift in uncertainty around a major economic events such as the European debt crisis, US debt-ceiling crises, and the Greek bailouts. In particular, dispersion in the forward measure due to inflation caps is associated with statements by the Board of Governors of the Federal Reserve or its Chair, while changes in dispersion due to inflation floors are typically attributable to structural economic performance (e.g., labor markets, oil prices).

The asymmetric in inflation caps and floors is our primary finding and can be attributed to the fact that our sample period (2012–2017) was dominated by deflationary, as opposed to inflationary, concerns as realized inflation was well below the stated 2% target of the Federal Reserve. Any statistic that portended structural weakness in the economy (e.g., a weak employment report) almost always caused an increase in the dispersion of inflation floors. While inflationary uncertainty was typically preceded by announcements by the Federal Reserve. Using a regime switching model to distinguish periods of high and low dispersion, Section 4.2 conducts a narrative view of changes in regime and we count only three exceptions to this stylized fact over the entire sample period.

Section 4.3 documents that our measures of expected inflation dispersion are significantly predicted by changes in recently developed metrics of uncertainty. Specifically, we regress dispersion on the financial and macroeconomic uncertainty of Jurado, Ludvigson, and Ng (2015) and policy uncertainty of Baker, Bloom, and Davis (2016). All measures of uncertainty are significant predictors of dispersion but the uncertainty of Jurado, Ludvigson, and Ng (2015) enters negatively for dispersion due to inflation caps and positively for floors. Thus, an increase in financial uncertainty decreases (increases) the dispersion in caps (floors). This asymmetric response is consistent with the deflationary concerns revealed in our regime-switching results, and explains why innovations to financial time series, on average, consolidated expectations in inflation caps while increasing dispersion in inflation floors.

1.1 Connections to the Literature We examine derivative data from inflation floors and caps, as opposed to the majority of the work in the inflation derivatives literature that attempts to back out expectations from Treasury Inflation-Protected Securities (TIPS). Absent market imperfections, the yield of an inflation protected treasury will be lower than that on a vanilla treasury by an amount equal to the expected inflation rate. The literature has achieved various levels of success in being able to back-out accurate forecasts of inflation with TIPS, with the primary concern being liquidity [see, Sack and Elsasser (2004), Fleming and Krishnan (2004), Gurkaynak, Sack, and Wright (2010), Grishchenko and Huang (2013), Fleckenstein, Longstaff, and Lustig (2014), Grishchenko, Vanden, and Zhang (2016), Andreasen, Christensen, and Riddell (2018)]. Of course liquidity is a concern for our data as well. We discuss this issue in the following section.
Wright (2013) also examine forward distributions for inflation implicit in cap and floor prices early in the market’s lifetime. Since their study, the volume for inflation caps and floors has quadrupled and thus worthy of additional study. More importantly, and unlike Kitsul and Wright (2013), we systematize the event analysis to econometrically pinpoint when and why events transmitted through to investor uncertainty via a narrative view of regime change.

Our methodological approach differs from the standard literature along two dimensions. First, a majority of the literature employs a “derivative method” based on the well known result that the second derivative of the price of a call option with respect to the strike delivers the risk-neutral distribution [Breeden and Litzenberger (1978), Ross (1976)]. We adapt the method of Buchen and Kelly (1996) and Stutzer (1996), which minimizes the Kullback-Leibler Information Criterion (KLIC) metric, to estimate the market forward distributions. We argue that this method is a relatively efficient and flexible procedure, and can closely replicate the distributions provided by the derivative method of Aït-Sahalia and Duarte (2003). Second, our paper does not attempt to recover expectations but instead focuses on connections between dispersion in forward distributions and underlying economic uncertainty. A simulation exercise in Section 4 demonstrates that if changes in risk premia amount primarily to time variation in the location parameter, our dispersion metric will correlate strongly across the physical and forward probabilities. Our focus on dispersion is empirically motivated by substantial time variation in tails of implied distributions and the associated pricing kernels found in our data. In addition, our empirical application establishes a strong case for informational content of the difference between the 25th and 75th percentiles of forward distributions for inflation, which are constrained to correctly price individual as well as multiple options. That there is something to learn about inflation expectations from these data relies on the underlying assumption that option prices contain information about extreme events relative to macroeconomic data [Backus, Chernov, and Martin (2011)].

Our primary results complement Christensen, Lopez, and Rudebusch (2015), Grishchenko, Vanden, and Zhang (2016), Fleckenstein, Longstaff, and Lustig (2017), and Gimeno and Ibanez (2018). Christensen, Lopez, and Rudebusch (2015) employ a term structure model with stochastic volatility to back out deflation protection embedded in TIPS. They show that the model accurately reflected the deflationary concerns prior to (and throughout) the financial crisis. The option value is shown to closely follow overall market uncertainty measures (e.g. VIX). Grishchenko, Vanden, and Zhang (2016) show that the information content contained in TIPS concerning future inflation remains statistically significant even when explanatory variables include lagged inflation, gold, crude oil, the VIX, liquidity, forecasting surveys, and the yield spread between nominal Treasuries and TIPS. Fleckenstein, Longstaff, and Lustig (2017) examine the relationship between deflation risk and financial and macroeconomic tail risks found in inflation swaps and options. They find that deflation risk varies with the horizon; short-term deflation risk correlates strongly with measures of risk in the financial markets such as Libor spreads, swap spreads, stock returns, and stock market volatility; intermediate-term deflation risk correlates with structural factors such as the risk of sovereign defaults in the Eurozone; and long-term deflation risk is driven primarily by macroeconomic fac-
tors. Gimeno and Ibanez (2018) focus on how risk-neutral densities, backed out from the forward 5-on-5 year inflation rate, respond to ECB’s decisions and communication since 2009. Their main finding is that these distributions have significant time-variation. Like these papers, we show the informational content embedded in the inflation-derivatives market is substantial. We also demonstrate a tight connection between our dispersion measure and financial, macroeconomic, and policy measures of uncertainty. Unlike these papers, we show [i] how inflation caps and floors respond differently to uncertainty measures and macroeconomic factors; [ii] we provide a narrative view of regime change in dispersion that is consistent with a compelling economic narrative.

2 Inflation Caps and Floors

A zero-coupon inflation cap of strike rate $k$ and maturity $h$ written at time $t$ is a contract in which the seller agrees to pay the buyer the difference between actual average annualized inflation rate (headline consumer price index, not seasonally adjusted) over the period $t$ to $t + h$ ($\bar{\pi}_{t,t+h}$) and the strike rate in the event that this difference is positive, $\max((1 + \bar{\pi}_{t,t+h})^h - (1 + k)^h, 0)$. In exchange for the contract, the seller receives a payment of $V_t(k, h)$ at time $t$, which is a function of the strike rate and time to maturity. An inflation floor is analogous, with the payment being $\max((1 + k)^h - (1 + \bar{\pi}_{t,t+h})^h, 0)$.

Our analysis considers daily prices for zero-coupon caps and floors over the period starting in October 2009 until May 2017. The data are Bloomberg composite prices (CMPN) which consist of averages of market quotes from various banks and brokers (e.g., Bank of America, Merrill Lynch, and BGC), with outliers removed. Figure 1 shows the substantial increase in volume over the initial years of our sample period, reaching 50bn in 2010 (up from 13bn in 2009 and 1bn in 2005). As a percentage of the overall US inflation derivative market based on interdealer volumes, inflation options grew from less than 10% of the market in 2009 to roughly 30% in 2011, exceeding the TIPS ASW market (BGC Partners). Fleming and Sporn (2013) argue that “the U.S. inflation swap market appears reasonably liquid and transparent despite the market’s over-the-counter nature and modest activity.” While the option market is smaller than the swap market studied by Fleming and Sporn, many of the same participants are active in both markets. Firms that offer inflation protection typically have inflation-adjusted inflows (e.g., utilities, real estate developers, retailers). Conversely, firms and entities that buy inflation protection have inflation-linked outflows (e.g., pension funds, inflation mutual funds). Both types of firms are active traders in the options, swaps, and TIPS markets, Kerkhof (2005). Moreover, as argued by Kitsul and Wright (2013), while the notional amount traded in these option markets is relatively small compared to, for example, the market for U.S. Treasuries, the amounts are “still big enough to presumably reflect the beliefs of traders in this market, and far bigger than those in experimental games and in prediction markets” where studies have shown prices are informative.

\footnote{We do not extend the data beyond 2017 due to liquidity concerns. The period of our analysis contains several strike prices and volume was increasing, indicating a relatively liquid market. These phenomena reversed course in 2018, which explains our end-point of 2017.}
For a given date in our sample, data will potentially contain market prices for one year caps with strikes $-1\%$, $-0.5\%$, ..., $6\%$. Likewise, the possible strikes for traded one year floors could range from $-3\%$ to $5\%$ in $0.5\%$ increments. For nearly all dates in our sample, there are observed prices for one year caps of strikes between $1\%$ and $3.5\%$, and for inflation floors between $-2\%$ and $3\%$. Price data for one year option strikes beyond this range are available only relatively early in the sample period, indicating an overall trend towards consolidation in the market around the middle of the initial band.

Figure 2 plots the maximum and minimum strikes which are available from late 2009 through 2016, along with the seasonally adjusted, year-over-year percentage change in the CPI (the base asset in the option contracts). Note that the inflation series falls below the available strike band for caps in late 2014 and stays outside this band for the following year and a half. The analogous plot for inflation floors is shown in Figure 2b. Generally the market for these options appears to be broader, with contracts being available across the range from $-2\%$ to $3\%$ for most of the sample period. On the other hand, the availability of floor contracts has been relatively more volatile than that of caps since 2014, with only strike rates of $0\%$ available on multiple days near the start of the 2015 deflationary episode.

3 Methodology

We now describe and compare a pair of nonparametric methods for extracting implied probability distributions for inflation from option strike-price curves. We begin by outlining the procedure of Aït-Sahalia and Duarte (2003) which was applied to the case of inflation caps and floors in Kitsul and Wright (2013). We then contrast this method with that of Stutzer (1996) which we apply in the next section.

3.1 Derivative Method

This method is based on the well known result that the second derivative of the price of a call option with respect to the strike delivers the risk-neutral distribution [Breeden and Litzenberger (1978), Ross (1976)]. To that end, let $V_t$ denote the time $t$ price of an
Figure 2: Maximum and minimum strike rates for traded inflation caps (a) and floors (b), along with inflation as calculated from CPI.

option linked to the annual inflation rate $\pi_{t,t+h}$ from time $t$ to time $t+h$ measured in years. Let $p^*$ denote the time $t$ forward probability density for $\pi_{t,t+h}$. Then $V_t$ satisfies the pricing formula

$$V_t = B_{t,t+h} \int_{-\infty}^{\infty} p^*(\pi) V_{t+h} \, d\pi$$

(1)

where we follow Kitsul and Wright (2013) in discounting by an $h$ year zero coupon bond $B_{t,t+h}$ taken from Gurkaynak, Sack, and Wright (2007). In particular, for an inflation cap of strike rate $k$ and a one-year horizon, the value at time $t+1$ is the expiry payoff, giving

$$V_t = B_{t,t+1} \int_{k}^{\infty} p(\pi) \max[(1 + \pi) - (1 + k), 0] \, d\pi$$

$$= B_{t,t+1} \int_{k}^{\infty} p(\pi) [(1 + \pi) - (1 + k)] \, d\pi$$

(2)

Differentiating twice with respect to $k$, we obtain

$$\frac{\partial V_t}{\partial k} = -B_{t,t+h} \int_{k}^{\infty} p(\pi) \, d\pi$$

$$\frac{\partial^2 V_t}{\partial k^2} = B_{t,t+h} p(k)$$

Hence, given prices for inflation caps with several different strikes on a given date, we can back out an implied forward cumulative distribution $P$ and the corresponding density $p$ at values of annualized inflation in the range covered by these strikes by using the prices to estimate the above
derivatives and setting

\[ P(k) = 1 + \frac{1}{h(1 + k)^{h-1}B_{t,t+h}} \frac{\partial V_t}{\partial k} \tag{3} \]

\[ p(k) = \frac{(h - 1) \int_k^\infty p(\pi) d\pi}{(1 + k)^h} \frac{\partial^2 V_t}{\partial k^2} \tag{4} \]

An analogous argument allows us to derive these objects from a collection of inflation floor prices.\(^6\)

As observed in Aït-Sahalia and Duarte (2003), the requirements

\[ 0 \leq P(k) \leq 1, \quad p(k) \geq 0 \tag{5} \]

combine with equations (3) and (4) to place sign and magnitude restrictions on the derivatives of the strike price curves. Financial market imperfections may result in these conditions being violated, with the consequence that the derived probability functions will be mathematically insensible. To address this issue, Aït-Sahalia and Duarte (2003) employ the algorithm of Dykstra (1983) to provide a method for minimizing the squared distance between the observed curves and the set of those which obey the constraints.

Since we only have prices \( \{V_t(k_i)\} \) for a finite selection of strikes \( k_i, \ i = 1, ..., n \) at each date, obtaining the derivatives in (3) and (4) is accomplished through local polynomial smoothing. This method, proposed in Aït-Sahalia and Duarte (2003) and applied to inflation options in Kitsul and Wright (2013), constructs Taylor coefficients for the price-strike curve of the options at each possible strike value by weighted least squares. In particular, for each strike \( k \) the objective of this problem is to choose coefficients \( \beta_j(k) \) to minimize

\[
\sum_{i=1}^{n} \left[ V_t(k_i) - \sum_{j=0}^{p} \beta_j(k) (k_i - k)^j \right]^2 K_w(k_i - k) \tag{6}
\]

where \( K_w \) is the weighting function. The derivatives of interest can subsequently be determined at each \( k \) from the estimated \( \beta_j(k) \).

The main advantage of the above procedure is that it derives empirical distributions directly from the underlying economic theory using all available information. There are two main disadvantages. First, the method requires selection of a bandwidth parameter \( b \) for the weighting function \( K_w \). While the literature proposes using an estimate of the asymptotic optimum (see Aït-Sahalia

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\(^6\)With horizons longer than one year, the expressions are more complicated, namely

\[
\frac{\partial V_t}{\partial k} = -h(1 + k)^{h-1}B_{t,t+h} \int_k^\infty p(\pi) d\pi
\]

and

\[
\frac{\partial V_t}{\partial k} = -h(h - 1)(1 + k)^{h-2}B_{t,t+h} \int_k^\infty p(\pi) d\pi + h(1 + k)^{h-1}B_{t,t+h}p(k)
\]
and Duarte (2003) and Fan and Gijbels (1996)), in practice one must take care to not under-smooth or over-smooth. Second, this method will also provide poor estimates of the forward distribution outside of the strike rates which were traded on a given day.

The former difficulty becomes an issue of practical importance in the latter half of our option price sample. Specifically, the number of strike rates being traded declines, so that estimated asymptotically optimal bandwidth does not sufficiently smooth between neighboring observations, resulting in severely multimodal estimated distributions or a break down of the method altogether. To adjust the bandwidth away from the theoretical optimum in a parsimonious way in our application below, we take the minimum bandwidth for which the distribution is unimodal.

To address the latter difficulty, we incorporate data from both cap and floor options on each date in order to construct a distribution over the widest range of inflation rates possible. Specifically, on a typical date there is price data available for caps of strikes $k_1^C, \ldots, k_m^C$ and floors of strikes $k_1^F, \ldots, k_n^F$, where $k_1^F < k_1^C$ and $k_n^F < k_m^C$, but $k_n^F > k_1^C$. In particular, the last inequality implies that there are strike rates for which prices of both a cap and a floor are available, say $k_1^{CF}, \ldots, k_\ell^{CF}$.

Since the implied forward distributions need not agree in the overlapping region, we compute the distribution function $F(k)$ at such a point by linearly interpolating as follows. Denoting the floor-implied distribution function as $G(k)$ and the cap-implied distribution as $H(k)$, we set $\delta = (k - k_1^{CF})/(k_\ell^{CF} - k_1^{CF})$ and

$$F(k) = (1 - \delta)G(k) + \delta H(k) \quad (7)$$

The strike-price curve estimated by applying constrained least squares and smoothing to five year inflation floors with strikes between -3% and 3% is shown in Figure 3. In contrast to the theory described above, the observed strike price curve on this date displays a non-convexity at strike rate -0.5%. This feature is smoothed over in the constrained least squares nearest neighbor, while the smoothed curve sits noticeably above the observed prices between strikes of 0% to 2.5%.

3.2 Canoninal Valuation Consider the empirical distribution $(\pi, p) = \{(\pi_i, p_i)\}_{i=1}^N$ of $h$ year annualized inflation $\pi_{t,t+h}$. That is, $\pi$ contains observations of $h$ year annualized inflation over the sample period while $p_i = 1/N$ for every $i$. Buchen and Kelly (1996) and Stutzer (1996) provide a simple method for estimating the risk-neutral distribution $(\pi, p^*)$ from $(\pi, p)$. Specifically, this method minimizes the Kullback-Leibler Information Criterion (KLIC) metric

$$I(p, p^*) = \sum_{i=1}^N p_i^* \log(p_i^* / p_i) \quad (8)$$

\footnote{Information theoretical approaches to statistics and econometrics have a long history (see Kullback (1968) and Judge and Mittlehammer (2012)). Generalizations of the method of Stutzer (1996) and their interpretation appear in Haley and Walker (2010) and Haley, Mcgee, and Walker (2013).}
subject to the constraints

\[ p^*_i \geq 0, \quad i = 1, ..., N \]
\[ 1 = p^*_1 + ... + p^*_N \]
\[ V_t = B_{t,t+h} \sum_{i=1}^{N} p^*_i V_{i,t+h} \]

where \( V_t \) denotes the time \( t \) value of an option expiring in \( h \) years, \( V_{i,t+h} \) denotes its expiration value if annualized inflation over the option’s lifetime is \( \pi_i \), and \( B_{t,t+h} \) denotes the price of an \( h \) year bond at time \( t \). Hence the third constraint stipulates that the probabilities \( \mathbf{p}^* \) should correctly price a particular option on a particular date. This constraint can be tightened to include multiple options.

When applied with a uniform distribution across \( N \) observed outcomes, as occurs for an empirical distribution, the KLIC minimization is equivalent to maximizing the Shannon entropy of the estimated forward distribution, given by

\[ -\sum_{i=1}^{N} p^*_i \log(p^*_i) \] (9)

The solution of the Shannon entropy constrained maximization problem is known to give a multi-
variante canonical distribution

\[
p_i^* = \frac{\exp \left( \sum_{m=1}^{M} \lambda^*_m V_{i,t+h}^{(m)} B_{t,t+h} \right)}{\sum_{i=1}^{N} \exp \left( \sum_{m=1}^{M} \lambda^*_m V_{i,t+h}^{(m)} B_{t,t+h} \right)}
\]

(10)
in the case of \( M \) option pricing constraints where the corresponding options have time \( t + h \) payoff \( V_{i,t+h}^{(m)} \) for each prevailing inflation state \( i = 1, ..., N \). Here the Lagrange multipliers \( \lambda^* = (\lambda^*_1, ..., \lambda^*_M) \) are given as solutions to the unconstrained minimization problem

\[
\lambda^* = \arg \min_{\lambda} \sum_{i=1}^{N} \exp \left( \sum_{m=1}^{M} \lambda^*_m \left[ V_{i,t+h}^{(m)} B_{t,t+h} - V_i^{(m)} \right] \right)
\]

(11)

Given \( h \) year treasury yields and prices for inflation derivatives with maturities of \( h \) years on a given date, we can therefore numerically solve (11). Once the Lagrange multipliers are found, the estimated forward probabilities are obtained by substitution into (10). The minimization in (11) is tractable for a low number \( M \) of options, but will face the curse of dimensionality as the number of constraints is increased.

The advantages to using this method are the simplicity of implementation and its ability to place reasonable forward weights on the entire range of historical inflation outcomes. Disadvantages of Stutzer (1996)’s method are that it will necessarily place zero weight on inflation rates outside the range of values in the empirical distribution, as well as the difficulty of scaling the number of option prices which are correctly valued by the estimated forward distribution.

3.3 COMPARISON OF METHODOLOGIES  
Figure 4 compares the forward cumulative distribution functions obtained from the Canonical and Derivative methodologies. Figure 4a and 4b plot the maximum and mean difference in the forward CDFs. We used the price of a one year cap with strikes of 1% and 2%, and a one year floor with a strike of 1% as constraints in the Canonical valuation. There are no clear trends in the figures, nor are there a significant number of outliers.

Figures 4c and 4d plot the one-year-ahead inflation on January 15, 2014 and January 13, 2015, obtained using each of the two methods described above for inflation caps and floors. The empirical distribution for post-1985 inflation, which is used in the application of Stutzer (1996)’s method, is plotted as well. These dates are of particular interest because they represent a period in which the one-year-ahead forward rate is roughly consistent with current levels of inflation (January 15, 2014) and a date in which market beliefs suggest substantial deviation from current inflation (January 13, 2015). The figure shows that the approaches have substantial overlap during both periods (with the exception of the far left tail for January 13, 2015). We take this as prima facie evidence that our methodologies are broadly consistent, with additional evidence provided below.
4 Modeling Dispersion

Our object of interest is the time variation in the dispersion of the forward inflation distributions, where we measure dispersion as the difference between the 25th and 75th percentiles of the distribution. Our interest in this measure is guided by several observations.

First, model implied pricing kernels estimated using data from floors and caps display substantial time variation in tail behavior. Using the approach of Rosenberg and Engle (2002), Kitsul and Wright (2013) specify the pricing kernel as a nonlinear function of average annual inflation over the next $h$ years, $\pi(h)$

$$M_t(\pi(h)) = \theta_0 T_0(\pi(h)) + \theta_1 T_1(\pi(h)) + \theta_2 T_2(\pi(h)) + \theta_3 T_3(\pi(h))$$

where $T_j(\cdot)$ are Chebyshev polynomials defined over the range of annual inflation (-2% to 6%) and
the vector of parameters $\theta_t$ are estimated by minimizing the distance between the actual price of the inflation floor or cap and the model-implied price. Figure 5 is taken from Kitsul and Wright (2013) and plots the empirical pricing kernels for various maturities and years. The distributions are all centered around 1.5% to 2% but the behavior in the tails of the distributions [$< 0\%; > 2.5\%$] show substantial variation with time.

Figure 5: Empirical pricing kernels of Kitsul and Wright (2013)

Second, and most importantly, we demonstrate the changes in tail behavior are not due to noise or numerical error; Sections 4.1–4.2 show that the changes in dispersion directly correlate to news concerning inflation (e.g., economic activity, Fed policy statements, etc.). Our dispersion data are well estimated by a regime switching model, where the change in regime aligns with monetary policy innovations or other substantial economic events. Financial and policy uncertainty measures are statistically significant predictors of dispersion. Moreover, we are able to identify important differences in dispersion between inflation caps and floors—a point discussed more thoroughly below.

Third, the difference between physical probabilities and forward probabilities is time-varying risk premia. If changes in risk premia amount primarily to time variation in the location parameter, our dispersion metric will correlate strongly across the two distributions. To show this more carefully, consider pricing a European call option with expiration date $T$ and strike price $X$. The price $C$ discounted at the risk-free rate of interest $r$ is given by

$$C = E_t^Q \left\{ \frac{\max[S_T - X, 0]}{(1 + r)^T} \right\}, \quad (12)$$
where $S_T$ is the price of the underlying asset at date $T$, and $E^Q_t$ implies that the expectation is taken with respect to the risk-neutral (equivalent-martingale) measure. Suppose further that the stock price follows Heston (1993)’s stochastic volatility model,

$$dS_t = \mu S_t dt + \sqrt{v_t} S_t dz_{1,t}$$

and the variance of the return follows a Ornstein-Uhlenbeck process

$$dv_t = \kappa (\theta - v_t) dt + \xi \sqrt{v_t} dz_{2,t}$$

where $\kappa$ is the speed of mean reversion, $\theta$ the long-run variance, $\xi$ is the volatility of the volatility generating process, and $dz_{1,t}$, and $dz_{2,t}$ are Wiener processes with correlation $\rho$. We then conduct the following steps:

1. Simulate data from the model using the standard parameter calibration: stock drift, $\mu$, 10%; long-run mean, $\theta$, 4%; mean reversion, $\kappa$, 3; volatility, $\xi$, 0.4; and correlation, $\rho$, -0.5.
2. Calculate the empirical distribution of returns, $R_{t,h} = (S_{t+h}/S_t)$, at horizon $h$.
3. Using the Canonical Valuation methodology of Section 3.2, compute the forward probabilities, $p^*_t$, that correctly price the European call option, (12).
4. Compute the 25th-75th dispersion in both the physical and forward densities, and calculate the statistical discrepancy between the two measures.

The simulation results are contingent on the number of observations. If we simulate 200 observations or more, the differences in the dispersion measures are negligible; the mean difference is not statistically different from zero. This is because our empirical distribution becomes more precise with the number of observations and is more closely aligned with the true option price. The canonical valuation method minimizes the discrepancy between the forward and physical densities, which includes maintaining the overall shape of the physical distribution. However, as the number of simulations falls to 100 or below, the differences in the discrepancy measures are no longer statistically different from zero. One caveat to our results is that Heston’s stochastic volatility model is a more realistic than the log-normal distribution of Black and Scholes because it can produce fatter tails, and thus a more realistic divergence measure for stock prices. Inflation does not exhibit the same level of volatility or leptokurtic behavior. If we set the volatility parameter, $\xi$, to 0.2 as opposed to 0.4, the discrepancy difference is negligible for observations greater than 75.

Finally, estimates of percentiles play an important role in value-at-risk calculations. It is quite likely that the firms and financial institutions discussed in Section 2 purchase caps and floors to protect portfolios from inflation risk. Value-at-risk calculations are particularly important for financial institutions to hedge risk given that regulators rely on such measures to determine capital ratios. Geweke (2005) shows that value-at-risk measures arise as the solutions to minimizing the
expected value of linear-linear loss functions of the form

$$L(k, \pi) = c_1(k - \pi)I_{(-\infty,k]}(\pi) + c_2(\pi - k)I_{(k,\infty)}(\pi)$$

over actions $k$, where $c_1, c_2$ are positive weights on low and high outcomes of an uncertain variable $\pi$ (e.g., one-year percentage change in the CPI). Specifically, the solution to minimizing $E_\pi L(k, \pi)$ over $k$ yields the corresponding action satisfying $P(\pi \leq k) = c_2/(c_1 + c_2)$. If we take $c_1 = 0.75$ and $c_2 = 0.25$, we find that the action of an agent who places a relatively heavier weight on downside losses corresponds to the 25th percentile of the distribution of inflation outcomes. Meanwhile, reversing the weights demonstrates that an agent relatively more exposed to losses from upside outcomes chooses an action corresponding to the 75th percentile. From this perspective, dispersion in the forward distribution of inflation outcomes reflects divergence in behavior between agents exposed to losses from upside and downside outcomes, providing further (admittedly speculative) evidence that changes in percentiles capture overall uncertainty. More succinctly, if inflation caps and floors are being used as hedges in value-at-risk calculations, percentiles will play an important role in the calculus.

Figure 6a plots the dispersion measure obtained via the derivative method and the canonical valuation by constraining the forward distribution for one year ahead inflation at each date to correctly price an inflation cap of strike rate 1% and 2%, and a floor of strike rate 1% all with a maturity of one year. We focus on the post-2012 period to exclude the era over which the market for caps and floors was developing. The figure shows that the dispersion measures follow the same trend with the derivative method nearly uniformly higher in the early part of the sample. Both methods agree on nearly all substantial changes in inflation expectations (e.g., January 2015) with the exception of the first few months of 2016 when the canonical measure adjusts more vigorously than the derivative method. Figure 6b plots the Canonical dispersion imposing the 1% cap and 1% floor separately. This distinction is relevant because it clearly shows the asymmetry between the cap and floor measures. Traders were much more worried about disinflation and reacted more strongly to potential deflationary shocks. This is especially true of much of 2015 and 2016 with dispersion in both caps and floors increasing, but the increase in the floor dispersion measure is several orders of magnitude higher.

4.1 Regime Switching Model Motivated by the visual features of Figure 6, we consider a simple regime switching model. The model disciplines the hypothesis of asymmetry between the canonical floor and cap measures. In particular, we specify a model for dispersion of the form,

$$\text{Disp}_t = \mu_{st} + \epsilon_{st}$$

in which the mean $\mu$ of the model stochastic process depends on the regime $s_t \in \{0, 1\}$. Likewise, the innovation variances are regime specific, so that $\epsilon_{st} \sim N(0, \sigma_{st})$. If in state 0, the process remains in state 0 with probability $p_{00}$, so that the expected duration of the state is $1/(1 - p_{00})$
and similarly for other states. With probability $p_{01}$, the state transitions from 0 to 1.

We estimate four iterations of the model using the Canonical measure of dispersion: 1. one-year inflation cap with two states; 2. one-year inflation cap with three states; 3. one-year inflation floor with two states; 4. one-year inflation floor with three states. We focus on floors and caps separately in order to determine if dispersion behaves differently for changes in expected inflation vis-a-vis expected disinflation. The model is estimated using using quasi-maximum likelihood estimation [White (1982), Cho and White (2007)]. Algorithms used to determine the predictive, filtered, and smoothed probabilities permit a “quasi” likelihood estimation that maximizes the log-likelihood of the weighted average of Gaussian distributions. Given an initial value for the state, the quasi-likelihood function is given by

$$L_T(\Theta) = \frac{1}{T} \sum_{t=1}^{T} \ln(f(x_t|x^{t-1}; \Theta))$$

$$f(x_t|x^{t-1}; \Theta) = pr(s_t = 0|x^{t-1}; \Theta)f(x_t|s_t = 0, x^{t-1}; \Theta) + pr(s_t = 1|x^{t-1}; \Theta)f(x_t|s_t = 1, x^{t-1}; \Theta)$$

where $\Theta = \{\mu_s, \sigma_s, p_{00}, p_{11}\}$ and $pr(s_t = j|x^{t-1}; \Theta)$ is the predictive probability of being in state $j$ conditional on information (dispersion) available through $t - 1$, $x^{t-1}$. The estimated filtered, smoothed and predictive probabilities are obtained in the usual recursive fashion [see, Hamilton (1994)].

The estimated parameters are given in Table 1. With two states, the estimated means are 1.24% and 1.44% respectively for caps, and 1.64% and 3.01% for floors. That the mean dispersion is twice as high when using floor data is not surprising given Figure 6b. Moving to a three-state model does not change the estimated means substantially for the caps with a range of 1.16% to 1.33%. However, the estimated means for the floor are quite different in the three-state regime.
model. The mean in the high state is nearly three times as large as the low state mean (4.44% vs. 1.63%). Volatility is also substantially different between floors and caps. The low dispersion state is an order of magnitude more volatile than the high dispersion state(s) for caps, while the opposite is true for floors. For the two-state regime model, the high dispersion state is an order of magnitude more volatile for floors, and five times more volatile in the three-state model. The estimated regime-switching model verifies the asymmetry apparent in Figure 6.

Regimes are persistent. Duration in each regime is slightly higher for floors relative to caps, with the low-mean state being the most persistent. The 3-state floor estimates show that regime progresses sequentially from low (State 0) to medium (State 1), and from high (State 2) to medium (State 1), but never from high to low or vice versa. For caps, transitions primarily occur between the high and medium dispersion states, while the low dispersion state decays to either of the other states with approximately equal probability. Figure 7 plots the two-state filtered probabilities over the sample period for caps and floors. The additional persistence of the floor regime is evident. For all of 2013 and most of 2014, the dispersion measure due to floors stayed in the low-mean regime, while the dispersion of caps changed regime several times. Visually, the transitions occur very quickly, while the states persist for a relatively long time with a few exceptions, consistent with the estimated mean durations.

### 4.2 A Narrative View of Regime Change

We next conduct a narrative study of events occurring at the same time as transitions in the two state model for both caps and floors. We focus on the two state model both for simplicity and because it is selected over the three period model by the Akaike information criterion. Specifically, a break in the series is identified as a period over which the filtered probabilities of the high dispersion state transition from values above 0.99 to below 0.01 or vice versa. A typical break in the model occurs over a period of one to 6 business days, and with a few exceptions states persist for a month or more. The clear breaks and long lived states gives us a fair degree of confidence that we are identifying events which do indeed lead to transitions, in response to the critique of Fair (2002).

A search was conducted to identify any major economic news or policy developments which coincided with a break in the series. Events of interest primarily occurred the day of or prior to either the start of the break, as well as the day of or prior to any particularly large jump in the
Figure 7: Filtered probabilities in two state regime switching models for dispersion in one year ahead inflation expectations, as implied by the canonical distributions which correctly price a cap or a floor with strike 1% at each date.

filtered odds. Table 2 displays the results of the study. The consistent timing of identified events relative to probability changes gives us further reassurance in our interpretations.

First and most importantly, we observe that nearly every transition in the model relating to caps can be associated with a statement by the Board of Governors of the Federal Reserve or its Chair, while transitions with respect to floors are typically preceded by changes in structural economic performance (e.g., labor markets, oil prices). There are only a few exceptions to this observation, in April 2013, August 2014, and October 2012, as well as a high dispersion event which lasted through July of 2013. The former break happened shortly following the bombing of the Boston marathon on Sunday, April 14, 2013. Markets reacted by turning sharply downward the day following, and then recovering on the day of the break. The August 2014 event, on the other hand, appears to possibly be misidentified. First, in Figure 7 the 2014 break corresponds to a series drop from \( \approx 0.014 \) to \( \approx 0.013 \), which was followed by a further, more drastic fall in mid September. The three state model identifies the first drop as a transition from High to Middle dispersion, and finds a break from Middle to Low dispersion from September 17 to 19. The largest jump in the latter transition occurred on September 18, accompanied by a decision by the FOMC to not raise interest rates. Finally, the July 2013 event does not have a clear explanation, although there is some indication that investor fears about the rollback of quantitative easing emerged at this time.

Looking more closely at the events associated with monetary policy, dispersion in the forward distributions generally decreases when policy is relatively tight and increases when it is loose, as is sensible for a period which saw persistently low inflation and stimulative policy. The series transitions several times in the wake of statements by former Federal Reserve Chairwoman Janet
Table 2: Economic events that coincident with breaks in the regime switching models for dispersion based on pricing of a 1% cap option maturing in 1 year (top) and 1% floor options maturing in 1 year (bottom). Notes: April 16, 2013 was the Tuesday after the Boston bomber. Equities dropped on Monday but recovered on Tuesday. There is an unexplained break to high dispersion in early July 2013 and returning to low dispersion in early August. In June of 2015, there were a few short lived switches, possibly following developments in negotiations between Greece and the EU. There are several additional breaks in July-Sept. 2016, which all coincide with Fed publication release dates.

Yellen, particularly in the weeks following her swearing in on February 3, 2014. Late in the sample period, switches are more associated with official Fed documentation, in particular the release of beige book summaries of economic conditions. Not listed in the table are breaks on July 28, August 18, August 30, and September 8-13 of 2016; each of these occurred in line with Fed releases and statements.
Early in the series history, breaks appear to be associated with actions by European leaders during the debt crisis. This feature reemerges in mid-2015, the period during which Greece considered leaving the European Union. Additional events associated with a transition include the oil price crash of 2014 and the day on which Hurricane Sandy made landfall in New York. The latter is notable as the second costliest disaster in the United States at the time, following Hurricane Katrina,\footnote{It has since been surpassed by Hurricane Harvey in 2017.} and the seventh costliest worldwide.

### 4.3 Connection to Measures of Uncertainty

Recently, several measures of uncertainty have been shown to be important drivers of business and financial cycles [Jurado, Ludvigson, and Ng (2015), Baker, Bloom, and Davis (2016)]. In this section, we examine the extent to which three such measures—financial, macro and policy—are able to explain the variation in dispersion of inflation expectations. As described in Ludvigson and Ng (2019), the financial uncertainty measure is constructed from 148 monthly financial series that consists of a number of indicators “measuring the behavior of a broad cross-section of asset returns, as well as some aggregate financial indicators. These data include valuation ratios such as the dividend-price ratio and earnings-price ratio, growth rates of aggregate dividends and prices, default and term spreads, yields on corporate bonds of different ratings grades, yields on Treasuries and yield spreads, and a broad cross-section of industry equity returns.” The “Macro” uncertainty measure is compiled from a database of 135 monthly U.S. indicators, taken from FRED-MD and described in McCracken and Ng (2014). These data included industrial production, weekly hours, personal inventories, monetary aggregates, interest rates and interest-rate spreads, stock prices, and consumer expectations. In both cases, the uncertainty measure taken from Jurado, Ludvigson, and Ng (2015) is the $h$-period ahead uncertainty in the variable $y_{jt}$ defined as the conditional volatility of the purely unforecastable component of the future value of the series,

$$U_{jt}(h) \equiv \sqrt{E[(y_{jt+h} - E[y_{jt+h}|I_t])^2|I_t]}$$

where $I_t$ is the information available to the economic agents at $t$ and is formulated according to a dynamic factor analysis. The large set of predictors described above are used to span the information set of the agent, while the volatility in the forecast error is estimated using a parametric stochastic volatility model. For further details see Jurado, Ludvigson, and Ng (2015).

We also examine the three-component policy uncertainty index of Baker, Bloom, and Davis (2016). The first component consists of monthly search results from 10 large newspapers with keywords ‘uncertainty’ or ‘uncertain’, the terms ‘economic’ or ‘economy’ and one or more of the following terms: ‘congress’, ‘legislation’, ‘white house’, ‘regulation’, ‘federal reserve’, or ‘deficit’. The second component of the index compiles a list of temporary federal tax code provisions as reported by the Congressional Budget Office, the idea being that “temporary tax measures are a source of uncertainty for businesses and households because Congress often extends them at the last minute, undermining stability in and certainty about the tax code.” The final component is a
measure of dispersion in the individual level forecasts of variables directly influenced by government policy (e.g., purchases of goods and services by the federal government) contained in the Federal Reserve Bank of Philadelphia’s Survey of Professional Forecasters.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deriv. (All)</td>
<td>0.016</td>
<td>0.003</td>
<td>0.011</td>
<td>0.026</td>
</tr>
<tr>
<td>Canon. (Cap)</td>
<td>0.013</td>
<td>0.002</td>
<td>0.010</td>
<td>0.016</td>
</tr>
<tr>
<td>Canon. (Floor)</td>
<td>0.019</td>
<td>0.006</td>
<td>0.015</td>
<td>0.045</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Correlation</th>
<th>Canon. (Floor)</th>
<th>0.019</th>
<th>0.006</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>Fin. (h=1)</td>
<td>0.796</td>
<td>0.052</td>
</tr>
<tr>
<td></td>
<td>Fin. (h=3)</td>
<td>0.856</td>
<td>0.043</td>
</tr>
<tr>
<td></td>
<td>Fin. (h=12)</td>
<td>0.950</td>
<td>0.016</td>
</tr>
<tr>
<td></td>
<td>Macro.</td>
<td>0.750</td>
<td>0.031</td>
</tr>
<tr>
<td></td>
<td>Policy</td>
<td>0.119</td>
<td>0.033</td>
</tr>
</tbody>
</table>

Table 3: Summary Statistics for Uncertainty and Dispersion Measures

Table 3 reports the descriptive statistics for the dispersion measures used in the regression analysis, along with the uncertainty measures. We scaled the policy uncertainty measure by 1/100 to place it roughly on the same scale as the dispersion statistics. The data are monthly observations from January 2012 through May 2017 (N = 65). For the financial uncertainty measure, we include three forecast horizons (h = 1, 3, 12), even though these measures are highly correlated. Our dispersion statistics are derived from one-year ahead strikes h = 12 and we want to test if the timing is relevant. Also noteworthy is the lack of correlation between the financial / macro uncertainty measures and the policy uncertainty. Meanwhile, the macro and financial uncertainty measures are weakly positively correlated.

Table 4 presents the results of our regression analysis. The top section employs the dispersion derived from the derivative method using one-year inflation expectations. Financial uncertainty measures are statistically significant predictors of dispersion, increasing in significance and magnitude as the horizon increases. That the most significant and sizable response comes from the one-year horizon (h = 12) should not be a surprise given that the options in Table 4 are all evaluated at strikes of one-year. The top panel also shows that policy uncertainty is a highly significant predictor of total dispersion. This significance goes away when we decompose total dispersion into dispersion due to floors and dispersion attributable to caps. The last column includes the best fitting regression and shows a respectable $R^2$ of 0.4.

The middle and last sections of Table 4 maintain the same independent variables but exchange the dependent variable—total dispersion—for floor and cap dispersion. This allows us to investigate if floors and caps can be explained by different measures of uncertainty as suggested in Section 4.2. Indeed, the policy uncertainty metric is no longer significant for either caps or floors, while the financial uncertainty remains significant and macro uncertainty is now also significant. Moreover, financial uncertainty enters negatively for cap dispersion and positively for floor dispersion. Thus, an increase in financial uncertainty decreases the dispersion in caps. Recall that over this time period, disinflation was more of a concern than inflation which is why innovations to financial time
<table>
<thead>
<tr>
<th>Dependent Variable: Derivative-Method Dispersion</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Fin. ((h=1))</td>
<td>0.016*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fin. ((h=3))</td>
<td>0.020*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fin. ((h=12))</td>
<td>0.067**</td>
<td>0.063**</td>
<td></td>
</tr>
<tr>
<td>Macro.</td>
<td>-0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Policy</td>
<td></td>
<td>0.054***</td>
<td>0.053***</td>
</tr>
<tr>
<td>Constant</td>
<td>0.004</td>
<td>-0.001</td>
<td>-0.048*</td>
</tr>
</tbody>
</table>

\[ R^2 \]

|       | 0.063 | 0.072 | 0.119 | 0.001 | 0.2971 | 0.400 |

<table>
<thead>
<tr>
<th>Dependent Variable: Floor-Dispersion</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Fin. ((h=1))</td>
<td>0.047***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fin. ((h=3))</td>
<td>0.058***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fin. ((h=12))</td>
<td>0.161***</td>
<td>0.102*</td>
<td></td>
</tr>
<tr>
<td>Macro.</td>
<td></td>
<td>0.101***</td>
<td>0.079***</td>
</tr>
<tr>
<td>Policy</td>
<td></td>
<td>0.016</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-0.018</td>
<td>-0.030*</td>
<td>-0.133***</td>
</tr>
</tbody>
</table>

\[ R^2 \]

|       | 0.165 | 0.175 | 0.200 | 0.272 | 0.01 | 0.339 |

<table>
<thead>
<tr>
<th>Dependent Variable: Cap-Dispersion</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Fin. ((h=1))</td>
<td>-0.011**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fin. ((h=3))</td>
<td>-0.014**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fin. ((h=12))</td>
<td>-0.034**</td>
<td>-0.024*</td>
<td></td>
</tr>
<tr>
<td>Macro.</td>
<td></td>
<td>-0.018**</td>
<td>-0.013*</td>
</tr>
<tr>
<td>Policy</td>
<td></td>
<td>0.007</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>0.022***</td>
<td>0.025***</td>
<td>0.046***</td>
</tr>
</tbody>
</table>

\[ R^2 \]

|       | 0.154 | 0.150 | 0.135 | 0.137 | 0.02 | 0.194 |

Table 4: Regression Analysis

series, on average, consolidated expectations in inflation caps while increasing dispersion in inflation floors. The asymmetry may be unique to this time period.
5 Conclusion

The frequency and richness of financial markets data makes it an attractive resource for market participants and policy making institutions, however linking asset price fluctuations to investor perceptions remains a difficult topic. While forward distributions for inflation implicit in cap and floor prices need not provide a direct measure about investor perceptions regarding the actual likelihood of events, we have argued that dispersion in these distributions may nonetheless provide a sense of broad uncertainty. Having adapted the method of Buchen and Kelly (1996) and Stutzer (1996) to back out such distributions from prices, we have shown that changes in the level and volatility of dispersion can be captured by a simple regime switching model. Exploiting the daily frequency of the data and the cleanliness of the breaks in the model, we have been able to closely link these breaks to Federal Reserve policy and major global and domestic sources of uncertainty. At a monthly frequency, we have shown that our dispersion metric is also tightly linked to nascent measures of economic and financial uncertainty.
REFERENCES


23


