The Causal Impact of Macroeconomic Uncertainty on Expected Returns

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Abstract

I quantify the causal impact of macroeconomic uncertainty on expected returns. The exogenous timing of macroeconomic announcements provides an instrument for uncertainty. Using realized returns and daily measures of macroeconomic uncertainty, I find announcements resolve uncertainty, which causes expected returns to fall. Under weak assumptions, macroeconomic uncertainty explains at most 32% of expected return variation. Under the additional, empirically justified assumption that other expected return drivers do not correlate with announcement timing, macroeconomic uncertainty explains 10% of expected return variation and a one standard deviation increase in macroeconomic uncertainty raises long-run expected returns by 173 basis points.

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"There is nothing investors hate more than uncertainty. Right now, that is all there is...The spiraling fears have caused financial carnage."

— New York Times. March 6, 2020.

What variables cause discount rate variation? This question is fundamental to asset pricing. Many models suggest that macroeconomic uncertainty — the subjective conditional covariance of dividend growth with the stochastic discount factor — should impact expected returns (e.g. Bansal & Yaron (2004); Bollerslev, Tauchen & Zhou (2009); Bansal et al. (2014); Campbell et al. (2018)). Furthermore, as is often highlighted by the financial press, there is a strong contemporaneous negative correlation between uncertainty and realized returns, which is consistent with uncertainty raising discount rates. On the other hand, the empirical evidence is mixed. Some work finds that investors will pay to hedge political uncertainty (Kelly, Pástor & Veronesi (2016)) while other work implies that hedging uncertainty shocks earns positive average returns (Dew-Becker, Giglio & Kelly (2019)). Additionally, a large related literature fails to find a strong risk-return tradeoff between volatility and future returns, which suggests uncertainty does not impact discount rates (Campbell (1987); Glosten, Jagannathan & Runkle (1993); Whitelaw (1994); Moreira & Muir (2017)). Moreover, even if one believes that increases in macroeconomic uncertainty do raise expected returns, the size of this effect still remains unclear. How much would expected returns rise due to an exogenous one standard deviation increase in macroeconomic uncertainty? What proportion of expected return variation does macroeconomic uncertainty account for? Although these questions quantify crucial structural parameters in asset pricing models, the field does not have definitive answers to them.

The fundamental issue in answering these questions lies in the difficulty of finding exogenous changes in uncertainty. Identifying causality in asset pricing and macrofinance proves extremely challenging in general because the aggregate quantities of interest are often jointly determined in equilibrium. Yet the identification problem in this setting is further exacerbated by the positive correlation of macroeconomic uncertainty with many other countercyclical variables. How does one credit a rise in discount rates to an increase in macroeconomic uncertainty instead of risk aversion or intermediary leverage when all three often move together at monthly or quarterly frequencies? Most previous work has sought to disentangle these variables at low frequency using structural models or vector autoregressions (VARs). Both these approaches, however, require strong structural assumptions.

My main contribution in this work is to propose a novel identification strategy to isolate exogenous variation in macroeconomic uncertainty at high frequency. In particular, I exploit the exogenous *timing* of prescheduled macroeconomic announcements as an instrument for uncertainty. The Bureau of Economic Analysis (BEA), Bureau of Labor Statistics (BLS), and Federal Reserve all schedule macroeconomic announcements up to a year in advance in a predictable manner. While the *content* of these announcements is surely endogenous to the contemporaneous state of the economy, the *timing* is not. The only source of variation I exploit is the timing of prescheduled announcements, not their content.

Moreover, since these announcements are prescheduled, investors cannot ex-ante expect their macroeconomic expectations to change in a predictable direction on announcement dates. Doing so would violate the martingale property of conditional expectations. For example, on April 28, 2020, investors cannot expect their second-quarter GDP growth expectations to predictably move when the BEA releases first-quarter GDP growth statistics on April 29, 2020. Any such forecasted changes would already be incorporated into conditional expectations. Only investors' uncertainty can depend on announcement timing.

Controlling for contemporaneous shifts in first moments represents a significant obstacle to identifying causal effects of uncertainty in many applications (Alfaro, Bloom & Lin (2018); Baker, Bloom & Terry (2020); Barrero, Bloom & Wright (2017)). The prescheduled nature of these macroeconomic announcements ensures that conditional expectations cannot predictably move on announcement days. The timing of prescheduled macroeconomic announcements therefore provides a valid instrument for uncertainty.

Thus, any movement in asset prices induced by *the timing* of announcements is due to changes in uncertainty. Yet changes in uncertainty can potentially affect asset prices through multiple channels. For example, a decrease in uncertainty about second-quarter GDP growth may lower expected returns through both a decrease in overall macroeconomic uncertainty and through a decrease in risk aversion. In reduced form, however, both these effects arise from the resolution of uncertainty. If changes in risk aversion do not correlate with announcement timing, then this entire reduced-form effect operates through the channel of macroeconomic uncertainty.

I demonstrate that the announcement resolution of uncertainty causes decreases in expected returns. Specifically, I construct a daily measure of macroeconomic uncertainty by projecting the monthly Jurado, Ludvigson & Ng (2015) macroeconomic uncertainty index onto the daily implied volatilities of a set of options, as done by Dew-Becker, Giglio & Kelly (2019). This daily measure of macroeconomic uncertainty falls by an average additional 0.21 standard deviations on GDP, unemployment, Consumer Price Index (CPI), Producer Price Index (PPI), Employment Cost Index, and scheduled FOMC announcement days as compared to non-announcement days. Thus, the timing of announcements is a relevant instrument for macroeconomic uncertainty.

Next, I quantify the causal effect of this exogenous resolution in uncertainty on expected returns. In particular, I consider daily changes in long-run expected returns (in the sense of Cochrane (2008)). Given the binary announcement timing instrument, the effect of the announcement resolution of uncertainty on long-run expected returns is the difference between the announcement-day and non-announcement day average changes in long-run expected returns. Since announcements are prescheduled, the law of iterated expectations implies that this average difference in long-run expected return changes approximately equals the negative difference between announcement-day and non-announcement day average realized returns. A reduced-form regression of negative returns on announcement timing indicates that the announcement resolution of uncertainty causes an 7.8 basis point decrease in long-run expected returns. Moreover, this estimated parameter implies that macroeconomic uncertainty can account for at most 32% of the daily variation in long-run expected returns. As discussed above, this upper bound accounts for the possibility that this reduced-form "announcement resolution of uncertainty effect" affects expected returns through multiple channels (e.g. macroeconomic uncertainty and risk aversion).

This upper bound can be tightened. If no driver of expected returns but macroeconomic uncertainty correlates with the announcement timing, then the entire reduced-form announcement resolution of uncertainty effect must go through the channel of macroeconomic uncertainty. Returning to the example from above, if the announcement-timing-induced decrease in uncertainty about second-quarter GDP growth only lowers overall macroeconomic uncertainty and does not affect risk aversion, then we can attribute the entire announcement-day average change in expected returns to the fall in macroeconomic uncertainty. I provide evidence that other theoretically-motivated expected return drivers do not correlate with the timing of announcements. Whereas macroeconomic uncertainty declines significantly on average on announcements, proxies for risk-aversion, disaster risk, and intermediary leverage do not correlate with announcement timing. In this case, one can conclude that macroeconomic uncertainty accounts for 10% of variation in long-run expected returns and that a one standard deviation increase in the level of macroeconomic uncertainty causes long-run expected returns to rise by 173 basis points.

Furthermore, I provide evidence of external validity for my main results by demonstrating that macroeconomic uncertainty also explains a significant amount of price variation in other asset classes, specifically government bonds, corporate bonds, and the variance risk premium.

In this paper I measure the total effect of macroeconomic uncertainty on expected returns. The definition of macroeconomic uncertainty I use throughout this paper encompasses both the time-varying physical volatility *and* posterior variance of macroeconomic fundamentals. Moreover, in general many different macroeconomic variables contribute to macroeconomic uncertainty. This paper focuses on overall macroeconomic uncertainty, not uncertainty in any particular macroeconomic variable (e.g. "inflation uncertainty", "monetary policy uncertainty", or "financial market uncertainty"). The general identification strategy I present can be paired with more specific uncertainty measures to determine which types of uncertainty fall on announcements and cause decreases in expected returns. For example, recent work suggests that at high frequencies only posterior variance, not macroeconomic volatility, changes (Ai, Han & Xu (2021)). Decomposition of overall macroeconomic uncertainty into more granular measures (e.g. either physical macroeconomic volatility versus posterior variance or uncertainty about specific macroeconomic variables) represents an important and promising line of work that I leave to future research.

While measuring expected returns and macroeconomic uncertainty proves difficult, the general identification strategy I present can be used regardless of the particular measures employed. I consider many alternative expected return, expected cash flow growth, and macroeconomic uncertainty time series to ensure my results prove robust to alternative measurement techniques. Specifically, measuring expected returns using the options-implied Martin (2017) equity premium lower bound and Gao & Martin (2019) *log* equity premium lower bound delivers quantitatively similar results to the baseline analysis. Measuring expected cash flow growth using the Pettenuzzo, Sabbatucci & Timmermann (2020), Gao & Martin (2019), and Gormsen & Koijen (2020) measures (extracted from dividend announcements, index options, and dividend strips, respectively) reveals that finite-sample variation in cash flow growth shocks does not drive my results. Measuring macroeconomic uncertainty at different horizons as well as by simply using S&P 500 implied volatility does not change the baseline results using the projected Jurado, Ludvigson & Ng (2015) one-year horizon macroeconomic uncertainty index. Any other expected return and macroeconomic uncertainty measures could also be used with my identification strategy.

Moreover, the baseline results prove robust to taking subsets of different announcement types. In particular, dropping all FOMC announcements from the sample does not undermine the baseline results.

The remainder of the paper proceeds as follows. The next section reviews the related literature. Section 1 develops my identification strategy. Sections 2 and 3 discuss my data and high-frequency measurement methodology. Section 4 contains my main empirical results. Section 5 provides evidence from other asset classes. Section 6 details the robustness checks I conduct. Lastly, Section 7 concludes. The internal Appendix contains generalizations of the results from Section 1. The Internet Appendix contains technical details and additional robustness checks.

Related Literature

This paper relates to four literatures: empirical identification of causality in asset pricing and macrofinance, investigations of macroeconomic and asset pricing effects of uncertainty, research into the drivers of expected returns, and studies of asset pricing dynamics around macroeconomic announcements.

First, this paper contributes to a small but growing literature on identifying causality in asset pricing and macrofinance via plausibly exogenous variation as opposed to strong structural assumptions (Nakamura & Steinsson (2018) discuss the benefits of this paradigm shift). The oldest work in this area identifies asset price effects of demand shocks by estimating asset price elasticities.[1] More recent work has used the exogenous timing of low-frequency events to identify the effects of intermediary constraints on asset prices (Du, Tepper & Verdelhan (2018)) and sustainability preferences on investment decisions (Hartzmark & Sussman (2019)). Cieslak & Pang (2020) employ sign restrictions and asset-class heterogeneity to identify common shocks to stock and bond prices at high-frequency. In this paper I propose an identification strategy that exploits the exogenous timing of macroeconomic announcements at high frequency as an instrument for uncertainty.

Second, most of the empirical literature examining the effects of uncertainty in macroeconomics and asset pricing either uses structural vector autoregressions (VARs) for identification or provides correlative evidence from predictive regressions or cross-sectional trading

[1] Shleifer (1986); Harris & Gurel (1986); Koijen & Yogo (2019); Gabaix & Koijen (2020).

strategies. Many macroeconomics papers find contractionary effects of uncertainty using VARs.[2] In asset pricing, Segal, Shaliastovich & Yaron (2015) find increases in uncertainty raise risk premia in VARs, while Bekaert, Engstrom & Xing (2009) and Bekaert, Engstrom & Xu (2019) find the same result in structural models. Bali & Zhou (2016) and Brogaard & Detzel (2015) show uncertainty positively predicts equity returns.[3]

Identification proves difficult in these areas. Low-frequency VARs require strong structural assumptions to argue for identification.[4] Predictive regressions and cross-sectional analyses provide only suggestive evidence. Several papers have made strides toward isolating exogenous variation in uncertainty. Barrero, Bloom & Wright (2017) and Alfaro, Bloom & Lin (2018) both use cross-sectional heterogeneity in firm-level exposures to multiple macroeconomic variables to identify the effects of macroeconomic uncertainty on real outcomes, while Baker, Bloom & Terry (2020) uses randomly occurring events such as terrorist attacks and natural disasters to instrument for uncertainty. My approach does not require firm-level data and provides a cleaner instrument for uncertainty (e.g. terrorist attacks may reduce growth directly through heightened risk aversion *and* increased uncertainty). The paper whose empirical strategy proves most similar to mine is Kelly, Pástor & Veronesi (2016), which uses the timing of prescheduled political events (e.g. elections, global summits) to isolate exogenous variation in uncertainty. They find prices of options whose lives span political events reflect a premium investors pay to hedge political uncertainty. In this paper I go beyond simply documenting that there is a premium for uncertainty in the cross section of one asset class (a within-period risk-return tradeoff): I quantify the causal effect of macroeconomic uncertainty on expected returns (an intertemporal risk-return tradeoff).

[2] Bloom (2009), Alexopoulos & Cohen (2009), Jurado, Ludvigson & Ng (2015), Leduc & Liu (2016), Caldara et al. (2016), and Baker, Bloom & Davis (2016) find contractionary effects on output, employment, investment, consumption, and credit spreads.

[3] Other work documents an unconditional negative risk premium for macroeconomic uncertainty in the cross section of equities (Boguth & Kuehn (2013); Bali, Brown & Tang (2017); Xyngis (2017); Heigermoser (2020)). Bali, Brown & Caglayan (2014) and Della Corte & Krecetovs (2019) find macroeconomic uncertainty exposures explain cross-sectional variation in hedge fund and currency returns. Dew-Becker, Giglio & Kelly (2019) find a *positive* uncertainty premium in options portfolios hedging macroeconomic uncertainty shocks.

[4] Cochrane & Piazzesi (2002) discuss the difficulties in achieving identification in VARs.

Third, a large literature in asset pricing examines the time-varying drivers of expected returns. Previous work has proposed time-varying risk aversion (Campbell & Cochrane (1999)), long-run risks and stochastic volatility (Bansal & Yaron (2004); Bansal et al. (2014); Campbell et al. (2018)), disaster risks (Barro (2006); Wachter (2013)), and intermediary leverage (He & Krishnamurthy (2013)) as potential drivers. However, since all of these variables are countercyclical, isolating exogenous variation in any of them and cleanly estimating their relative importance for expected returns prove difficult. In this work I use exogenous variation in macroeconomic uncertainty to pin down its contribution to expected returns.

Lastly, much work examines asset pricing dynamics around macroeconomic announcements. Previous work has noted that the timing, but not content, of announcements is exogenous to other economic shocks and has documented announcement-day declines in implied volatilities.[5] However, no previous work takes the next step of exploiting announcement timing as an instrument for uncertainty with respect to some dependent variable of interest in asset pricing or macrofinance.

Other work finds high average returns on macroeconomic announcements (Jones, Lamont & Lumsdaine (1998); Savor & Wilson (2013)).[6] Lucca & Moench (2015) find "pre-announcement drift:" positive equity returns leading up to announcements. Both of these phenomena have been attributed to the resolution of uncertainty in previous work (Ai & Bansal (2018); Laarits (2019); Hu et al. (2019)). Unlike this previous literature, the primary goal of the present paper is not to explain why announcements experience high average returns. Instead, I use the timing of announcements as an instrument to gauge the causal effect of macroeconomic uncertainty on expected returns.

[5] Ederington & Lee (1996); Fornari & Mele (2001); Beber & Brandt (2006, 2009); Vähämaa & Äijö (2011); Jiang, Konstantinidi & Skiadopoulos (2012); Amengual & Xiu (2018).

[6] Balduzzi & Moneta (2017) and Law, Song & Yaron (2018) find average returns and sensitivities of returns to announcement content vary across the business cycle.

1 Identification Strategy

This section presents my identification strategy. I first provide the high-level intuition and then explain in detail how the identification strategy works in a stylized environment in Section 1.1. Section 1.2 generalizes this environment to explain why my identification strategy works in the real world. Section 1.3 discusses potential threats to identification and explains why my identification strategy proves robust to them.

At a high level, the main identification problem involved in measuring the effect of macroeconomic uncertainty on expected returns is omitted variable bias. Assume expected returns (μ_t) are linear in two factors: macroeconomic uncertainty (σ_t^2) and some other driver (x_t):

$$\Delta\mu_t = \lambda_{\sigma^2}\Delta\sigma_t^2 + \lambda_x \Delta x_t. \tag{1}$$

Macroeconomic uncertainty is the subjective conditional covariance between dividend growth and the (negative) stochastic discount factor (SDF). From the Campbell (1991) realized return decomposition, one can express the risk premium as:

$$\begin{aligned}\mathbb{E}_t[R_{t+1}] - R_t^f &= -Cov_t(SDF_{t+1}, R_{t+1}) \\ &= Cov_t(SDF_{t+1}, \text{ Discount Rate Shock}) + \underbrace{Cov_t(-SDF_{t+1}, \text{ Dividend Growth Shock})}_{\text{Macroeconomic Uncertainty}}.\end{aligned} \tag{2}$$

In general macroeconomic uncertainty reflects both the time-varying physical volatility *and* posterior variance of macroeconomic fundamentals.[7] In this paper, I do not decompose

[7] For example, let consumption and dividend growth Δc_{t+1} and Δd_{t+1} have the following dynamics:

$$\begin{aligned}\Delta c_{t+1} &= \underbrace{\mu_{c,t}}_{\equiv \phi_c \mu_t + \eta_{c,t}} + \epsilon_{c,t+1} + \rho_c s_t \epsilon_{t+1} \\ \Delta d_{t+t} &= \underbrace{\mu_{d,t}}_{\equiv \phi_d \mu_t + \eta_{d,t}} + \epsilon_{d,t+1} + \rho_d s_t \epsilon_{t+1}\end{aligned}$$

macroeconomic uncertainty into these two components.[8] Moreover, in general both the SDF and dividend growth may depend on many different macroeconomic variables. The time-varying physical volatilities and posterior variances of common components to any of these variables will contribute to macroeconomic uncertainty. This paper focuses on overall macroeconomic uncertainty, not uncertainty in any particular macroeconomic variable.[9] Thus, in this paper I structurally define and empirically measure macroeconomic uncertainty as the subjective conditional variance of the common component to many different macroeconomic series. Again, this definition includes both time-varying physical volatility *and* posterior variance.

In most models the first covariance in (2) between the SDF and the discount rate shock is driven by variables such as risk aversion, intermediary leverage, etc. Thus, in general, the second variable x_t could be time-varying risk aversion, intermediary leverage, or any of the other expected return drivers proposed by asset pricing theory.[10]

I assume that an outside econometrician in this environment observes only expected returns μ_t and macroeconomic uncertainty σ_t^2, not the other variable x_t, and wants to identify the effect of macroeconomic uncertainty on expected returns: λ_{σ^2}. While measuring expected returns and macroeconomic uncertainty proves difficult, the general identification strategy I

where the investor has posterior distribution $\mu_t \sim N(\bar{\mu}_t, v_t^2)$ over the common component μ_t of the expected growth rates. All $\epsilon_{\cdot,t}$ and $\eta_{\cdot,t}$ are uncorrelated and ϵ_{t+1} is i.i.d. with variance of one. Then in a model with a consumption-based SDF, macroeconomic uncertainty reflects both posterior variance in growth rates (v_t^2) and physical macroeconomic volatility (s_t^2):

$$\sigma_t^2 \equiv Cov_t(\Delta c_{t+1}, \Delta d_{t+t}) = \underbrace{\phi_c \phi_d v_t^2}_{\text{Posterior Variance Contribution}} + \underbrace{\rho_c \rho_d s_t^2}_{\text{Macro Volatility Contribution}} .$$

Changes in either posterior variance or physical macroeconomic volatility will change overall macroeconomic uncertainty, which in turn affects expected returns.

In a rational expectations setting where expected growth rates are known, macroeconomic uncertainty reflects only time-varying physical volatility (e.g. as in Bansal & Yaron (2004)).

[8] Although it is likely that at high frequencies only posterior variance, not physical macroeconomic volatility, changes (Ai, Han & Xu (2021)).

[9] For example, I will not decompose macroeconomic uncertainty into more granular variables such as "inflation uncertainty", "monetary policy uncertainty", or "financial market uncertainty". Each of these variables contributes to macroeconomic uncertainty.

[10] As an example, in Internet Appendix A I provide a simple model with HARA utility where the log expected excess return takes the form in (1) and Δx_t captures the effect of time-varying risk aversion on expected return.

present can be used with any measures of μ_t and σ_t^2. In addition to the baseline measurement methodologies laid out in Section 3, I consider many alternative measurement techniques in Section 6. All of my baseline results prove robust to these alternative measurement techniques. Any other measures of μ_t and σ_t^2 could also be used with this identification strategy.

In general, expected return drivers are correlated. Thus, without further information the econometrician can only identify — and estimate via OLS regression — the following parameter:

$$\lambda_{\sigma^2} + \frac{Cov(\Delta\sigma_t^2, \Delta x_t)}{V[\Delta\sigma_t^2]}\lambda_x.$$

However, introducing announcements into this environment enables the econometrician to identify λ_{σ^2}. Consider the following factor structure for the expected return drivers σ_t^2 and x_t:[11]

$$\begin{aligned} \Delta\sigma_t^2 &= \epsilon_{v,t} + \rho_v \epsilon_{c,t} + \alpha 1(t = \text{announcement}). \\ \Delta x_t &= \epsilon_{x,t} + \rho_x \epsilon_{c,t}. \end{aligned} \tag{3}$$

Macroeconomic uncertainty falls deterministically on announcement days: α represents the average difference between announcement-day and non-announcement day changes in σ_t^2. However, note that the *timing* of announcements *does not affect* x_t. The other shocks $\epsilon_{\cdot,t}$ capture all other variation in both expected return drivers, including (but not limited to) any announcement *content* revealed on announcement day t.

If the announcement timing is uncorrelated with the other shocks $\epsilon_{\cdot,t}$ (i.e. the standard

[11] Note that this structure does not necessarily imply martingale dynamics for $\Delta\sigma_t^2$ as it also nests the following AR(1) structure:

$$\begin{aligned} \sigma_t^2 &= \pi_v \sigma_{t-1}^2 + \tilde{\epsilon}_{v,t} + \rho_v \epsilon_{c,t} + \alpha 1(t = \text{announcement}) \\ \leftrightarrow \Delta\sigma_t^2 &= \underbrace{(\pi_v - 1)\sigma_{t-1}^2 + \tilde{\epsilon}_{v,t}}_{\equiv \epsilon_{v,t}} + \rho_v \epsilon_{c,t} + \alpha 1(t = \text{announcement}). \end{aligned}$$

instrument exclusion restriction), then the econometrician can identify λ_{σ^2}:

$$\lambda_{\sigma^2} = \frac{\mathbb{E}[\Delta\mu_t \,|\, 1(t\!=\!\text{announcement})\!=\!1] - \mathbb{E}[\Delta\mu_t \,|\, 1(t\!=\!\text{announcement})\!=\!0]}{\mathbb{E}[\Delta\sigma_t^2 \,|\, 1(t\!=\!\text{announcement})\!=\!1] - \mathbb{E}[\Delta\sigma_t^2 \,|\, 1(t\!=\!\text{announcement})\!=\!0]}$$
$$= \frac{\mathbb{E}[\Delta\mu_t \,|\, 1(t\!=\!\text{announcement})\!=\!1] - \mathbb{E}[\Delta\mu_t \,|\, 1(t\!=\!\text{announcement})\!=\!0]}{\alpha}$$

The numerator represents the reduced-form causal effect of announcement timing on expected returns. Scaling by the denominator causal effect of announcement timing on macroeconomic uncertainty delivers the desired causal effect of macroeconomic uncertainty on expected returns.

Note that the only source of variation I exploit to identify λ_{σ^2} is the timing of announcements, not the content of announcements. In particular, I measure both $Cov(\Delta\mu_t, 1(t = \text{announcement}))$ and $Cov(\Delta\sigma_t^2, 1(t = \text{announcement}))$. I do *not* measure $Cov(\Delta\mu_t, \Delta\sigma_t^2 \,|\, t = \text{announcement})$. Using only the timing of announcements ensures that contemporaneous shifts in first moments do not contaminate the identification of λ_{σ^2} because conditional expectations cannot covary with the announcement timing. Any such correlation would imply ex-ante predictable changes in conditional expectations, which would violate the martingale property of conditional expectations.

Thus, the credibility of my identification strategy rests on the validity of the following two conditions: 1) the timing of prescheduled announcements is uncorrelated with all other macroeconomic shocks and 2) the timing of prescheduled announcements impacts no driver of expected returns other than macroeconomic uncertainty. The next three sections establish and justify four formal assumptions under which these two conditions are true.

1.1 Identification in a Stylized Environment

In this section I first introduce a stylized environment and then present the four formal assumptions required to identify the parameter of primary interest: the causal effect of macroeconomic uncertainty on expected returns λ_{σ^2}. In spite of the stylized nature of the environment, this section contains all of the core ideas of my identification strategy. In particular, all of these core ideas will carry over to the generalized environment in Section 1.2.

Environment

I model a representative agent who learns about the latent state of the economy over time and prices assets based on his conditional distributions over economic variables. For now, the only state variable is next quarter's consumption growth. This setup proves similar to the model in Ai & Bansal (2018), which also features a representative agent who learns about future consumption. Assume the representative agent's conditional distribution over consumption growth can be parameterized by mean and variance (e.g. as in a normal distribution). Section 1.2 generalizes to an arbitrary number of state variables and allows for higher moments. Let $Q(t)$ be the quarter that day t belongs to and $\Delta C_{Q(t)+1}$ represent next quarter's consumption growth. Furthermore, let $\Delta \mathbb{E}_t[\Delta C_{Q(t)+1}]$ and $\Delta V_t[\Delta C_{Q(t)+1}]$ denote the day-over-day change in the conditional mean and conditional variance of next quarter's consumption growth, respectively.

As above, I model expected returns μ_t as linear in two factors: macroeconomic uncertainty σ_t^2 and some other driver x_t (e.g. risk aversion, intermediary leverage, etc.):

$$\Delta \mu_t = \lambda_{\sigma^2} \Delta \sigma_t^2 + \lambda_x \Delta x_t.$$

Section 1.2 generalizes to an arbitrary number of expected return drivers.

Now consider the following factor structure for the expected return drivers σ_t^2 and x_t:

$$\begin{aligned} \Delta \sigma_t^2 &= \alpha_1 \Delta V_t[\Delta C_{Q(t)+1}] + \alpha_2 \Delta \mathbb{E}_t[\Delta C_{Q(t)+1}] + \rho_v \epsilon_{f,t} + \epsilon_{v,t} \\ \Delta x_t &= \delta_1 \Delta V_t[\Delta C_{Q(t)+1}] + \delta_2 \Delta \mathbb{E}_t[\Delta C_{Q(t)+1}] + \rho_x \epsilon_{f,t} + \epsilon_{r,t}, \end{aligned} \tag{4}$$

where $\epsilon_{\nu,t}, \epsilon_{r,t}$, and $\epsilon_{f,t}$ are all uncorrelated. This factor structure captures the correlation between expected return drivers and links asset prices to the agent's conditional distribution over the state variable.

In this setting, I introduce macroeconomic announcements (e.g. announcements that reveal the current quarter's GDP growth). These announcements are prescheduled: at all days $t-j, j>0$, the indicator variable $1(t=\text{announcement})$ is deterministically known. The timing of announcements can potentially affect all moments of the representative agent's conditional distribution, which means both coefficients $\theta_{1,1}$ and $\theta_{2,1}$ are potentially non-zero in the following equations:

$$\Delta V_t[\Delta C_{Q(t)+1}] = \theta_{1,0} + \theta_{1,1} 1(t=\text{announcement}) + \nu_{1,t} \tag{5}$$

$$\Delta \mathbb{E}_t[\Delta C_{Q(t)+1}] = \theta_{2,0} + \theta_{2,1} 1(t=\text{announcement}) + \nu_{2,t}. \tag{6}$$

As above, I impose the empirically relevant assumption that an outside econometrician observes only:

1. The announcement calendar: $1(t=\text{announcement})$.
2. Changes in macroeconomic uncertainty: $\Delta\sigma_t^2$.
3. Changes in expected returns: $\Delta\mu_t$.

The econometrician does not observe the other expected return driver x_t. The next section lays out the assumptions required to identify the parameter of interest λ_{σ^2} using only the timing of announcements and discusses why these assumptions hold in the real world.

Identifying Assumptions

The first two identifying assumptions are exclusion restrictions about the announcement timing with respect to other shocks and the moments of the representative agent's conditional distribution over the state variable.

Assumption 1. (Exclusion with respect to other economic shocks) *The timing of prescheduled macroeconomic announcements is uncorrelated with all other relevant shocks:*

$$Cov(\epsilon_{\cdot,t}, 1(t=announcement)) = 0,$$

and in the following reduced-form regressions

$$\Delta V_t[\Delta C_{Q(t)+1}] = \theta_{1,0} + \theta_{1,1} 1(t = \textit{announcement}) + \nu_{1,t}$$
$$\Delta \mathbb{E}_t[\Delta C_{Q(t)+1}] = \theta_{2,0} + \theta_{2,1} 1(t = \textit{announcement}) + \nu_{2,t}.$$

we have $Cov(\nu_{\cdot,t}, 1(t = \textit{announcement})) = 0$.

Assumption 2. (Exclusion with respect to conditional expectations) *The timing of prescheduled macroeconomic announcements does not systematically affect the investor's conditional expectations of macroeconomic variables:*

$$Cov\Big(\Delta \mathbb{E}_t[\Delta C_{Q(t)+1}], 1(t = \textit{announcement})\Big) = 0.$$

That is, $\theta_{2,1} = 0$ *in (6).*

Assumption 1 proves reasonable because the relevant agencies (e.g. BLS, BEA, Fed) schedule macroeconomic announcements up to a year in advance, often to fall on the same day of the week and week of the month in each year. This long lag prevents these agencies from timing announcements to co-occur with future shocks. The prior knowledge that the BEA will release the 2020 first-quarter GDP advance estimate on April 29, 2020, is uncorrelated with any of the other economic shocks that occur on that day (e.g. coronavirus news).[12] Why? Because the BEA could not possibly have known months in advance what other economic shocks would occur on April 29, 2020. Moreover, GDP announcements are scheduled for the last Thursday of the month, regardless of what the BEA might expect to happen on that day. Thus, the timing of these announcements is exogenous to other relevant economic shocks. On the other hand, the content of announcements (captured by $\nu_{\cdot,t}$) is surely endogenous to other economic shocks, but that is not the source of variation I exploit.

Assumption 2 also proves reasonable because failure of this assumption would violate the

[12] Unscheduled announcements (e.g. unscheduled FOMC announcements) do not satisfy this property.

martingale property of conditional expectations. Failure of Assumption 2 implies $\theta_{2,1} \neq 0$ in (6). But if $\theta_{2,1} \neq 0$, then for any announcement day t' and any prior day $t' - j, j > 0$:

$$\mathbb{E}_{t'-j}\left[\Delta \mathbb{E}_{t'}[\Delta C_{Q(t)+1}]\right] \neq 0,$$

which violates the martingale property. The investor cannot ex-ante expect his conditional expectations to change in the future in a predictable direction. For example, on April 28, 2020 the investor cannot expect his second-quarter expected consumption growth to predictably move on the April 29 first-quarter GDP growth announcement. Any such forecasted changes would already be incorporated into the conditional expectation on April 28.

Controlling for contemporaneous shifts in first moments represents a significant obstacle in much of the uncertainty literature (e.g. Alfaro, Bloom & Lin (2018); Baker, Bloom & Terry (2020); Barrero, Bloom & Wright (2017)). The prescheduled nature of these macroeconomic announcements ensures that conditional expectations cannot predictably move on announcement days.[13]

Second and higher moments, on the other hand, can predictably move on announcement days. That is, $\theta_{1,1}$ can be nonzero in (5). Indeed, $\alpha_1 \theta_{1,1} \neq 0$ is the relevance condition required for announcement timing to have any impact on macroeconomic uncertainty.[14] Given an empirical measure of σ_t^2, one can empirically verify this relevance condition via the following first-stage regression:

$$\Delta \sigma_t^2 = \beta_{\sigma^2,0} + \beta_{\sigma^2,1} 1(t = \text{announcement}) + \epsilon_t. \tag{7}$$

Note in this regression $\beta_{\sigma^2,1} = \alpha_1 \theta_{1,1}$. Thus, the third identifying assumption is:

Assumption 3. (Relevance) *The loading $\beta_{\sigma^2,1}$ of macroeconomic uncertainty $\Delta \sigma_t^2$ on the announcement timing $1(t = \textit{announcement})$ in first-stage regression (7) is non-zero.*

[13] Of course, the *content* of announcements will cause conditional expectations to move (e.g. as captured by $\nu_{2,t}$ in (6)). However, by the martingale property of conditional expectations, these movements are not ex-ante predictable and so Assumption 2 is justified.

[14] Note that this setup is consistent with the model of Ai & Bansal (2018), in which macroeconomic announcements resolve uncertainty about future consumption.

Under Assumptions 1, 2, and 3, the econometrician can identify the *announcement resolution of uncertainty (ARU) effect*:

$$\lambda_{ARU} = \lambda_{\sigma^2}\alpha_1\theta_{1,1} + \lambda_x\delta_1\theta_{1,1}. \tag{8}$$

This parameter is the causal effect of the announcement-timing-induced change in uncertainty about next quarter's consumption growth on expected returns. It accounts for all channels through which changes in uncertainty can affect expected returns: both macroeconomic uncertainty and the other expected return driver x_t. For example, an average reduction in conditional variance about next quarter's consumption growth on announcement days may reduce overall macroeconomic uncertainty and lower risk aversion. Both of these channels will reduce expected returns. In reduced form, however, both of these effects arise from the resolution of uncertainty. Thus, λ_{ARU} is a causal effect of uncertainty on expected returns; it is not at all polluted by contemporaneous shifts in first moments.

One can estimate this parameter via the following reduced form regression:

$$\Delta\mu_t = \lambda_0 + \lambda_{ARU} 1(t = \text{announcement}) + \epsilon_t. \tag{9}$$

Note that the identification of λ_{ARU} *does not use changes in expected returns on particular announcements*. As shown by (9), λ_{ARU} is the difference between the announcement-day and non-announcement day *average* changes in expected returns. The only source of variation used to identify λ_{ARU} is the timing of announcements.

Given estimated regressions (7) and (9), the econometrician can also identify:

$$\frac{\lambda_{ARU}}{\beta_{\sigma^2,1}} = \lambda_{\sigma^2} + \lambda_x \frac{\delta_1\theta_{1,1}}{\alpha_1\theta_{1,1}}. \tag{10}$$

This parameter, however, is still not the parameter of primary interest λ_{σ^2}. Identifying λ_{σ^2}, requires a fourth assumption:

Assumption 4. (Exclusion with respect to other expected return drivers) *Announcements* *do not systematically affect any driver of expected returns except macroeconomic uncertainty:*

$$Cov(\Delta x_t, 1(t = announcement)) = 0.$$

Assumption 4 implies that $\beta_{r,1} = 0$ in the following reduced-form regression:

$$\Delta x_t = \beta_{r,0} + \beta_{r,1} 1(t = \text{announcement}) + \epsilon_t, \tag{11}$$

where $\beta_{r,1} = \delta_1 \theta_{1,1}$. Thus, the second term in (10) vanishes and the econometrician can identify *the effect of macroeconomic uncertainty*:

$$\frac{\lambda_{ARU}}{\beta_{\sigma^2,1}} = \lambda_{\sigma^2}. \tag{12}$$

To summarize, the outside econometrician who only observes expected returns, macroeconomic uncertainty, and the announcement calendar can identify the announcement resolution of uncertainty effect λ_{ARU} if Assumptions 1, 2, and 3 are satisfied. If Assumption 4 is also satisfied, then the econometrician can identify the effect of macroeconomic uncertainty λ_{σ^2}. Crucially, under these four assumptions the only source of variation required to identify λ_{ARU} and λ_{σ^2} is the timing of announcements. Section 1.3 discusses potential threats to identification.

I estimate both λ_{ARU} and λ_{σ^2}. Since Assumptions 1 and 2 prove uncontroversial, I take them as given. I then empirically verify Assumption 3 and estimate λ_{ARU} via the reduced form regression (9). Unfortunately, I cannot prove Assumption 4 since many variables, including those not yet considered by theoretical or empirical research, may impact expected returns. However, I provide strong suggestive evidence in support of Assumption 4 by demonstrating proxies for risk aversion, disaster risk, and intermediary leverage do not correlate with the timing of announcements. In light of this evidence, I take Assumption 4 as given and estimate λ_{σ^2}.

The next section generalizes the environment from this section. In particular, the generalized environment allows for:

1. Multiple expected return drivers.
2. Multiple state variables.
3. Conditional distributions with time-varying higher moments.

All of the intuition and structural interpretations from this section carry over to the generalized environment.

1.2 Identification in a Generalized Environment

This section generalizes the environment from Section 1.1 and demonstrates how λ_{ARU} and λ_{σ^2} are still identified under Assumptions 1—4.

In contrast to Section 1.1, I now allow for an arbitrary number of state variables and relax the assumption that the representative agent's conditional distributions can be parameterized by mean and variance. Let $\boldsymbol{E}_t \in \mathbb{R}^N$ be the vector of the agent's conditional expectations over all N state variables (e.g. future consumption growth, future interest rates, etc.). Let $\boldsymbol{H}_t \in \mathbb{R}^M$ be the vector of all second and higher conditional moments for these N economic variables. For example, if the agent's conditional distributions can all be parameterized by conditional mean and variance (as in a normal distribution), then $M = N$ and $\boldsymbol{H}_t$ is the vector of all conditional variances.

Unlike in Section 1.1, I now allow for an arbitrary number of expected return drivers. Expected returns are now linear in macroeconomic uncertainty σ_t^2 and some general residual term $\Delta\check{\mu}$:

$$\Delta\mu_t = \lambda_{\sigma^2}\Delta\sigma_t^2 + \Delta\check{\mu}_t. \tag{13}$$

Here $\Delta\check{\mu}_t$ captures all variation in expected returns not driven by macroeconomic uncertainty. Whereas x_t in Section 1.1 represented a single alternative expected return driver, $\Delta\check{\mu}_t$ may include variation from many expected return drivers (e.g. $\Delta\check{\mu}_t$ may include variation from both risk aversion and intermediary leverage).

Additionally, I generalize the factor structure from (4) to now depend on all moments of the representative agent's conditional distributions over state variables:

$$\Delta\sigma_t^2 = \boldsymbol{\alpha}_1^{'}\Delta\boldsymbol{H}_t + \boldsymbol{\alpha}_2^{'}\Delta\boldsymbol{E}_t + \rho_v\epsilon_{f,t} + \sigma_v\epsilon_{v,t} \tag{14}$$
$$\Delta\check{\mu}_t = \boldsymbol{\delta}_1^{'}\Delta\boldsymbol{H}_t + \boldsymbol{\delta}_2^{'}\Delta\boldsymbol{E}_t + \rho_x\epsilon_{f,t} + \sigma_r\epsilon_{r,t},$$

where $\epsilon_{\nu,t}$,$\epsilon_{r,t}$, and $\epsilon_{f,t}$ are all uncorrelated. Lastly, the timing of announcements can potentially affect all moments of the representative agent's conditional distributions, which means both coefficient vectors $\boldsymbol{\theta}_{1,1}$ and $\boldsymbol{\theta}_{2,1}$ are potentially non-zero in the following generalizations of (5) and (6):

$$\Delta\boldsymbol{H}_t = \boldsymbol{\theta}_{1,0} + \boldsymbol{\theta}_{1,1}1(t = \text{announcement}) + \boldsymbol{\nu}_{1,t} \tag{15}$$

$$\Delta\boldsymbol{E}_t = \boldsymbol{\theta}_{2,0} + \boldsymbol{\theta}_{2,1}1(t = \text{announcement}) + \boldsymbol{\nu}_{2,t}. \tag{16}$$

Nothing fundamentally changes in this environment. Appendix A formalizes the changes in the four identifying assumptions, but all of the same intuition from Section 1.1 carries over. In this generalized environment, the first-stage coefficient $\beta_{\sigma^2,1}$ from (7) becomes $\beta_{\sigma^2,1} = \boldsymbol{\alpha}_1^{'}\boldsymbol{\theta}_{1,1}$. Under Assumptions 1, 2, and 3, the econometrician can still identify the announcement resolution of uncertainty (ARU) effect:

$$\lambda_{ARU} = \lambda_{\sigma^2}\boldsymbol{\alpha}_1^{'}\boldsymbol{\theta}_{1,1} + \boldsymbol{\delta}_1^{'}\boldsymbol{\theta}_{1,1},$$

and estimate it via reduced-form regression (9). The ARU effect is now the causal effect of the announcement-timing-induced change in uncertainty on expected returns, where uncertainty broadly includes all higher moments of all state variables. It still accounts for all channels through which changes in uncertainty can affect expected returns: both macroeconomic uncertainty and all expected return drivers in the residual term $\Delta\check{\mu}_t$. As in Section 1.1, however, λ_{ARU} is still a causal effect of uncertainty on expected returns because it is not at all polluted by contemporaneous shifts in first moments (i.e. by Assumption 2 $\boldsymbol{\theta}_{2,1} = \mathbf{0}$ in (16)).

Given estimated regressions (7) and (9), in this generalized environment the econometrician can also identify:

$$\frac{\lambda_{ARU}}{\beta_{\sigma^2,1}} = \lambda_{\sigma^2} + \frac{\boldsymbol{\delta}_1^{'}\boldsymbol{\theta}_{1,1}}{\boldsymbol{\alpha}_1^{'}\boldsymbol{\theta}_{1,1}}. \tag{17}$$

As in Section 1.1, under Assumption 4 no other expected return driver correlates with the announcement timing. Thus, $\beta_{r,1} = 0$ in the following reduced-form regression:

$$\Delta\check{\mu}_t = \beta_{r,0} + \beta_{r,1} 1(t = \text{announcement}) + \epsilon_t,$$

where $\beta_{r,1} = \boldsymbol{\delta}_1^{'}\boldsymbol{\theta}_{1,1}$. Thus, the second term in (17) vanishes and the econometrician can still identify the effect of macroeconomic uncertainty:

$$\frac{\lambda_{ARU}}{\beta_{\sigma^2,1}} = \lambda_{\sigma^2}.$$

The next section discusses potential threats to identification.

1.3 Potential Threats to Identification

This section discusses potential threats to identification and explains why my identification strategy proves robust to them. Many threats involve potential biases that can arise from announcement heterogeneity. Yet since the timing of announcements is exogenous and I only exploit average differences between announcement and non-announcement days, these concerns do not undermine my identification strategy. I consider several such threats in detail below to elucidate this general point.

1. **What if announcement content affects macroeconomic expectations?** For example, a positive surprise in the announcement of last quarter's GDP growth may

induce upward revisions about future expected consumption growth, which in turn could affect expected returns. That is, on any given announcement conditional expectations of macroeconomic variables can change (i.e. $\Delta \boldsymbol{E}_t \neq 0$). However, the *average* announcement-day change in conditional expectations is zero by the martingale property. Thus, any average announcement-day changes in expected returns must come from average announcement-day changes in uncertainty. Hence, the content of particular announcements is irrelevant to my identification strategy since I use only the differences between announcement-day and non-announcement day averages.

2. **What if the quantity of uncertainty resolved varies across announcements?** For example, the Federal Reserve might deliberately vary the informativeness of FOMC announcements depending on macroeconomic conditions. Alternatively, GDP announcements might endogenously be more informative in times of unprecedented crisis (e.g. April 2020) than in times of stable macroeconomic conditions. These scenarios pose no problems for my identification because *I do not exploit heterogeneity in the amount of uncertainty resolved across announcements*. I only use the timing of announcements. Even if the quantity of uncertainty resolved on announcements is endogenous to other macroeconomic developments, the timing of these announcements is exogenous because they are prescheduled far in advance and follow a predictable schedule (e.g. the BEA does not make more GDP growth announcements in bad times than in good times). As Section 1.1 details, my identification strategy requires only the exogeneity of announcement timing, not the exogeneity of announcement content.

3. **What if some announcements create more uncertainty?** For example, a particular FOMC announcement may confuse market participants or a poor GDP growth announcement may raise macroeconomic uncertainty. Again, these scenarios pose no problems for my identification because I do not use the changes in uncertainty on particular announcements. I only use the average announcement-day and non-announcement

day changes in uncertainty. Section 4.1 verifies empirically that on average macroeconomic uncertainty falls on announcements.

Macroeconomic announcements are surely heterogeneous and the content of these announcements is surely endogenous to prevailing macroeconomic conditions. But that is not the source of variation I exploit. I only use the timing of these announcements, which is exogenous. As long as announcements are not scheduled to coincide with future economic shocks, the timing of announcements is a valid instrument for uncertainty.

2 Data

This section discusses the data sources I use. To measure macroeconomic uncertainty, I use the monthly uncertainty index of Jurado, Ludvigson & Ng (2015) (JLN index). As discussed in Section 3.1, I construct a daily measure of uncertainty by projecting the JLN index onto the implied volatilities of a set of options. I use CME data for options on futures for the following underlyings: corn, crude oil, gold, soybean, S&P 500, ten-year Treasury notes, and wheat.[15] My baseline time sample is limited by this data: November 20, 1986 to December 22, 2016.

I use macroeconomic announcements for three groups of variables: output, prices, and monetary policy. For variables related to output I use quarterly real GDP growth announcements from the BEA and monthly unemployment announcements from the BLS.[16] For price variables I use monthly CPI and PPI announcements as well as quarterly Employment Cost Index announcements, all from the BLS. For monetary policy variables I use scheduled

[15] These underlyings are a subset of those from Dew-Becker, Giglio & Kelly (2019) whose options and futures have high daily liquidity in a long time period in the CME data. The assets used in Dew-Becker, Giglio & Kelly (2019) but not in this paper 1) are not available in my CME data, 2) have time series starting after 1986, or 3) do not have average daily volume per options contract (among all contracts with positive volume) of at least 100 trades. I choose 1986 as the cutoff year since it is the start year for many assets.

[16] The BEA releases three measurements for each quarter's real GDP growth, roughly one month apart. I use all three dates; all results prove robust to using just each quarter's first release date.

FOMC announcements.[17] This sample includes 1675 announcements in total.[18]

I use the CRSP value-weighted market portfolio as my proxy for the aggregate stock market.[19]

For the other assets in Section 5, I use CRSP Treasury Fixed Term Indexes, AAA and BAA seasoned corporate bond yields from FRED (series DAAA and DBAA), NYSE TAQ data from WRDS for measuring the variance risk premium, five and ten-year TIPS spreads from FRED (series T5YIE and T10YIE), and dollar exchange rates versus broad and major trade-weighted currency baskets from FRED (series DTWEXB and DTWEXM).

3 High-Frequency Measurement

In this section I describe how I measure changes in macroeconomic uncertainty and expected returns at the daily frequency.

3.1 Measuring Macroeconomic Uncertainty

Following Dew-Becker, Giglio & Kelly (2019), I construct a daily measure of macroeconomic uncertainty by projecting the monthly uncertainty index of Jurado, Ludvigson & Ng (2015) onto the implied volatilities of a set of options. The JLN index measures the common component of the unforecastable variation in 132 macroeconomic series.[20] In this sense, it

[17] I use the date of the post-meeting FOMC statement. Prior to 1994, when the Fed did not release FOMC statements, I use the date of the first open market operation following the meeting (Gürkaynak, Sack & Swanson (2005) argue financial markets inferred policy decisions on these dates). These open market operations usually occurred on the first business day after the meeting. I use the same dates as Gürkaynak, Sack & Swanson (2005) for 1990-1994 since that paper does not extend back to 1986. For 1989 I use the dates from Kuttner (2003). For 1986-1988 I use the first business day after the meeting.

[18] 324 GDP, 349 unemployment, 336 CPI, 352 PPI, 94 Employment Cost Index, and 220 FOMC.

[19] Section 6 considers alternative expected return and expected cash flow growth measures. I construct the Martin (2017) equity premium lower bound and the Gao & Martin (2019) log equity premium lower bound using options data from OptionMetrics. I obtain the Pettenuzzo, Sabbatucci & Timmermann (2020) expected dividend growth series from the supplemental data of that paper. I use high-frequency options data from Market Data Express and the zero-coupon yield curve data from OptionMetrics to extract dividend strip prices to construct the Gormsen & Koijen (2020) expected dividend growth measure.

[20] I use the twelve-month horizon JLN index. In the robustness checks discussed in Section 6.3 I find that the one and three-month indices yield similar results.

represents an empirical analogue to the theoretical quantity discussed in Section 1. Jurado, Ludvigson & Ng (2015) model the joint time series dynamics of the macroeconomic series as a factor-augmented VAR and derive the dynamics of the forecast error covariance matrix. Macroeconomic uncertainty is then the average of the conditional forecast error standard deviations across all series.

To obtain a daily index, I run a monthly regression of the JLN index on the average monthly implied volatilities of the seven underlyings (corn, crude oil, gold, soybean, S&P 500, ten-year Treasury notes, and wheat)[21]:

$$JLN_t = \alpha + \sum_{i=1}^{7} \beta_i \overline{IV}_{it} + \epsilon_t. \tag{18}$$

Internet Appendix H Table H.1 displays the results of this regression. I then apply the obtained weights to daily implied volatilities to construct a daily JLN index.[22] Figure 1 displays the daily and original monthly JLN indices. The daily index tracks the monthly index well, with a monthly correlation of 0.826.

The robustness checks in Section 6.3 consider alternative measures of macroeconomic uncertainty. I reproduce my main results using variants of the Jurado, Ludvigson & Ng (2015) index that measure uncertainty over different horizons, an out-of-sample daily JLN index constructed by performing regression (18) in a rolling window, and S&P 500 implied volatility.

[21] In principle, since implied volatilities are measures of risk-neutral volatility, they will also respond to daily changes in risk aversion. However, this potential contamination by risk aversion does not undermine my empirical analysis. Recall from the first-stage regression (7) that I only care about the difference in average changes in macroeconomic uncertainty on announcement and non-announcement days. Section 4.3 verifies that other proxies for risk aversion do not correlate with the timing of macroeconomic announcements. Thus, even if daily changes in risk aversion do contaminate this daily measure of macroeconomic uncertainty, they do not contaminate the estimated $\beta_{\sigma^2,1}$ coefficient from (7). For this reason, daily changes in risk aversion will also not contaminate my empirical estimate of λ_{σ^2}.

[22] I take a volume-weighted average of implied volatilities of all contracts. See Internet Appendix B for details.

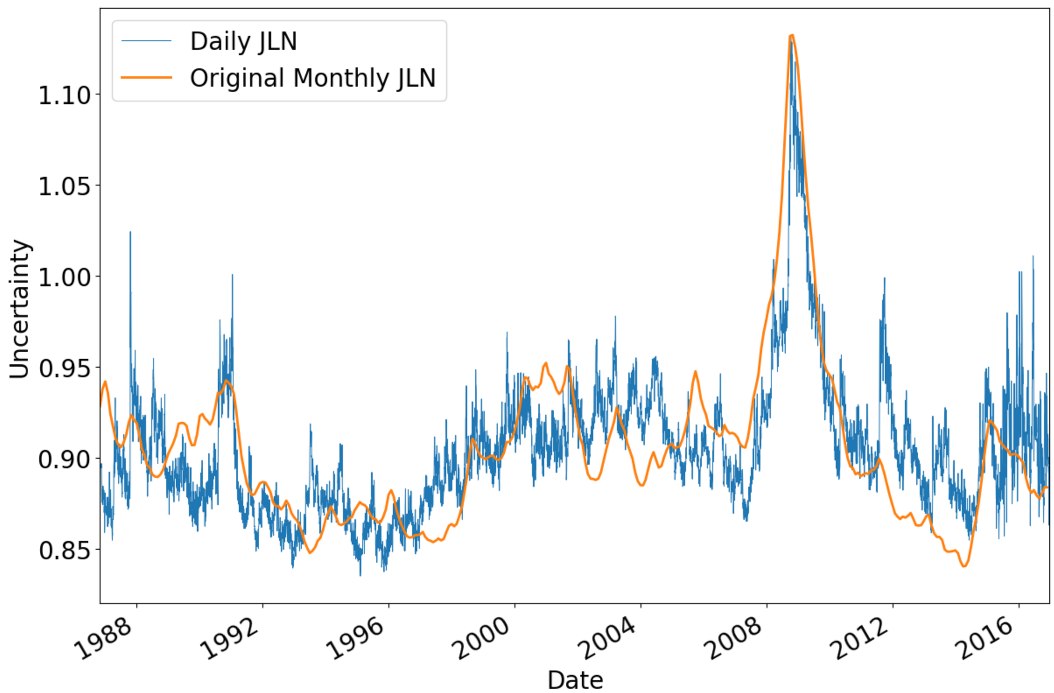

Figure 1: Time Series of Monthly and Daily JLN Indices
This figure displays the time series of the monthly uncertainty index from Jurado, Ludvigson & Ng (2015) and the daily JLN uncertainty index constructed in Section 3.1.

3.2 Measuring Daily Changes in Expected Returns

In this section I discuss how I measure daily changes in expected returns. Recall from Section 1 that I seek to measure the difference between the announcement-day and non-announcement day average changes in expected returns. This difference in average changes in expected returns is the ARU effect (λ_{ARU}) and allows for estimation of the causal effect of macroeconomic uncertainty (λ_{σ^2}).

In particular, I consider daily changes in long-run expected log returns. The present value identity of Campbell & Shiller (1988) decomposes the log price-dividend ratio into long-run expected cash flow growth and long-run expected returns:

$$p_t - d_t = \frac{k}{1-\rho} + \underbrace{\sum_{j\geq 0} \rho^j \mathbb{E}_t[\Delta d_{t+1+j}]}_{\text{Long-run expected cash flow growth}} - \underbrace{\sum_{j\geq 0} \rho^j \mathbb{E}_t[r_{t+1+j}]}_{\text{Long-run expected returns}},$$

where d_t is log dividends paid on day t, r_t is log return on day t, and ρ and k are log-linearization constants that depend on the average log price-dividend ratio.[23] Let $\mu_{r,t} = \sum_{j\geq 0}\rho^j \mathbb{E}_t[r_{t+1+j}]$ and $\mu_{d,t} = \sum_{j\geq 0}\rho^j \mathbb{E}_t[\Delta d_{t+1+j}]$ represent the long-run expected return and long-run expected cash flow growth at the end of day t, respectively. The daily change in long-run expected returns is given by[24]:

$$\Delta\mu_{r,t} = -\mathbb{E}_{t-1}[r_t] + \mu_{r,t} - \rho\mathbb{E}_{t-1}[\mu_{r,t}].$$

The average change in long-run expected returns on announcement days is given by

$$\mathbb{E}[\Delta\mu_{r,t} \,|\, t = \text{announcement}] = -\mathbb{E}[r_t \,|\, t = \text{announcement}] + (1-\rho)\mathbb{E}[\mu_{r,t} \,|\, t = \text{announcement}].$$

This equality follows from the law of iterated expectations. For any day $t+j, j \geq 0$

$$\mathbb{E}[-\mathbb{E}_{t-1}[r_{t+j}] \,|\, t = \text{announcement}] = \mathbb{E}[-\mathbb{E}_{t-1}[r_{t+j} \,|\, t = \text{announcement}] \,|\, t = \text{announcement}],$$

because *the timing of the announcements is known in advance* (i.e. $1(t = \text{announcement})$ is in the information set at time $t-1$). At day $t-1$, investors know if day t is an announcement. Therefore, applying the law of iterated expectations yields

$$\mathbb{E}[-\mathbb{E}_{t-1}[r_{t+j}] \,|\, t = \text{announcement}] = \mathbb{E}[-r_{t+j} \,|\, t = \text{announcement}]$$
$$\mathbb{E}[\mu_{r,t} - \rho\mathbb{E}_{t-1}[\mu_{r,t}] \,|\, t = \text{announcement}] = (1-\rho)\mathbb{E}[\mu_{r,t} \,|\, t = \text{announcement}].$$

A symmetric argument holds for non-announcement days.

Thus, the difference between the announcement-day and non-announcement day average

[23] Specifically, $\rho = 1/(1+\exp[\mathbb{E}[d_t - p_t]])$, and $k = -\ln(\rho) - (1-\rho)\ln(1/\rho - 1)$.

[24] Note that

$$\mu_{r,t-1} = \sum_{j\geq 0}\rho^j \mathbb{E}_{t-1}[r_{t+j}] = \mathbb{E}_{t-1}[r_t] + \rho\sum_{j\geq 0}\rho^j \mathbb{E}_{t-1}[r_{t+1+j}] = \mathbb{E}_{t-1}[r_t] + \rho\mathbb{E}_{t-1}[\mu_{r,t}].$$

changes in long-run expected returns is

$$\lambda_{ARU} = -(\mathbb{E}[r_t \mid t = \text{announcement}] - \mathbb{E}[r_t \mid t \neq \text{announcement}]) \\ + (1-\rho)(\mathbb{E}[\mu_{r,t} \mid t = \text{announcement}] - \mathbb{E}[\mu_{r,t} \mid t \neq \text{announcement}]). \quad (19)$$

The first term is just the negative difference between average announcement-day and non-announcement day realized log returns. The second term involves the difference between the average announcement-day and non-announcement day *levels* of long-run expected returns. Note that a difference in the average *levels* of long-run expected returns would very likely imply a difference in the average levels of the price-dividend ratio (Cochrane (2008)).[25] As it turns out, however, average end-of-day price-dividend ratios are not significantly different between announcement-day and non-announcement days. Using the daily estimate $\rho = 0.99998$ from Pettenuzzo, Sabbatucci & Timmermann (2020), a regression of $(1-\rho)(p_t - d_t)$ on the announcement timing indicator

$$(1-\rho)(p_t - d_t) = b_0 + b_1 1(t = \text{announcement}) + \epsilon_t$$

yields an insignificant $b_1 = 2.36 \times 10^{-8}$ (standard error of 1.72×10^{-7}).[26] I take this null result as evidence that the second term in (19) is approximately zero.[27]

Thus, I measure the difference between the announcement-day and non-announcement

[25]In principle, average announcement-day and non-announcement day long-run expected return levels could be different without announcement-day and non-announcement day average price-dividend ratios differing. For this to be the case, average announcement-day and non-announcement day *long-run expected cash flow growth levels* would have to exactly offset the difference in long-run expected returns:

$$\mathbb{E}[\mu_{r,t} \mid t = \text{announcement}] - \mathbb{E}[\mu_{r,t} \mid t \neq \text{announcement}] = \mathbb{E}[\mu_{d,t} \mid t = \text{announcement}] - \mathbb{E}[\mu_{d,t} \mid t \neq \text{announcement}].$$

However, this situation proves unlikely since expected returns and expected cash flow growth are usually assumed to be negatively correlated (Gormsen & Koijen (2020); Lochstoer & Tetlock (2020)).

[26]Note heterogeneity in the set of firms paying renders the time series of daily dividends noisy. Thus, I view the daily d_t as a noisy realization of the true level of dividends investors price, which I proxy by smoothing over the last year. In a model where noise in the observed level is large relative to the daily growth rate, smoothing yields more efficient estimates of the true level. I use the sum of the previous four quarterly dividends as it better removes seasonality than a daily rolling sum. Using a daily rolling sum as well as alternative smoothing horizons yields similar results. See Internet Appendix H Table H.2 for details.

[27]Indeed a significant difference in the *level* of expected returns between announcement and non-announcement days would cast doubt on the exogeneity of announcement timing.

day average changes in long-run expected returns as:

$$\lambda_{ARU} \approx -(\mathbb{E}[r_t \,|\, t = \text{announcement}] - \mathbb{E}[r_t \,|\, t \neq \text{announcement}]). \tag{20}$$

Note that a regression of negative realized log returns ($-r_t$) on the announcement timing indicator ($1(t = \text{announcement})$) will estimate λ_{ARU} in (20):

$$-r_t = \lambda_0 + \lambda_{ARU} 1(t = \text{announcement}) + \epsilon_t. \tag{21}$$

As suggested by the form of regression (21), the negative of the reduced-form macroeconomic announcement premium documented by Savor & Wilson (2013) is an estimate of the structural parameter of interest here: λ_{ARU}.

What is the role of finite-sample variation? In any finite sample, empirical averages may differ from population means. The realized log return decomposition of Campbell (1991) implies

$$r_t = \mathbb{E}_{t-1}[r_t] + \underbrace{(\mathbb{E}_t - \mathbb{E}_{t-1}) \sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j}}_{\text{Cash Flow Growth Shock}} - \underbrace{(\mathbb{E}_t - \mathbb{E}_{t-1}) \sum_{j=1}^{\infty} \rho^j r_{t+1+j}}_{\text{Discount Rate Shock}} \tag{22}$$

By the martingale property of conditional expectations, the cash flow and discount rate shocks have true conditional expectations of zero, so (22) implies $\mathbb{E}[r_t \,|\, t = \text{announcement}] = \mathbb{E}[E_{t-1}[r_t] \,|\, t = \text{announcement}]$. Yet in any finite sample the empirical average announcement-day cash flow growth shock may be non-zero.[28] If the in-sample average announcement-day and non-announcement day cash flow growth shocks differ, then the estimate of λ_{ARU} from (21) will reflect this finite-sample variation.[29] Specifically, if the in-sample announcement-

[28] Law, Song & Yaron (2018) and Cieslak & Pang (2020) find FOMC and non-farm payroll announcements can have large growth expectations shocks depending on announcement content and state of the business cycle. Savor & Wilson (2013) consider and reject the possibility that the average announcement in a finite sample involves a non-zero cash flow shock.

[29] On the other hand, note that finite-sample differences in the average announcement-day and non-announcement day discount rate shocks are changes in long-run expected returns. Thus, they prove less problematic for the interpretation of the estimated λ_{ARU}.

Table 1: Summary Statistics

	r_t	$\Delta\sigma_t^2$	$1(t\!=\!\text{announcement})$
Count	7561	7561	7561
Mean	0.0369	-2.9953e-06	.22100
Std	1.1230	7.8697e-03	.41495
Min	-18.7956	-8.0745e-02	0
Median	0.0813	-1.1239e-04	0
Max	10.8749	9.8578e-02	1

Summary statistics for daily log realized returns (r_t, in percentage points), changes in the daily JLN macroeconomic uncertainty index ($\Delta\sigma_t^2$), and the daily announcement timing indicator $1(t\!=\!$ announcement). Units are in percentage terms (i.e. 1.0 is 100 basis points). The time period is 1986-11-20:2016-12-22.

day average cash flow growth shock is higher than the non-announcement day average, then the estimated λ_{ARU} from (20) will be smaller (i.e. more negative and larger in magnitude) than the true parameter.

The robustness checks in Section 6 rule out the possibility that finite-sample variation in cash flow growth shocks drives my results. In Section 6.1 I reproduce my main results by directly measuring conditional expected returns using the options-implied Martin (2017) equity premium lower bound and Gao & Martin (2019) log equity premium lower bound. As direct measures of conditional expected returns, these lower bounds cannot suffer from finite-sample variation in cash flow growth shocks. In Section 6.2 I provide evidence that the average announcement-day and non-announcement day changes in expected cash flow growth do not differ using the Pettenuzzo, Sabbatucci & Timmermann (2020) expected dividend growth series, the Gao & Martin (2019) options-implied expected log dividend growth lower bound, and the Gormsen & Koijen (2020) dividend-strip-implied expected dividend growth measure.

Table 1 exhibits summary statistics for daily log realized returns for the CRSP value-weighted market portfolio, changes in the daily JLN index, and the announcement timing indicator variable.

4 Empirical Results

This section presents my main empirical results. First, Section 4.1 establishes that macroeconomic uncertainty falls on average on announcement days more than on non-announcement days, which means announcement timing is a relevant instrument for uncertainty. Second, Section 4.2 demonstrates that this announcement resolution of uncertainty causes decreases in expected returns. Third, Section 4.3 justifies Assumption 4 and estimates the pure effect of macroeconomic uncertainty on expected returns.

4.1 Macroeconomic Uncertainty Falls on Announcements

Macroeconomic uncertainty falls significantly on announcement days. Motivated by the first-stage regression (7), I run the following regression of the change in the daily JLN index constructed in Section 3.1 on a set of timing indicators representing how many days j after an announcement day t is:

$$\Delta\sigma_t^2 = \beta_0 + \sum_{j=-5}^{5} \beta_j 1(t-j = \text{announcement}) + \epsilon_t, \tag{23}$$

where $\Delta\sigma_t^2$ is the change in the daily JLN index. To facilitate interpretation, I scale $\Delta\sigma_t^2$ to have mean zero and standard deviation one. Figure 2 graphically displays the regression results.

The daily JLN index experiences a highly significant additional 0.21 standard deviation drop on macroeconomic announcement days than on non-announcement days (with a t-statistic of over 7 in magnitude). Internet Appendix H Table H.3 reports the full regression results.[30] These results validate the relevance condition of $\beta_{\sigma^2,1} \neq 0$ in Assumption 3 from Section 1.1. In the parlance of instrumental variables, the announcement timing is a relevant

[30]Several other coefficients $\beta_j, j \neq 0$, are also statistically significant, in part since many announcements cluster at the start of the month. The subsequent analysis only uses the resolution of uncertainty on the announcement day and so ignores β_j for $j \neq 0$. A placebo test running regression (23) in random 11-day windows instead of windows centered at announcements yields all insignificant coefficients (Internet Appendix H Figure H.1).

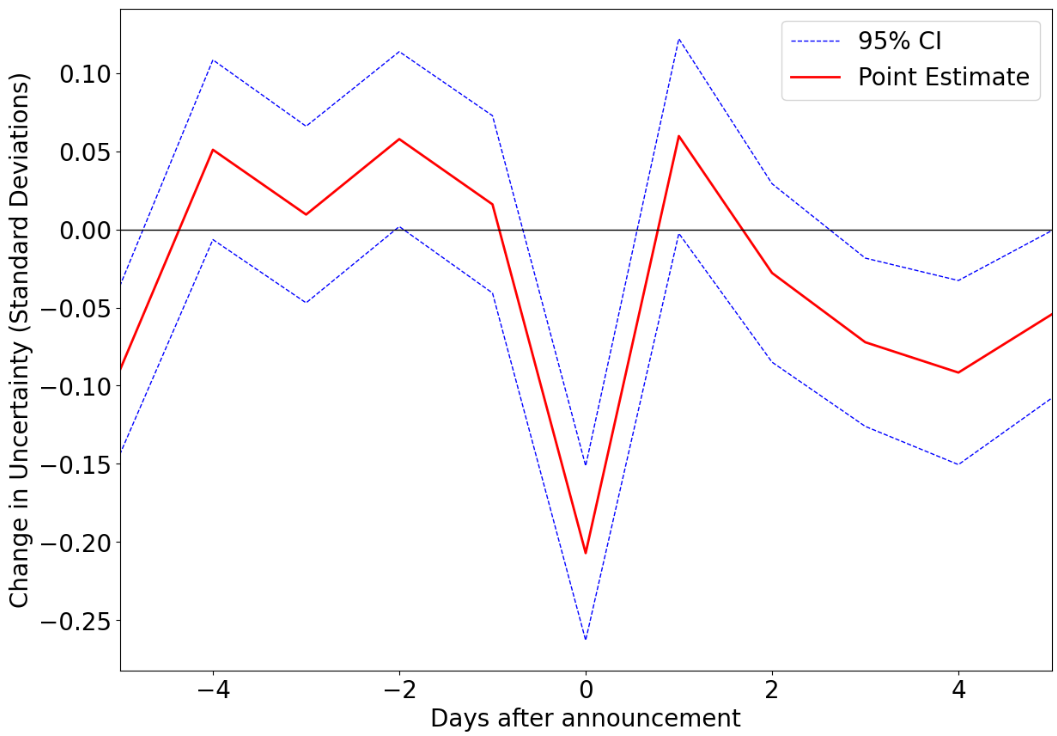

Figure 2: Response of Daily JLN Index to Announcement Timing
Coefficients and 95% confidence intervals from regression (23) (full results in Internet Appendix H Table H.3). Y-axis units are standard deviations (i.e. $\Delta\sigma_t^2$ is scaled to have mean zero and standard deviation one).

instrument for macroeconomic uncertainty.[31]

Having established the relevance of announcement timing, going forward I will only use the timing of announcements ($1(t = \text{announcement})$), not the timing of adjacent days, as discussed in Section 1.

4.2 Announcement Resolution of Uncertainty Effects

The announcement resolution of uncertainty causes a significant decrease in expected returns. As discussed in Section 3.2, I estimate the ARU effect via the following reduced-form

[31]As displayed in Table 3, the F-statistic of the univariate regression of $\Delta\sigma_t^2$ on $1(t\text{=announcement})$ is 64.26, much greater than the standard threshold of 10 in weak instrument tests.

Additionally, announcements resolve uncertainty up to intermediate horizons. I construct fixed-horizon counterparts to my baseline daily JLN index by applying the coefficients from regression (18) to the implied volatilities of subsets of options with the same time to expiration. Internet Appendix H Figure H.2 displays significant resolutions of uncertainty up to 7 months. Measurement error increases with maturity as volume falls and so may explain the loss of significance after 7 months.

Table 2: Announcement Resolution of Uncertainty Effect Regressions

	$-r_t$
Announcement	-0.0781**
	(0.0304)
const	-0.0196
	(0.0148)
N	7561
R^2	0.00

Results of reduced form regression (9) of negative log realized excess returns $-r_t$ on the announcement timing indicator $1(t{=}\text{announcement})$. Units are in percentage terms (i.e. a coefficient of 1.0 is 100 basis points).

regression:

$$-r_t = \lambda_0 + \lambda_{ARU} 1(t{=}\text{announcement}) + \epsilon_t,$$

where r_t is the log realized return for the CRSP value-weighted market portfolio on day t. Table 2 displays the regression results and finds a significant $\lambda_{ARU} = -7.8$ basis points. Thus, given Assumptions 1, 2, and 3, the resolution of uncertainty on macroeconomic announcements causes long-run expected log returns to fall 7.8 basis points.[32] This estimate is consistent with the reduced-form macroeconomic announcement premium from Savor & Wilson (2013).[33]

[32]Since $E_t[r_{t+1}] = \log E_t[R_{t+1}] - \frac{1}{2} V_t[r_{t+1}]$, one may worry this reduction in expected log returns reflects an increase in conditional volatility, not a decrease in expected returns. Section 6.3 shows S&P 500 implied volatility falls more on announcement days than on non-announcement days, which suggests log expected returns for the CRSP value-weighted market portfolio fall more than expected log returns.

[33]These results are also consistent with pre-announcement drift (Lucca & Moench (2015)), attributed by some work to the resolution of uncertainty (Ai & Bansal (2018); Laarits (2019); Hu et al. (2019)). Lucca & Moench (2015) find that the high average returns on FOMC announcement days accrue mostly in the hours prior to the announcement at 2:30 P.M. Hu et al. (2019) document that uncertainty (as measured by VIX) also falls in those same hours prior to the announcement. Both the high-frequency pre-announcement returns and change in uncertainty will be picked up by my daily measures. Ai & Bansal (2018) note that the resolution of uncertainty on the announcement day but prior to the announcement is consistent with information leakage, for which they cite empirical evidence from Bernile, Hu & Tang (2016) and Cieslak, Morse & Vissing-Jorgensen (2019).

4.3 Macroeconomic Uncertainty Moves Expected Returns

This section provides evidence of Assumption 4 and estimates λ_{σ^2} via two-stage least squares. Recall Assumption 4: no expected return driver other than macroeconomic uncertainty correlates with the announcement timing. From (17) in Section 1.2, scaling the ARU effect by the first-stage coefficient allows the econometrician to estimate

$$\frac{\lambda_{ARU}}{\beta_{\sigma^2,1}} = \lambda_{\sigma^2} + \frac{\boldsymbol{\delta}_1^{'}\boldsymbol{\theta}_{1,1}}{\boldsymbol{\alpha}_1^{'}\boldsymbol{\theta}_{1,1}}. \tag{24}$$

Under Assumption 4 though,

$$\frac{\lambda_{ARU}}{\beta_{\sigma^2,1}} = \lambda_{\sigma^2}.$$

That is, Assumption 4 implies that the only channel through which the ARU effect operates is through a reduction in macroeconomic uncertainty. To justify this assumption, I demonstrate that proxies for other theoretically-motivated expected return drivers do not load on the timing of announcements.

Specifically, I use daily measures from theories of time-varying risk aversion, time-varying disaster risk, and intermediary asset pricing. First, as a measure of time-varying risk aversion I use the risk aversion index from Bekaert, Engstrom & Xu (2019), which comes from structural estimation of an external habit model. Second, I use two measures of disaster risk. First, I use the options-implied risk-neutral weekly left-tail volatility and negative ten-percent crash probability for the S&P 500 from Bollerslev, Todorov & Xu (2015). These risk-neutral crash-risk measures also move due to changes in risk-aversion and so provide a robustness check for the risk aversion index from Bekaert, Engstrom & Xu (2019). Additionally, to gauge disaster risk at longer horizons I use the options-implied crash probabilities from Martin (2017). These measures track the probability of a negative twenty percent decrease in the S&P 500 over the next one, three, six, and twelve months that a log-utility investor would perceive from options prices. Third, I use the squared intermediary leverage ratio from He, Kelly & Manela (2017), which is the squared ratio of aggregate market equity and book debt to aggregate market equity of all primary dealers for the Federal Reserve Bank of New York.

Theory suggests daily changes in all of these variables should positively correlate with daily changes in expected returns. Internet Appendix H Table H.4 illustrates that daily changes in all of these variables correlate positively with changes in the daily JLN index. However, all of these correlations prove relatively mild in magnitude, which already begins to assuage omitted variable bias concerns.

To demonstrate that none of these alternative variables correlate with the announcement timing, I run the following regression:

$$\Delta y_t = \beta_0 + \beta_1 1(t = \text{announcement}) + \epsilon_t,$$

where y_t is one of: risk aversion index, risk-neutral crash risk, log-utility crash risk, squared intermediary leverage, or daily JLN index. To facilitate comparison, I standardize all left-hand side variables to have mean zero and standard deviation one. Table 3 demonstrates that none of the alternative expected return drivers load significantly negatively on the announcement timing.[34] The highest F-statistic for any of these alternative variables is 3.40 for the risk-neutral left-tail volatility of Bollerslev, Todorov & Xu (2015), which is far below the conventional threshold of ten for weak instrument tests and actually corresponds to a positive β_1 estimate. Moreover, the largest negative difference between announcement-day and non-announcement day average changes in any of the alternative variables is -0.04 standard deviations (for the 12-month log-utility crash probability). On the other hand, the daily JLN index declines an additional 0.21 standard deviations on announcement days than on non-announcement days with an F-statistic of over sixty.

These results lend credence to Assumption 4. In principle, the announcement resolution of uncertainty could impact expected returns through many channels. In practice however,

[34]To maximize power, I use the longest available time series for each left-hand side variable. Using the longest sample common to all variables (2000-2012) yields similar results.

Table 3: Regression Results for Response of Potential Expected Return Drivers to Announcement Timing

	ΔILR^2	ΔLTV	$\Delta{-10\%}\ Prob$	$\Delta 1MO\ CP$	$\Delta 2MO\ CP$	$\Delta 3MO\ CP$	$\Delta 6MO\ CP$	$\Delta 12MO\ CP$	ΔRA	$\Delta\sigma_t^2$
const	0.0005	-0.0123	-0.0003	0.0023	0.0054	0.0085	0.0079	0.0093	-0.0003	0.0473***
	(0.0172)	(0.0155)	(0.0150)	(0.0187)	(0.0181)	(0.0183)	(0.0176)	(0.0183)	(0.0132)	(0.0131)
Announcement	-0.0022	0.0554*	0.0015	-0.0104	-0.0244	-0.0387	-0.0360	-0.0422	0.0012	-0.2158***
	(0.0301)	(0.0300)	(0.0309)	(0.0329)	(0.0362)	(0.0353)	(0.0388)	(0.0351)	(0.0238)	(0.0269)
N	4764	5634	5822	4047	4047	4047	4047	4047	8053	7561
R^2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01
F	0.01	3.40	0.00	0.10	0.45	1.20	0.86	1.45	0.00	64.26
Date Range	2000 - 2018	1996 - 2019	1996 - 2019	1996 - 2012	1996 - 2012	1996 - 2012	1996 - 2012	1996 - 2012	1988 - 2020	1986 - 2016

This table presents results for regressions

$$\Delta y_t = \beta_0 + \beta_1 1(t = \text{announcement}) + \epsilon_t$$

where y_t is one of: squared intermediary leverage ratio (ILR^2) from He, Kelly & Manela (2017), options-implied risk-neutral weekly left-tail volatility (LTV) and negative ten-percent crash probability (-10% Prob) for the S&P 500 from Bollerslev, Todorov & Xu (2015), options-implied log-utility-perceived 1, 2, 3, 6, and 12 month S&P 500 negative twenty-percent crash probabilities (XMO CP) from Martin (2017), risk aversion index (RA) from Bekaert, Engstrom & Xu (2019), or daily JLN macroeconomic uncertainty index (σ_t^2). All of these left-hand-side variables Δy_t are scaled to have mean zero and standard deviation one.

macroeconomic uncertainty appears to be the only relevant channel since it is the only driver of expected returns that correlates with the timing of announcements. Thus, I proceed by taking Assumption 4 as given and interpreting the ratio $\lambda_{ARU}/\beta_{\sigma^2,1}$ as λ_{σ^2}. To cast doubt on the results I present below, an omitted driver of expected returns would have to: 1) correlate significantly positively with expected returns and 2) load significantly negatively on the announcement timing (or correlate negatively and load positively).

I estimate λ_{σ^2} via the following two-stage least squares regression

$$\begin{aligned}\Delta\sigma_t^2 &= \beta_0 + \beta_1 1(t = \text{ announcement}) + \epsilon_t \\ -r_t &= \lambda_0 + \lambda_1 \widehat{\Delta\sigma_t^2} + \nu_t.\end{aligned} \tag{25}$$

Since the first-stage regression here estimates $\beta_{\sigma^2,1}$ and the reduced-form regression of $-r_t$ on $1(t = \text{ announcement})$ estimates λ_{ARU}, the second-stage coefficient from (25) estimates $\lambda_{ARU}/\beta_{\sigma^2,1} = \lambda_{\sigma^2}$.

Table 4 displays the results of the two-stage least squares regression (25). The fourth column indicates that a positive one standard-deviation move in $\Delta\sigma_t^2$ causes a $\lambda_1 = 36$ basis point increase in long-run expected returns. This estimate implies that a positive one standard deviation change in the *level of* σ_t^2 causes a 173 basis point increase in expected returns.

We can also view these results through the lens of a variance decomposition. The following expression represents the proportion of variance of daily changes in long-run expected returns explained by changes in macroeconomic uncertainty:

$$\frac{\widehat{\lambda}_1^2 \text{Var}[\Delta\sigma_t^2]}{\text{Var}[\Delta\mu_{rt}]} = 10.35\%, \tag{26}$$

where I use the variance of the price-dividend ratio to approximate the denominator variance of long-run expected returns.[35]

[35]This approximation is justified since expected-return variation drives most of the variation in the price-dividend ratio (Cochrane (2008)). Moreover, note that by the present value identity of Campbell & Shiller

Table 4: Two-Stage Least Squares Regression Results for Expected Returns

	OLS	First Stage	Reduced Form	2SLS
$\Delta\sigma_t^2$	0.2986***			0.3619***
	(0.0326)			(0.1380)
Announcement		-0.2158***	-0.0781**	
		(0.0269)	(0.0304)	
const	-0.0368***	0.0473***	-0.0196	-0.0367***
	(0.0125)	(0.0131)	(0.0148)	(0.0125)
N	7561	7561	7561	7561
R^2	0.07	0.01	0.00	-

Results for two-stage least squares regression (25). The first stage regresses $\Delta\sigma_t^2$ (standardized to have mean zero and standard deviation one) on $1(t=$ announcement$)$. The second stage regresses $-r_t$ on $\widehat{\Delta\sigma_t^2}$. Units are in percentage terms (i.e. a coefficient of 1.0 represents 100 basis points).

The aggressive interpretation of this result is, in light of the evidence supporting Assumption 4, macroeconomic uncertainty accounts for about 10% of daily long-run expected return variation.[36] A less aggressive interpretation would be to allow for Assumption 4 to potentially not hold and acknowledge that $\widehat{\lambda}_1$ from (25) may suffer from omitted variable bias due to other expected return drivers. In this case, we can provide an upper bound for the variance proportion in (26). To do so, I plug the upper bound of the 95% confidence interval for the estimate of $\widehat{\lambda}_1$ into (26) to obtain[37]

$$\frac{\left(\widehat{\lambda}_1 + 1.96 \cdot SE_{\widehat{\lambda}_1}\right)^2 \text{Var}[\Delta\sigma_t^2]}{\text{Var}[\Delta\mu_{rt}]} = 31.62\%.$$

(1988):

$$\text{Var}[\Delta\mu_{rt}] = \text{Var}[p_t - d_t] - \text{Var}[\Delta\mu_{dt}] + 2 \cdot \text{Cov}(\Delta\mu_{rt}, \Delta\mu_{dt}).$$

Under the usual assumption that expected returns and expected cash flow growth are negatively correlated (Gormsen & Koijen (2020); Lochstoer & Tetlock (2020)), $\text{Var}[\Delta\mu_{rt}] < \text{Var}[p_t - d_t]$. Thus, using $\text{Var}[p_t - d_t]$ to measure $\text{Var}[\Delta\mu_{rt}]$ provides a conservative estimate (i.e. an underestimate) of the true variance proportion in (26).

[36] For comparison, Bekaert, Engstrom & Xing (2009) and Bekaert, Engstrom & Xu (2019) find in structural models that "uncertainty" accounts for 17% and 3% of quarterly and monthly equity premium variation. However, one must be careful with this comparison. First, these papers use different the definitions of uncertainty than Jurado, Ludvigson & Ng (2015) and this work. Second, the expected return horizon differs as this paper focuses on long-run expected returns. Lastly, these papers force uncertainty and risk aversion to explain all expected return variation whereas the reduced-form setting here allows for many expected return drivers.

[37] This expression gives an upper bound for the variance explained proportion *if* the second term in (24) is positive. If the second term is negative, then $\widehat{\lambda}_1$ underestimates λ_{σ^2}.

Thus, a less aggressive interpretation of the two-stage least squares results in Table 4 is that macroeconomic uncertainty can account for *at most* 32% of daily long-run expected return variation.

In summary, the results in this section demonstrate that time-varying macroeconomic uncertainty causes significant changes in and accounts for an important part of the daily variation in long-run expected equity returns.

5 Evidence from Other Asset Classes

This section presents evidence of external validity for my baseline results by examining the effect of macroeconomic of uncertainty on other assets: government bonds, corporate bonds, currencies, and the variance risk premium. Motivated by the present value identity of Campbell & Shiller (1988), the baseline analysis measures the difference between announcement-day and non-announcement day average changes in long-run expected returns using the negative difference between average realized returns. Justifying this measurement methodology for alternative assets proves beyond the scope of this paper. Instead, I demonstrate macroeconomic uncertainty causally impacts *prices* of other assets and appeal to these results as corroborating evidence of a causal effect on expected returns. In principle, many disparate objects (e.g. expected future interest rates, expected future cash flows, etc.) could move to deliver coordinated average price changes across assets on announcements. I view this scenario, however, as less likely than the simpler explanation that discount rate movements drive all these price changes.

I run the following two-stage least squares regression in the style of (25):

$$\begin{aligned}\Delta\sigma_t^2 &= \beta_0 + \beta_1 1(t = \text{ announcement}) + \epsilon_t \\ \Delta P_t &= \lambda_0 + \lambda_1 \widehat{\Delta\sigma_t^2} + \nu_t,\end{aligned} \tag{27}$$

where P_t is a measure of price (bond yields, level of variance risk premium, or exchange rate).

Figure 3 displays the proportions of price variance explained by macroeconomic uncertainty for each asset, while Internet Appendix H Table H.5 reports full regression results. Overall, macroeconomic uncertainty explains a significant amount of the variation in government bond yields, corporate bond yields, and the variance risk premium. I summarize these results below.

Government Bond Yields: I consider U.S. Treasury bonds with 1,2,5,7,10,20, and 30-year maturities, term structure slope (10-year minus 2-year yield), and term structure curvature (5-year yield minus average of 10-year and 2-year yields). Per column one in Table H.5, the announcement resolution of uncertainty lowers yields across maturities (with stronger effects for maturities of at least 5 years), and flattens the term structure. The second-stage coefficients in column four imply that macroeconomic uncertainty drives 11% of the variation in 2-year yields, over 20% of the variation in yields for maturities of at least 5 years, and 6% of variation in term structure slope. The second-stage coefficients for 1-year yields and curvature are insignificant.

Corporate Bond Yields: For corporate bonds I use Moody's seasoned AAA and BAA corporate bond yields, as well as the credit spread between these two yields. The ARU effect lowers both AAA and BAA yields between 0.4 and 0.5 basis points but is insignificant for credit spreads. Macroeconomic uncertainty explains 24% and 23% of the variation in AAA and BAA yields, respectively, and an insignificant amount of variation in credit spreads.

Variance Risk Premium (VRP): I calculate the VRP in two ways. Following Bollerslev, Tauchen & Zhou (2009) I measure the daily VRP level as the squared VIX minus the realized variance of the S&P 500 calculated from non-overlapping five-minute returns over both the past 22 days and the past day.[38] I find both VRP measures fall significantly on average on announcements with the 22-day version exhibiting a stronger response. Macroeconomic uncertainty explains 17% and 45% of the variation in the 1-day and 22-day versions.

TIPS Spreads: I do not find 5 or 10-year TIPS spreads (nominal Treasury minus TIPS

[38] Measuring realized variance over the past day (and multiplying by 22 to scale it to the monthly level) assuages concerns of a timing discrepancy since VIX updates more quickly than monthly realized variance.

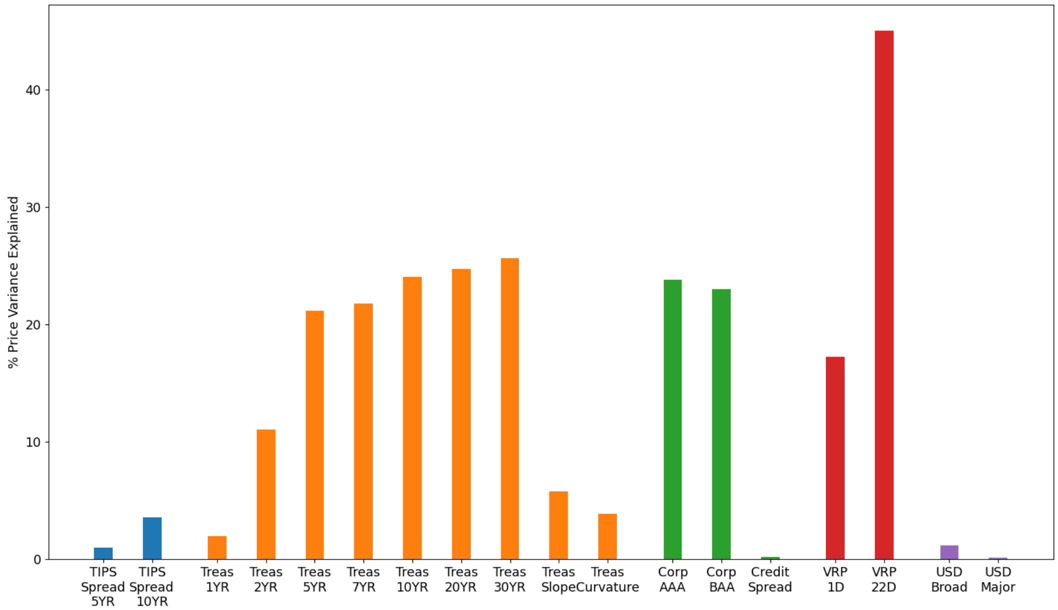

Figure 3: Price Variation Proportion due to Macroeconomic Uncertainty
Price variance proportions explained across assets: $\hat{\lambda}_1^2 \text{Var}[\Delta\sigma_t^2]/\text{Var}[\Delta P_t]$, where $\hat{\lambda}_1$ is estimated from 2SLS regression (27) and P_t is a price measure (bond yields, level of variance risk premium, or exchange rate). Internet Appendix H Table H.5 reports full regression results.

yields) correlate significantly with announcement timing or that macroeconomic uncertainty explains a significant amount of their variation.

Currencies: I do not find the dollar exchange rate versus broad or major trade-weighted baskets of currencies correlates significantly with announcement timing or that macroeconomic uncertainty explains a significant amount of its variation.

6 Robustness Checks

This section provides robustness checks for the baseline results. Section 6.1 considers direct measures of expected returns to supplement the baseline analysis, which relies on the difference between announcement-day and non-announcement day average *realized* returns. Section 6.2 provides measures of expected cash flow growth to rule out the possibility that finite-sample variation in cash flow growth shocks drives my results. Section 6.3 reproduces the baseline results using alternative macroeconomic uncertainty measures. Section

6.4 discusses heterogeneity across announcement types to assuage the concern that particular subsets of announcements (e.g. FOMC announcements) drive my results. I relegate robustness check tables to Internet Appendix G unless noted otherwise.

6.1 Alternative Expected Return Measures

I consider two direct daily measures of expected returns and also provide corroboratory evidence from the cross section of equity returns. Using the Martin (2017) equity premium lower bound and Gao & Martin (2019) log equity premium lower bound over horizons of two to six months, I find that macroeconomic uncertainty explains $7\% - 12\%$ of expected return variation (see Table G.1), which is very similar to the baseline result of 10%. In the cross section I find that portfolios with higher discount rate betas earn lower announcement-day average returns, which is consistent with announcements involving decreases in discount rates.

Options-Implied Equity Premium Lower Bounds

First, I use the equity premium lower bound from Martin (2017). Martin (2017) derives a lower bound for the conditional equity premium over the next $h \in \{1,2,3,6,12\}$ months in terms of the risk-neutral variance of the market, which can be expressed in terms of market index option prices. Martin (2017) uses the S&P 500 as a proxy for the market equity portfolio and argues this lower bound might actually be a tight bound.

Table G.1 displays two-stage least squares results for the following regression using the equity premium lower bounds:

$$\Delta\sigma_t^2 = \beta_0 + \beta_1 1(t = \text{ announcement}) + \epsilon_t$$
$$\Delta\text{Expected Return}_t^h = \lambda_0 + \lambda_1 \widehat{\Delta\sigma_t^2} + \nu_t.$$

These results corroborate those from Table 4: increases in macroeconomic uncertainty cause significant increases in the equity premium lower bounds. These results imply macroeconomic uncertainty explains 7% − 12% of the variation in expected returns at horizons of two and six months, which is quantitatively similar to the baseline result of 10.35%. At longer and shorter horizons, macroeconomic uncertainty explains a larger proportion of expected return variation (42% and 30% at one and twelve months, respectively).[39]

Second, I calculate the "LVIX" *log* equity premium lower bound over the next $h \in \{1,2,3,6,12\}$ months from Gao & Martin (2019), which takes a similar functional form to the equity premium lower bound from Martin (2017). Table G.1 exhibits quantitatively similar results using this measure to those using the Martin (2017) lower bound. For horizons of two to six months, macroeconomic uncertainty explains 8% − 11% of expected return variation. At longer and shorter horizons, macroeconomic uncertainty explains a larger proportion of expected return variation (80% and 27% at one and twelve months, respectively).

As direct measures of expected returns, the Martin (2017) and Gao & Martin (2019) lower bounds allow for estimation of λ_{ARU} and λ_{σ^2} without relying on the law of iterated expectations argument from Section 3.2. For this reason, the estimates in this section prove immune to any potential finite-sample variation in cash flow growth shocks that could impact the baseline results. But since both the lower bounds and my daily JLN index are calculated from options prices, I prefer the baseline methodology to avoid concerns of a mechanical link. Nonetheless, the quantitative similarity of the results in this section to my baseline results suggests that the latter are not driven by finite-sample variation in cash flow growth shocks.

Evidence from the Cross Section of Equity Returns

Internet Appendix F provides corroboratory evidence from the cross section of equity returns. Sorting stocks into decile portfolios based on discount-rate betas (estimated as in Campbell & Vuolteenaho (2004)), the highest decile portfolio has a 7 basis point lower average announcement-day return than the lowest decile portfolio, which is consistent with

[39]The large variance explained proportion for the one-month lower bound is consistent with macroeconomic uncertainty explaining much of the variation in the variance risk premium (Section 5), which itself contributes primarily to short-run expected equity returns. The variance explained proportions for the other horizons lie within the 95% percent confidence interval around the baseline 10.35% result.

discount rates falling on announcements. This result further establishes that the baseline λ_{ARU} estimated from the difference between announcement-day and non-announcement day average realized returns is not driven by finite-sample variation in cash flow growth shocks.

6.2 Expected Cash Flow Growth Measures

In this section I provide further evidence that finite sample variation in cash flow growth shocks does not drive the baseline results by directly measuring expected cash flow growth. Recall from Section 3.2 that if the in-sample announcement-day average cash flow growth shock is *higher* than the non-announcement day average, then the estimated λ_{ARU} from (20) will be smaller (i.e. more negative and larger in magnitude) than the true ARU effect. To rule out this possibility, I use the Pettenuzzo, Sabbatucci & Timmermann (2020) expected dividend growth series, the Gao & Martin (2019) options-implied expected log dividend growth lower bound, and the Gormsen & Koijen (2020) dividend-strip-implied expected dividend growth measure. Even though these three measures are derived under very different assumptions, they all yield the same result: average expected cash flow growth changes are not *more positive* on announcement days than on non-announcement days (see Table G.2). These results imply that the negative baseline λ_{ARU} estimate from Section 4.2 is not an artifact of finite sample cash flow growth shock variation. In the cross section I find that cash flow betas do not correlate with announcement-day returns, which further corroborates the lack of problematic finite sample cash flow growth shock variation.

Pettenuzzo, Sabbatucci & Timmermann (2020) Expected Dividend Growth

First I consider the expected dividend growth series form Pettenuzzo, Sabbatucci & Timmermann (2020). They begin with a time-series model of the daily year-over-year growth rate in dividends announced. The authors define D_t^i and I_t^i as the dividend announced by firm i on day t and an indicator for if firm i announces a dividend on day t, respectively. For all firms that announce dividends today ($I_t^i = 1$), let $\tilde{t}(i,t)$ represent the day $\tilde{t}$ in the same quarter of the previous year when firm i announced its dividend. The authors define the aggregate growth rate of dividends on day t then as

$$G_t = \frac{\sum_{i=1}^{N_t} I_t^i D_t^i}{\sum_{i=1}^{N_t} I_{\tilde{t}(i,t)}^i D_{\tilde{t}(i,t)}^i},$$

where N_t is the total number of firms on day t. This expression for G_t is the ratio of the total amount of dividends announced by the same set of firms in the same quarter in two consecutive years. Denoting the yearly growth rate in dividends announced $\Delta d_{t+1}^A = \log(G_t)$, Pettenuzzo, Sabbatucci & Timmermann (2020) provide the following structural time-series decomposition

$$\Delta d_{t+1}^A = \tilde{\mu}_{d,t+1} + \xi_{d,t+1} J_{d,t+1} + \epsilon_{d,t+1}, \tag{28}$$

where $\tilde{\mu}_{d,t+1}$ is a smoothly evolving expected component, $\xi_{d,t+1} J_{d,t+1}$ is a (mean-zero) jump process with time-varying probability and magnitude, and $\epsilon_{d,t+1}$ is a (mean-zero) normally distributed noise term with stochastic volatility. Internet Appendix C provides the details and motivation for this decomposition. The authors model the expected component as a mean-reverting AR(1) process[40]:

$$\tilde{\mu}_{d,t+1} = \mu_d + \phi_\mu(\tilde{\mu}_{d,t} - \mu_d) + \sigma_\mu \epsilon_{\mu,t+1}, \quad \epsilon_{\mu,t+1} \sim \mathcal{N}(0,1). \tag{29}$$

I then scale this expected growth component $\tilde{\mu}_{d,t}$ to a daily growth rate and convert it to a measure of long-run expected cash flow growth[41]:

$$\mu_{d,t+1}^{PST} = \sum_{j \geq 0} \rho^j \mathbb{E}_t[\Delta d_{t+1+j}] = \frac{\phi_\mu}{1 - \rho\phi_\mu} \tilde{\mu}_{d,t+1},$$

where Pettenuzzo, Sabbatucci & Timmermann (2020) estimate $\phi_\mu = .998$ and $\rho = .9998$.

[40] Figure C.1 in Internet Appendix C illustrates the daily time series of $\tilde{\mu}_{d,t+1}$.

[41] While Pettenuzzo, Sabbatucci & Timmermann (2020) model the growth rate of dividends announced (d_t^A), the Campbell & Shiller (1988) identity uses dividends paid (d_t). I thus impose the following restriction on expected cash flow growth: $E_t[\Delta d_{t+1}] = E_t[\tilde{\mu}_{dt+1}]$ (i.e. the expected growth rate in dividends paid equals the expected growth rate in dividends announced).

Table G.2 reports results from this two-stage least squares regression:

$$\Delta\sigma_t^2 = \beta_0 + \beta_1 1(t = \text{ announcement}) + \epsilon_t$$
$$\Delta\mu_{d,t}^{PST} = \lambda_0 + \lambda_1 \widehat{\Delta\sigma_t^2} + \nu_t.$$

The first row reports an insignificant estimate for the reduced-form regression coefficient of $\Delta\mu_{d,t}^{PST}$ on $1(t = \text{ announcement})$ ($\lambda_1\beta_1 = 0.06$ basis points). Thus, average changes in this Pettenuzzo, Sabbatucci & Timmermann (2020) long-run expected cash flow growth measure are not significantly different on announcement and non-announcement days.

Gao & Martin (2019) Subjective Expected Log Dividend Growth Lower Bound

Second, I consider the lower bound on subjective expected log dividend growth from Gao & Martin (2019). Using the LVIX lower bound on one-year market (S&P 500) expected excess log returns, Gao & Martin (2019) provide the following lower bound on subjective expected log dividend growth:

$$\begin{aligned}\mathbb{E}_t[g_{t+1}] &= \mathbb{E}_t[r_{t+1}] - \mathbb{E}_t[r_{t+1} - g_{t+1}] \\ &\geq r_{f,t+1} + LVIX_t - \mathbb{E}_t[r_{t+1} - g_{t+1}],\end{aligned}$$

where g_{t+1} is log dividend growth. They then derive a dynamic generalization of the Gordon growth model and find that if either log dividend-price ratio ($dp_t = \log(D_t/P_t)$) or log dividend yield ($y_t = \log(1 + D_t/P_t)$) follows an AR(1) process, then $\mathbb{E}_t[r_{t+1} - g_{t+1}]$ is linear in that quantity and can be replaced with the fitted value from linear regressions of $r_{t+1} - g_{t+1}$ on dp_t or y_t. Thus, let:

$$\mu_{dt}^{GM} \equiv r_{f,t+1} + LVIX_t - (a_0^v + a_1^v v_t)$$

where v_t is dp_t or y_t. Internet Appendix D details the construction of μ_{dt}^{GM}.[42]

[42] Internet Appendix D Figure D.1 plots μ_{dt}^{GM} calculated from dp_t and y_t.

Table G.2 reports results from this two-stage least squares regression:

$$\Delta\sigma_t^2 = \beta_0 + \beta_1 1(t = \text{ announcement}) + \epsilon_t$$
$$\Delta\mu_{dt}^{GM} = \lambda_0 + \lambda_1 \widehat{\Delta\sigma_t^2} + \nu_t.$$

The second and third rows report negative estimates for the reduced-form regression coefficient of $\Delta\mu_{d,t}^{PST}$ on $1(t = \text{ announcement})$ ($\lambda_1\beta_1 \approx -2$ basis points). These results suggest that average changes in expected cash flow growth are *lower* on announcement days than on non-announcement days, which would imply that my baseline $\lambda_{ARU} = -7.8$ basis points underestimates (in magnitude) the true ARU effect.[43]

Gormsen & Koijen (2020) Dividend-Strip-Implied expected Dividend Growth

Third, I use options-implied dividend strip prices to construct the expected dividend growth measure from Gormsen & Koijen (2020). Van Binsbergen, Brandt & Koijen (2012) show one can recover prices on dividend strips — claims to all dividends paid by an asset over a fixed horizon — from put-call parity:

$$\mathcal{P}_{t,T} = p_{t,T} - c_{t,T} + S_t - Xe^{-r_{t,T}(T-t)}, \tag{30}$$

where $\mathcal{P}_{t,T}$ is the price at time t for a claim to all dividends paid from time t to T, $p_{t,T}$ and $c_{t,T}$ are prices on put and call options that expire at time T and have strike price X, S_t is the spot price, and $r_{t,T}$ is the risk-free rate.[44] I extract 12 and 24 month S&P 500 dividend strip prices from index options.[45]

[43] Internet Appendix D details an alternative lower bound using the 95% a_1^v confidence interval upper bounds to assuage concerns that the a_1^v estimates are too small (e.g. attenuation bias from measurement error), which would render μ_{dt}^{GM} too dependent on $LVIX_t$ and insufficiently dependent on dp_t or y_t. This alternative μ_{dt}^{GM} also does not correlate significantly positively with the announcement timing (Internet Appendix G Table G.2).

[44] I construct synthetic dividend strip prices because data on traded dividend futures are not available for a long enough time period.

[45] Following Van Binsbergen, Brandt & Koijen (2012), I minimize measurement error by using index option tick data to match put, call, and spot prices at high-frequency (e.g. within 1 second). This matching yields thousands of prices per maturity per day, among which I take the median. See Internet Appendix E for details.

Following Gormsen & Koijen (2020), I convert dividend strip prices to expected dividend growth via the following quarterly forecasting regression:

$$\Delta_{(h)} D_t = \beta_0^{(h)} + \beta_1^{(h)} e_t^{(h)} + \epsilon_t^{(h)}, \tag{31}$$

where $\Delta_{(h)} D_t = (D_{t+4h} - D_t)/D_t$ is h-year dividend growth and $e_t^{(h)}$ is the h-year equity yield

$$e_t^{(h)} = \frac{1}{h} \ln\left(\frac{D_t}{\mathcal{P}_{t,t+4h}}\right),$$

for current level of dividends D_t. I use fitted values $g_t^{(h)} \equiv \widehat{\Delta_{(h)} D_t}$ from (31) for $h = 1$ and 2 years as expected cash flow growth measures.[46]

As with all prices, variation in both cash flow expectations and discount rates drives dividend strip price variation. Thus, the equity yields $e_t^{(h)}$ and fitted expected dividend growth $g_t^{(h)}$ also respond to discount rate movement. Yet since dividend strips are short-term assets, discount rate variation should impact their prices less than stock prices. Moreover, if expected dividend growth rates and discount rates are negatively correlated, then $\Delta g_t^{(h)}$ provides an *upper bound in magnitude* for the true change in expected cash flow growth.

Table G.2 reports results from this two-stage least squares regressions:

$$\Delta \sigma_t^2 = \beta_0 + \beta_1 1(t = \text{announcement}) + \epsilon_t$$
$$\Delta g_t^{(h)} = \lambda_0 + \lambda_1 \widehat{\Delta \sigma_t^2} + \nu_t.$$

The last two rows reports mixed and insignificant estimates for the reduced-form regression coefficient of $\Delta g_t^{(h)}$ on $1(t =$ announcement$)$ ($\lambda_1 \beta_1 \approx 13$ and -3 basis points at the 1 and 2 year horizons, respectively). Thus, I do not find consistent evidence that average changes in expected cash flow growth are higher on announcement days than on non-announcement days in my sample.[47]

[46]Internet Appendix H Table H.6 reports the forecasting regression results. Internet Appendix E Figure E.1 plots $\mathcal{P}_{t,t+4h}$ and $g_t^{(h)}$.

[47]The equity market beta on $\Delta g_t^{(1)}$ is 0.1008 (Internet Appendix H Table H.7), which likely overestimates the true beta due to omitted variable bias (i.e. omitted discount rate shock). Per Table G.2, $g_t^{(1)}$ rises 13.32

Evidence from the Cross Section of Equity Returns

Internet Appendix F provides corroboratory evidence from the cross section of equity returns. Average announcement-day returns do not correlate significantly with cash-flow betas (estimated as in Campbell & Vuolteenaho (2004)), which is consistent with expected cash flow growth not correlating with the announcement timing. This result further establishes that the baseline λ_{ARU} estimated from the difference between announcement-day and non-announcement day average realized returns is not driven by finite-sample variation in cash flow growth shocks.

6.3 Alternative Macroeconomic Uncertainty Measures

I consider three alternative measures of macroeconomic uncertainty and also provide corroboratory evidence from the cross section of equity returns. Specifically, I use variants of the Jurado, Ludvigson & Ng (2015) index that measure uncertainty over different horizons, an out-of-sample daily JLN index constructed by performing regression (18) in a rolling window, and S&P 500 implied volatility. The estimated effect of macroeconomic uncertainty λ_{σ^2} from two-stage least squares regression (25) using these alternative measures ranges from 40 to 93 basis points (see Table G.3), which is similar to the baseline second-stage coefficient estimate of 36 basis points.

Alternative Horizons for JLN Index

First, I construct daily macroeconomic uncertainty series using the 1 and 3-month horizon JLN indices, which measure uncertainty over shorter horizons than the baseline 12-month index, via the same projection procedure discussed in Section 3.1. Table G.3 reports the

basis points on announcements. The implied expected dividend growth contribution to announcement-day returns is $13.32 \cdot 0.1008 = 1.34$ basis points out of the total ARU effect on realized returns of 8.31 basis points (i.e. 16.1%). However, this figure is not significant at the 5% level and, since some discount rate variation contaminates $\Delta g_t^{(1)}$, likely overstates the true contribution. Still, even a charitable interpretation implies that finite-sample variation in expected cash flow growth shocks can account for very little of the estimated ARU effect.

two-stage least squares regression results from (25) using these alternative measures. A one standard deviation increase in these measures raises long-run expected returns by 41 and 40 basis points for the 1 and 3-month indices, respectively, which is quantitatively similar to the baseline result of 36 basis points.

Out-of-Sample JLN Index

Second, I construct an out-of-sample version of the baseline 12-month horizon daily JLN index. Specifically, I run the monthly regression (18) of the original JLN index on the average option implied volatilities in a rolling five-year look-back window and then apply the fitted weights to one month out of sample.[48] Table G.3 exhibits the two-stage least squares regression results using this alternative measure. The second-stage coefficient estimate is qualitatively similar to and quantitatively larger than the baseline result. A one standard deviation increase in this out-of-sample measure raises long-run expected returns by 93 basis points as compared to the baseline result of 36 basis points. I prefer the in-sample JLN index for the baseline analysis, however, since the first-stage regression for the out-of-sample index is weaker, due in part to the shorter sample period (five years lost to the rolling window) and measurement error from the time-varying weights.[49]

S&P 500 Futures Implied Volatility

Third, I use S&P 500 futures implied volatility.[50] Table G.3 displays that the effect of macroeconomic uncertainty on long-run expected returns proves significant under this measure as

[48] Internet Appendix H Figure H.3 displays the time-varying weights. For each day in the out-of-sample month, I use are a convex combination of the previous window's fitted weights ($\tilde{\boldsymbol{w}}$) and those from this window ($\boldsymbol{w}$). For day t in a month with T days, the convex combination weight on $\boldsymbol{w}$ is t/T. This smooth evolution of weights prevents artificially large daily changes at the start of each month.

[49] The 1st-stage F-statistic for the out-of-sample index is 10.98 — much smaller than the 64.26 for the in-sample index, though greater than the conventional threshold (10). Moreover, a weak instrument biases the 2nd stage coefficient towards the OLS coefficient, so 93 basis points might underestimate the true effect.

[50] As in Section 3.1, I use the volume-weighted average implied volatility of all contracts. Thus, this index is not the VIX, which applies a particular weighting scheme to options with one month until expiration. I use the volume-weighted average implied volatility of all outstanding contracts so that the option maturities of this index align with those of the baseline daily JLN index. Moreover, the VIX time series only starts in 1990 and so is three years shorter. Nevertheless, using VIX yields similar results.

well. A one standard deviation increase in this measure raises long-run expected returns by 41 basis points as compared to the baseline result of 36 basis points. Since macroeconomic uncertainty is not just uncertainty about the S&P 500 (as illustrated by Table H.1), I prefer the daily JLN index for the baseline analysis.

Evidence from the Cross Section of Equity Returns

Internet Appendix F provides corroboratory evidence from the cross section of equity returns. Sorting stocks into decile portfolios based on betas to the original monthly JLN index, the highest decile portfolio has a 7 basis point lower average announcement day return than the lowest decile portfolio, which is consistent with uncertainty falling on announcements. This result further corroborates the first-stage result that macroeconomic uncertainty falls on average more on announcement days than on non-announcement days.

6.4 Heterogeneity Across Announcements

This paper's main results prove qualitatively robust to taking subsets of different announcement types.

Table G.4 performs the two-stage least squares analysis from (25) using four subsets of announcements: output, price, monetary policy, and all but monetary policy. The reduced form and two-stage least squares results across all subsets prove similar in magnitude to the baseline results in Table 4, though not all attain statistical significance since we lose power by dropping many of the announcements. In particular, FOMC announcements do not drive the baseline results. Dropping all FOMC announcements from the set of announcement dates yields an estimated $\lambda_{\sigma^2} = 29$ basis points, which is similar to the baseline result of $\lambda_{\sigma^2} = 36$ basis points.[51]

[51] Cieslak, Morse & Vissing-Jorgensen (2019) and Cieslak & Pang (2020) raise the concern unexpectedly dovish monetary policy news has driven the high equity returns on FOMC announcements since 1994. Since my empirical results are robust to dropping FOMC announcements from the set of announcement dates, any such unexpectedly dovish monetary policy news does not drive my baseline results. Moreover, Savor & Wilson (2013) document higher average returns on announcement days than on non-announcement days in

Additionally, I run Sargan's overidentification test for two-stage least squares regression (25) by labeling alternating announcements as even and odd. I cannot reject the null hypothesis that the overidentifying restrictions are valid.[52]

7 Conclusion

I estimate the causal effect of macroeconomic uncertainty on time-varying expected returns. Previous work has provided suggestive evidence for such an effect and for an unconditional risk premium for uncertainty. Yet previous causal estimates require strong structural assumptions.

My main contribution in this work is to propose a novel identification strategy to isolate exogenous variation in macroeconomic uncertainty at high frequency. I exploit the exogenous timing of prescheduled macroeconomic announcements to instrument for macroeconomic uncertainty and quantify its impact on expected returns. While the *content* of announcements is surely endogenous to the contemporaneous state of the economy, the *timing* is not. The only source of variation I exploit is the timing of prescheduled announcements, not their content.

My results reveal four main findings. First, announcements resolve a significant amount

a sample going back to 1958, which predates the dovish monetary policy cycle of concern in Cieslak, Morse & Vissing-Jorgensen (2019) and Cieslak & Pang (2020).

Ernst, Gilbert & Hrdlicka (2019) raise the concerns that the subset of announcements focused on in the macroeconomic announcement literature may not be representative of the entire set of macroeconomic announcements and that high returns on announcement days may be due simply to a correlation between announcement timing and other important market events (e.g. monthly capital flows from institutional investors). These concerns do not undermine my analysis. First, I do not focus on particular announcement types and instead treat all announcements homogeneously. Using a larger set of announcement types, Ernst, Gilbert & Hrdlicka (2019) also find that announcement days experience higher average returns than non-announcement days. This result holds even after controlling for day-of-the-month fixed effects, although this latter estimate is not statistically significant, likely in part due to the shorter sample used (1990-2018) as compared to this paper (1986-2016) or Savor & Wilson (2013) (1958-2009).

Second, the alternative explanations in Ernst, Gilbert & Hrdlicka (2019) for high average returns on announcement days (e.g. the timing of capital flows) do not explain why these days experience large decreases in macroeconomic uncertainty. Indeed, the smaller difference between average announcement and non-announcement day returns they find may be due to their inclusion of announcement types that do not resolve a significant amount of uncertainty.

[52] The test statistic is $\chi^2_1 = 1.0217$ with p-value 0.3121.

of uncertainty. Second, this announcement resolution of uncertainty causes an 7.8 basis point drop in long-run expected returns. Third, macroeconomic uncertainty accounts for up to 32% of long-run expected return variation. Fourth, I present evidence that other expected return drivers *do not* correlate with the timing of announcements, in which case I can tighten this upper bound to conclude macroeconomic uncertainty explains 10% of long-run expected return variation. Moreover, a one standard deviation increase in the level of macroeconomic uncertainty raises long-run expected returns 173 basis points. I also find macroeconomic uncertainty explains a significant proportion of price variation in other asset classes.

These results have implications for asset pricing and macroeconomics. In asset pricing, models of time-varying expected returns should consider macroeconomic uncertainty as one driver and should be calibrated to match the quantitative results above. In macroeconomics, heightened macroeconomic uncertainty may depress investment through a discount rates channel.

Immediate extensions of this work include assessing the causal impact of macroeconomic uncertainty in other markets and asset classes. More generally however, the exogenous timing of prescheduled events can provide an instrument for uncertainty in other applications as well. Furthermore, the success of my empirical strategy motivates future research using high-frequency measures to isolate exogenous variation in expected return drivers in order to pin down their causal effects. Identifying causality at the frequencies employed in most asset pricing research proves difficult; too many variables co-move at monthly or quarterly frequencies. At daily or even higher frequencies, however, one can potentially disentangle these effects and shed light on how and why discount rates move.

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Appendix

A Identifying Assumptions in Generalized Environment

Assumptions 1 and 2 generalize as follows:

Assumption 5. (Exclusion with respect to other economic shocks) *The timing of prescheduled macroeconomic announcements is uncorrelated with all other relevant shocks:*

$$Cov(\epsilon_{\cdot,t} \cdot 1(t = announcement)) = 0,$$

and in the following reduced-form regressions

$$\Delta \boldsymbol{H}_t = \boldsymbol{\theta}_{1,0} + \boldsymbol{\theta}_{1,1} 1(t = announcement) + \boldsymbol{\nu}_{1,t}$$
$$\Delta \boldsymbol{E}_t = \boldsymbol{\theta}_{2,0} + \boldsymbol{\theta}_{2,1} 1(t = announcement) + \boldsymbol{\nu}_{2,t},$$

we have $Cov(\boldsymbol{\nu}_{\cdot,t}, 1(t = announcement)) = \mathbf{0}$.

Assumption 6. (Exclusion with respect to conditional expectations) *The timing of prescheduled macroeconomic announcements does not systematically affect the investor's conditional expectations of macroeconomic variables:*

$$Cov(\Delta \boldsymbol{E}_t, 1(t = announcement)) = \mathbf{0}.$$

That is, $\boldsymbol{\theta}_{2,1} = \mathbf{0}$ in (16).

All of the intuition from Section 1.1 persists. Assumption 5 still proves reasonable because announcements are scheduled far in advance to follow a fixed schedule. The justification for Assumption 6 also remains the same: failure of this assumption would violate the martingale property of conditional expectations.

In this generalized environment, the first-stage coefficient $\beta_{\sigma^2,1}$ from (7) becomes $\beta_{\sigma^2,1} = \boldsymbol{\alpha}_1^{'} \boldsymbol{\theta}_{1,1}$. Assumption 3 does not change:

Assumption 7. (Relevance) *The loading $\beta_{\sigma^2,1}$ of macroeconomic uncertainty $\Delta\sigma_t^2$ on the announcement timing $1(t = announcement)$ in first-stage regression (7) is non-zero.*

Under Assumptions 5, 6, and 7, the econometrician can still identify the announcement resolution of uncertainty (ARU) effect:

$$\lambda_{ARU} = \lambda_{\sigma^2} \boldsymbol{\alpha}_1^{'} \boldsymbol{\theta}_{1,1} + \boldsymbol{\delta}_1^{'} \boldsymbol{\theta}_{1,1}. \tag{32}$$

The ARU effect is now the causal effect of the announcement-induced change in uncertainty on expected returns, where uncertainty broadly includes all higher moments of all state variables. It still accounts for all channels through which changes in uncertainty can affect expected returns: both macroeconomic uncertainty and the residual term $\Delta\check{\mu}_t$. As in Section 1.1, however, λ_{ARU} is still a causal effect of uncertainty on expected returns because it is not at all polluted by contemporaneous shifts in first moments. The reduced-form regression (9) will still estimate the ARU effect.

Given estimated regressions (7) and (9), in this generalized environment, the econometrician can also identify:

$$\frac{\lambda_{ARU}}{\beta_{\sigma^2,1}} = \lambda_{\sigma^2} + \frac{\boldsymbol{\delta}_1^{'}\boldsymbol{\theta}_{1,1}}{\boldsymbol{\alpha}_1^{'}\boldsymbol{\theta}_{1,1}}. \tag{33}$$

Assumption 4 generalizes as follows:

Assumption 8. (Exclusion with respect to other expected return drivers) *Announcements do not systematically affect any driver of expected returns except macroeconomic uncertainty:*

$$Cov(\Delta\check{\mu}_t, 1(t = announcement)) = 0.$$

Assumption 8 implies that $\beta_{r,1} = 0$ in the following reduced-form regression:

$$\Delta\check{\mu}_t = \beta_{r,0} + \beta_{r,1} 1(t = \text{announcement}) + \epsilon_t,$$

where $\beta_{r,1} = \boldsymbol{\delta}_1^{'}\boldsymbol{\theta}_{1,1}$. Thus, the second term in (33) vanishes and the econometrician can identify *the effect of macroeconomic uncertainty*:

$$\frac{\lambda_{ARU}}{\beta_{\sigma^2,1}} = \lambda_{\sigma^2}.$$

Internet Appendix — For Online Publication

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A Internet Appendix A: Model with HARA Utility

In this appendix I provide a simple example of a model in which the risk premium depends on two factors: macroeconomic uncertainty and risk aversion. For simplicity, this model features only time-varying physical macroeconomic volatility, but can easily be extended to include posterior variance of macroeconomic fundamentals.

Following Bekaert, Engstrom & Xu (2019), I assume there is a representative investor with HARA-type period utility over consumption:

$$U(C_t) = \frac{(C_t/Q_t)^{1-\gamma}}{1-\gamma},$$

where Q_t is a function of consumption C_t and an exogenous process H_t (i.e. external habit):

$$Q_t = \frac{C_t}{C_t - H_t}.$$

Here Q_t is a quantity proportional to the representative investor's time-varying relative risk aversion:

$$RRA_t = -C_t \frac{\partial^2 U/\partial C_t^2}{\partial U/\partial C_t} = \gamma Q_t.$$

In this economy, log consumption growth and log dividend growth are i.i.d. with stochastic volatility:

$$\begin{aligned}
\Delta c_{t+1} &= \mu_c + \sigma_c \epsilon_{n,t+1} + \rho_c \sigma_t \epsilon_{t+1} \\
\Delta d_{t+1} &= \mu_d + \sigma_d \epsilon_{d,t+1} + \rho_d \sigma_t \epsilon_{t+1} \\
\sigma_{t+1}^2 &= \sigma_0^2 + \nu(\sigma_t^2 - \sigma_0^2) + \sigma_\nu \epsilon_{\nu,t+1} + \rho_\sigma \epsilon_{c,t+1}.
\end{aligned}$$

Note that both consumption and dividend growth are exposed to idiosyncratic shocks ($\epsilon_{n,t+1}$ and

$\epsilon_{d,t+1}$, respectively) as well as a common shock (ϵ_{t+1}). The time-varying variance σ_t^2 of this common shock is macroeconomic uncertainty. I also model $q_t = \log Q_t$ as a mean-reverting AR(1) process:

$$q_{t+1} = q_0 + \delta(q_t - q_0) + \sigma_q \sqrt{q_t}\epsilon_{q,t+1} + \rho_q \epsilon_{c,t+1} + \alpha_q(\Delta c_{t+1} - \mu_c),$$

where $\epsilon_{c,t+1}$ is a common shock to both macroeconomic uncertainty and risk aversion (e.g. a recessionary shock). All shocks $\epsilon_{\cdot,t+1}$ are i.i.d. and have standard normal distributions. The representative investor's stochastic discount factor (SDF) here is:

$$M_{t+1} = \beta\left(\frac{C_{t+1}}{C_t}\right)^{-\gamma}\left(\frac{Q_t}{Q_{t+1}}\right)^{-\gamma}$$

$$\leftrightarrow m_{t+1} \equiv \log M_{t+1} = \log\beta - \gamma\Delta c_{t+1} + \gamma\Delta q_{t+1},$$

for subjective discount factor β. The gross returns R_{t+1} for the asset that pays out dividends D_t here must satisfy

$$\mathbb{E}_t\left[\beta\left(\frac{C_{t+1}}{C_t}\right)^{-\gamma}\left(\frac{Q_t}{Q_{t+1}}\right)^{-\gamma} R_{t+1}\right] = 1.$$

I derive an approximate log-linearized solution using the decomposition of Campbell & Shiller (1988), under which log returns have the following form:

$$r_{t+1} = \kappa_0 + \kappa_1 z_{t+1} - z_t + \Delta d_{t+1},$$

where $r_{t+1} = \log R_{t+1}$, $z_t = \log(P_t/D_t)$, and κ_0 and κ_1 are constants that depend only on the average level of z_t. I solve the model by guess and verify. I conjecture the following form for z_t:

$$z_t = A_0 + A_1 q_t + A_2 \sigma_t^2.$$

Plugging this expression into

$$\mathbb{E}_t[\exp[m_{t+1} + r_{t+1}]] = 1 \tag{34}$$

and solving yields[53]

$$A_1 = \frac{-(2\gamma\kappa_1 + \kappa_1\delta - 1)\sigma_q - \sqrt{(2\gamma\kappa_1 + \kappa_1\delta - 1)^2\sigma_q^2 - 4\kappa_1^2\sigma_q^2(\gamma\sigma_q^2 + \delta - 1)\gamma}}{2\kappa_1^2\sigma_q^2}$$

$$A_2 = \frac{-1}{\kappa_1\nu - 1}(\gamma\alpha_q\rho_c(A_1 + 1) - \gamma\rho_c + \rho_d)^2.$$

The log returns expression is then:

$$r_{t+1} = \kappa_0 + A_0(\kappa_1 - 1) + A_1(\kappa_1 q_{t+1} - q_t) + A_2(\kappa_1\sigma_{t+1}^2 - \sigma_t^2) + \Delta d_{t+1}.$$

Since returns R_{t+1} are log-normal in this model, the log risk premium on this asset is given by:

$$\begin{aligned} \mu_t \equiv \log \mathbb{E}_t[R_{t+1} - R_{f,t}] &= \mathbb{E}_t[r_{t+1}] - r_{f,t} + \frac{1}{2}V_t[r_{t+1}] \\ &= \mathbb{E}_t[r_{t+1}] + \left(\mathbb{E}_t[m_{t+1}] + \frac{1}{2}V_t[m_{t+1}]\right) + \frac{1}{2}V_t[r_{t+1}] \\ &= -Cov_t(m_{t+1}, r_{t+1}), \end{aligned}$$

where $R_{f,t}$ is the risk-free rate from time t to $t+1$ and the last equation follows from (34) and using that m_{t+1} and r_{t+1} are jointly log-normally distributed. Plugging in the expressions for m_{t+1} and r_{t+1} yields

$$\Delta\mu_t = \lambda_{\sigma^2}\Delta\sigma_t^2 + \lambda_q\Delta q_t, \tag{35}$$

where

$$\lambda_{\sigma^2} = \gamma\rho_c(\alpha_q - 1)(A_1\kappa_1\alpha_q\rho_c + \rho_d)$$

$$\lambda_q = \gamma\rho_q(A_1\kappa_1\rho_q + A_2\kappa_1\rho_\sigma).$$

One can further extend this model by introducing "announcements" that exogenously move macroeconomic uncertainty:

$$\sigma_{t+1}^2 = \sigma_0^2 + \nu(\sigma_t^2 - \sigma_0^2) + \sigma_\nu\epsilon_{\nu,t+1} + \rho_\sigma\epsilon_{c,t+1} + \alpha_\sigma 1(t = \text{announcement}),$$

[53] This expression for A_1 is one root of a quadratic equation. In principle the other root also provides a valid solution.

where:

1. The announcement timing is known in advance (i.e. $1(t\!=\!\text{announcement})$ is in the information set at time $t-j$ for all $j>0$ and is not a "shock" at time t).

2. All shocks $\epsilon_{\cdot,t+1}$ are uncorrelated with $1(t\!=\!\text{announcement})$:

$$\begin{aligned}&\mathbb{E}_t[\epsilon_{\cdot,t+1}\cdot 1(t\!=\!\text{announcement})]=0\\ \leftrightarrow\,&\mathbb{E}_t[\epsilon_{\cdot,t+1}\big|1(t\!=\!\text{announcement})=0]=\mathbb{E}_t[\epsilon_{\cdot,t+1}\big|1(t\!=\!\text{announcement})=1].\end{aligned} \tag{36}$$

Note that (36) is the standard exclusion restriction for a binary instrument.

The same guess and verify procedure from above yields the following returns expression for this economy with announcements:

$$r_{t+1}=\kappa_0+A_0(\kappa_1-1)+A_1(\kappa_1 q_{t+1}-q_t)+A_2(\kappa_1\sigma^2_{t+1}-\sigma^2_t)+\sum_{i,j\in\{A,NA\}}A_{ij}(\kappa_1 1(t+1=i)-1(t=j))+\Delta d_{t+1},$$

for $A=$Announcement and $NA=$Non-Announcement where [54]

$$\begin{aligned}A_{A,A}&=0\\ A_{AN}&=\frac{-A_2\kappa_1\alpha_\sigma(1-2\kappa_1)}{2\kappa_1(1-\kappa_1)}\\ A_{NA}&=\frac{-A_2\kappa_1\alpha_\sigma}{2(\kappa_1-1)}\\ A_{NN}&=\frac{A_2\alpha_\sigma}{2}.\end{aligned}$$

Note that the expression for the risk premium (35) does not change since $1(t\!=\!\text{announcement})$ is uncorrelated with all shocks. But since $\Delta\sigma^2_t$ now depends on the announcement timing, so does $\Delta\mu_t$.

[54] One coefficient A_{ij} is undetermined, so I set $A_{A,A}=0$ for simplicity.

B Internet Appendix B: Details of Implied Volatility Calculation

In this appendix I discuss the construction of the daily implied volatility series. I consider all outstanding weekly and monthly expiration options from the CME for the following underlyings:

- S&P 500 futures
- Crude oil futures
- Gold futures
- Wheat futures
- 10-year Treasury note futures
- Corn futures
- Soybean futures

I back out implied volatility for all these contracts using the Black Scholes formula given the observed options price, time to expiration, strike price, spot price, and risk-free rate. I linearly interpolate the risk-free rate to match time to expiration based on the prevailing yields to 4, 13, and 26-week Treasury bills from the CRSP Treasuries Riskfree series. For longer expiration options I interpolate using the 1-year yield from the CRSP Treasury Fixed Term Index.

Due to measurement error in the data as well as the potential illiquidity of daily options, I exclude contracts that satisfy any of the following conditions:

- Contracts with non-positive price
- Contracts with non-positive volume[55]
- Contracts with non-positive time to expiration

[55] The CME data contains a field for purported total volume of each contract on each day as well as separate fields for Globex, Floor, and PNT volumes. For my measure of volume I use the maximum of the former volume field and the sum of the latter three fields.

- Any other contracts where calculated implied volatility is non-positive or greater than one

Furthermore, if on this day there are any contracts for this underlying with time to expiration of at least two days (after applying the above filters), then I drop all contracts with one day to expiration. Otherwise, I retain contracts with only one day to expiration. Lastly, I exclude contracts with calculated implied volatility outside two standard deviations from the mean implied volatility for all contracts for the same underlying and date that survive the above filtering.
I then take a volume-weighted average of the calculated implied volatilities of all remaining contracts for each underlying on each day. Internet Appendix H Table H.8 displays some summary statistics for this options data.

C Internet Appendix C: Motivation for Functional Form of Pettenuzzo, Sabbatucci & Timmermann (2020) Decomposition

In the interest of self-containment, in this appendix I provide the motivation from Pettenuzzo, Sabbatucci & Timmermann (2020) for the functional form of the decomposition of announced dividend growth in (28).

Assume that aggregate dividend growth has the following dynamics:

$$\Delta d_{A,t+1} = \tilde{\mu}_{d,t+1} + \sigma_A \epsilon_{A,t+1}, \quad \epsilon_{A,t+1} \sim N(0,1), \tag{37}$$

where the conditional mean $\tilde{\mu}_{d,t+1}$ follows the dynamics in (29):

$$\tilde{\mu}_{d,t+1} = \mu_d + \phi_\mu(\tilde{\mu}_{d,t} - \mu_d) + \sigma_\mu \epsilon_{\mu,t+1}, \quad \epsilon_{\mu,t+1} \sim \mathcal{N}(0,1), \quad E[\epsilon_{A,t+1}\epsilon_{\mu,t+1}] = 0.$$

In reality, we do not observe aggregate dividend growth daily, but instead the dividend growth of a time-varying subset of firms. Thus, let Δd^A_{it+1} be firm i's observed year-over-year growth rate in dividends announced and assume it follows

$$\Delta d^A_{i,t+1} = \beta_i \Delta d_{A,t+1} + \sigma_i \epsilon_{i,t+1}, \quad \epsilon_{i,t+1} \sim N(0,1), \tag{38}$$

where $\epsilon_{i,t+1}$ is uncorrelated across firms. We keep track of time-variation in the set of announcing firms using weights

$$\omega_{i,t} = \frac{D^i_t}{\sum_{i=1}^{N_{d,t}} D^i_t},$$

where D^i_t and $N_{d,t}$ are the dividend announced by firm i on day t and the total number of firms announcing dividends on day t, respectively. Thus, $\omega_{i,t}$ is the weight of dividends announced by firm i on day t relative to the total dividends announced on day t . Aggregating (38) across all announcing firms on day $t+1$ yields:

$$\begin{aligned}\Delta d_{t+1}^{A} &= \sum_{i=1}^{N_{d,t+1}} \omega_{i,t+1} \Delta d_{i,t+1}^{A} \\ &= \sum_{i=1}^{N_{d,t+1}} \omega_{i,t+1} (\beta_i \Delta d_{A,t+1} + \sigma_i \epsilon_{i,t+1}) \\ &= \underbrace{\left(\sum_{i=1}^{N_{d,t+1}} \omega_{i,t+1} \beta_i\right)}_{\equiv \beta_{t+1}} \Delta d_{At+1} + \underbrace{\left(\sum_{i=1}^{N_{dt+1}} \omega_{i,t+1}^2 \sigma_i^2\right)^{\frac{1}{2}} \epsilon_{t+1}}_{\equiv \sigma_{d,t+1}\epsilon_{t+1}}, \quad \epsilon_{t+1} \sim \mathcal{N}(0,1) \end{aligned} \tag{39}$$

Here, β_{t+1} is the time-varying weighted-average cash flow beta of all announcing firms on day $t+1$ and

$$\sigma_{d,t+1} = \sqrt{\sum_{i=1}^{N_{dt+1}} \omega_{i,t+1}^2 \sigma_i^2},$$

since ϵ_{it+1} are uncorrelated across firms. Pettenuzzo, Sabbatucci & Timmermann (2020) note that total dividends announced on a day can be dominated by a small number of firms or by firms within the same industry. Systematic variation in cash flow betas across these firms or industries will lead to time-variation in β_{t+1}, especially since N_{dt} is not always large. Nevertheless, these shifts in composition prove temporary and so β_{t+1} is mean-reverting toward its unconditional mean $\bar{\beta}$. Hence, we can rewrite (39) as

$$\begin{aligned}\Delta d_{t+1}^{A} &= \bar{\beta} \Delta d_{A,t+1} + (\beta_{t+1} - \bar{\beta}) \Delta d_{A,t+1} + \sigma_{d,t+1} \epsilon_{t+1} \\ &= \bar{\beta}(\tilde{\mu}_{d,t+1} + \sigma_A \epsilon_{A,t+1}) + (\beta_{t+1} - \bar{\beta})(\tilde{\mu}_{d,t+1} + \sigma_A \epsilon_{A,t+1}) + \sigma_{d,t+1} \epsilon_{t+1} \\ &\propto \tilde{\mu}_{d,t+1} + \frac{(\beta_{t+1} - \bar{\beta})}{\bar{\beta}} \tilde{\mu}_{d,t+1} + \left(1 + \frac{\beta_{t+1} - \bar{\beta}}{\bar{\beta}}\right) \sigma_A \epsilon_{A,t+1} + \frac{\sigma_{d,t+1}}{\bar{\beta}} \epsilon_{t+1}. \end{aligned} \tag{40}$$

Pettenuzzo, Sabbatucci & Timmermann (2020) note that, compared to the law of motion for unobserved aggregate dividend growth (37), the observed dividend growth law of motion (40) has three additional time-varying components:

1. A term with a time-varying loading $\frac{(\beta_{t+1} - \bar{\beta})}{\bar{\beta}}$ on $\tilde{\mu}_{d,t+1}$.

2. A term with time-varying loading $\left(1 + \frac{\beta_{t+1} - \bar{\beta}}{\bar{\beta}}\right) \sigma_A$ on the aggregate dividend shock $\epsilon_{A,t+1}$.

3. A term with a time-varying loading $\frac{\sigma_{d,t+1}}{\bar{\beta}}$ on the shock ϵ_{t+1}.

The time-varying loading in the first component can be very volatile due to large time-variation in the number and types of firms that announce dividends each day. The last two components introduce stochastic volatility into the dynamics of Δd^A_{t+1}. If firms with similar β_i and σ_i (e.g. firms in the same industry) cluster temporally in their dividend announcements, then this stochastic volatility will be persistent.

Pettenuzzo, Sabbatucci & Timmermann (2020) introduce two components to absorb this time-variation. First, they add a jump component $\xi_{d,t+1}J_{d,t+1}$ to account for the large effect of daily changes in β_{t+1}. Since time variation in β_{t+1} will be largest on days with few announcing firms, they let the jump probability depend on $N_{d,t+1}$:

$$P(J_{dt+1}=1)=\Phi(\lambda_1+\lambda_2 N_{d,t+1}),$$

where Φ is the standard normal CDF. Given a jump occurs, the magnitude of the jumps has a time-invariant distribution: $\xi_{d,t+1}\sim N\left(0,\sigma^2_\xi\right)$. Second, they explicitly model the stochastic volatility process by introducing a new shock

$$\epsilon_{d,t+1}\sim N\left(0,e^{h_{dt+1}}\right),$$

where the log-variance follows a mean-reverting AR(1) process

$$h_{d,t+1}=\mu_h+\phi_h(h_{d,t}-\mu_h)+\sigma_h\epsilon_{h,t+1},\quad \epsilon_{h,t+1}\sim\mathcal{N}(0,1),$$

and

$$E[\epsilon_{d,t+1}\epsilon_{\mu,t+1}]=E[\epsilon_{d,t+1}\epsilon_{t+1}]=0.$$

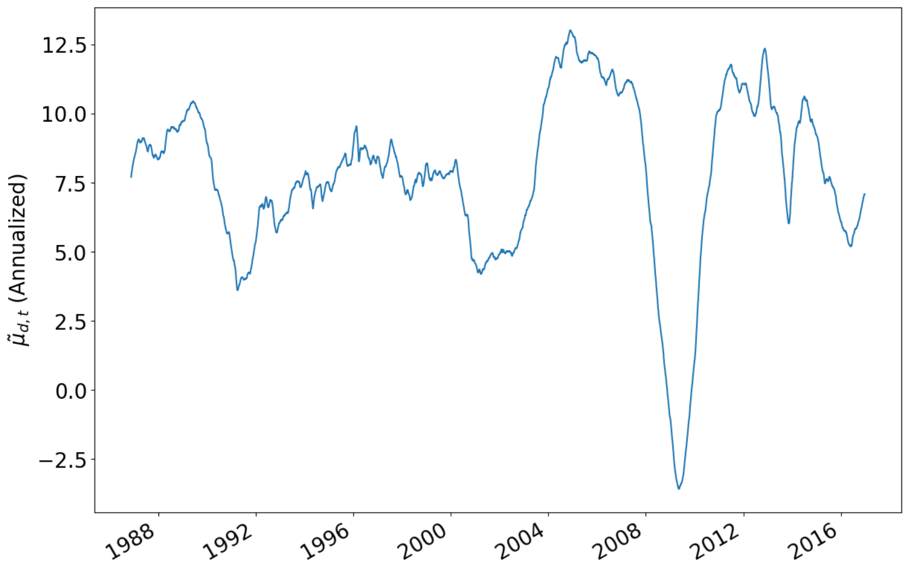
Therefore, Pettenuzzo, Sabbatucci & Timmermann (2020) arrive at the following model from (28) as their decomposition for daily dividend announced growth:

$$\Delta d^A_{t+1}=\tilde{\mu}_{d,t+1}+\xi_{d,t+1}J_{d,t+1}+\epsilon_{d,t+1}.$$

The authors estimate the model using Bayesian structural estimation. I refer the reader to the original paper for the estimation details.

Figure C.1 illustrates the time series of $\tilde{\mu}_{d,t}$ (expressed as an annualized growth rate).

Figure C.1: Time Series of Expected Dividend Growth $\tilde{\mu}_{dt}$ (Annualized)



This figure displays the time series of expected dividend growth $\tilde{\mu}_{d,t}$ from Pettenuzzo, Sabbatucci & Timmermann (2020), scaled to a annual growth rate. Y-axis units are in percentage terms (i.e. 1.0 is 100 basis points per year).

D Internet Appendix D: Details of Construction of Gao & Martin (2019) Expected Dividend Growth Lower Bound

As discussed in Section 6.2, the Gao & Martin (2019) lower bound on subjective expected log dividend growth takes the following form:

$$\begin{aligned} E_t[g_{t+1}] &\geq r_{f,t+1} + LVIX_t - E_t[r_{t+1} - g_{t+1}] \\ &= r_{f,t+1} + LVIX_t - (a_0^v + a_1^v v_t) \\ &\equiv \mu_{dt}^{GM}, \end{aligned}$$

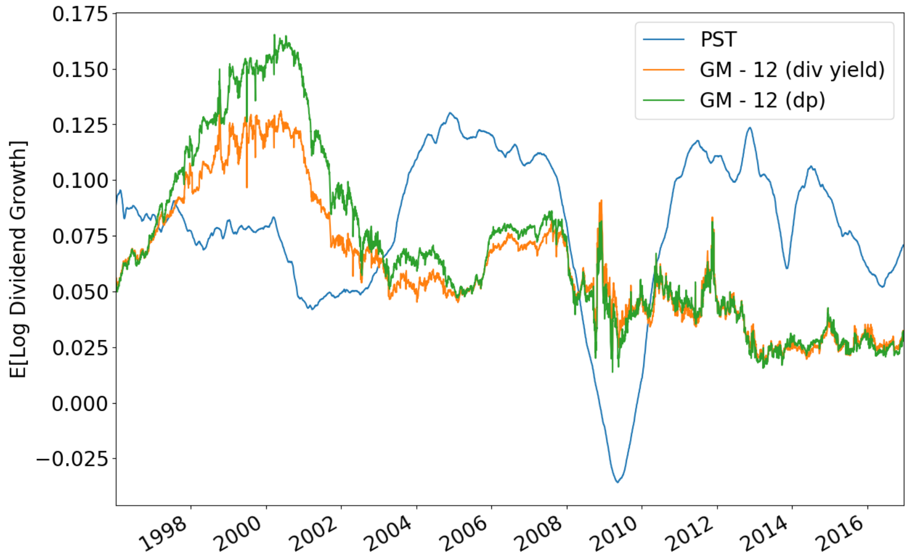
where v_t is $dp_t = \log(D_t/P_t)$ or $y_t = \log(1 + D_t/P_t)$. Here P_t is the price level of the CRSP value-weighted market portfolio and I measure the level of dividends D_t as the sum of the previous four quarterly dividend payments. I use the following coefficient estimates for a_0^v and a_1^v in Gao & Martin (2019) obtained from annual regressions of $r_{t+1} - g_{t+1}$ on dp_t and y_t:

$$\begin{aligned} a_0^{dp} &= 0.43 \\ a_1^{dp} &= 0.111 \\ a_0^{y} &= -0.073 \\ a_1^{y} &= 3.541. \end{aligned}$$

For the ninety-five percent upper bounds (in magnitude) for these coefficients I use the following values implied by the standard errors reported in Gao & Martin (2019):

$$\begin{aligned} a_0^{dp} &= 0.43 + 1.96(0.144) = 0.712 \\ a_1^{dp} &= 0.111 + 1.96(0.41) = 0.915 \\ a_0^{y} &= -0.073 - 1.96(0.048) = -0.0211 \\ a_1^{y} &= 3.541 + 1.96(1.302) = 6.093. \end{aligned}$$

Figure D.1: Time Series of Expected Dividend Growth μ_{dt}^{GM}



This figure displays the daily time series of expected dividend growth $\tilde{\mu}_{dt}$ from Pettenuzzo, Sabbatucci & Timmermann (2020) (expressed as an annual rate) as well as the twelve-month subjective expected log dividend growth lower bounds (extracted from $dp = \log(D/P)$ and $y = \log(1+D/P)$) from Gao & Martin (2019). Y-axis units are in absolute terms (i.e. 0.100 is an annual expected growth rate of 10%).

Note that since my regressions only use $\Delta\mu_{dt}^{GM}$ the values of a_0^v are not important. Since I calculate the lower bound on expected twelve-month log dividend growth, I use the twelve-month LVIX, which I calculate following the procedure in Gao & Martin (2019) using S&P 500 index options data from OptionMetrics via WRDS. Figure D.1 displays the twelve-month subjective expected log dividend growth lower bounds μ_{dt}^{GM} extracted from dp_t and y_t.

E Internet Appendix E: Details of Dividend Strip Price Calculation

I follow the procedure from Van Binsbergen, Brandt & Koijen (2012) to extract dividend strip prices from the following put-call parity relationship:

$$\mathcal{P}_{t,T} = p_{t,T} - c_{t,T} + S_t - Xe^{-r_{t,T}(T-t)}. \tag{41}$$

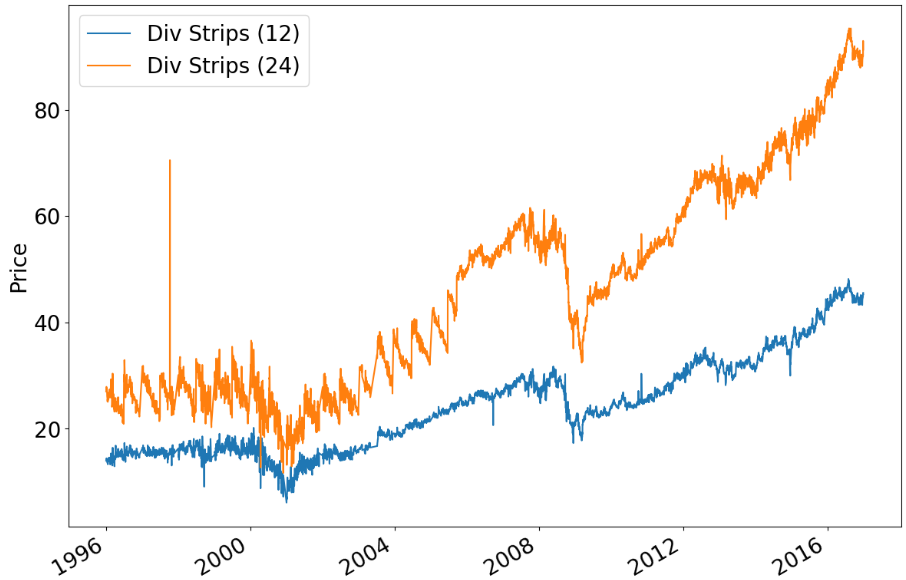
In particular, I use S&P 500 index options tick data from Market Data Express. On each day I collect all call option quotes between 10:00 A.M. and 2:00 P.M. and match each with the put quote of equal strike price and maturity that occurs temporally closest.[56] Each call and put quote is accompanied by a spot index quote.[57] This matching process usually yields thousands of matched call-put pairs over the course of the day. I calculate the interest rate by linearly interpolating among the zero-coupon interest rate curve from OptionMetrics. I apply (41) to each matched pair. For each maturity on each day I then take the median over all calculated prices to mitigate the effect of outliers. To obtain constant-maturity prices (for 12 and 24 months), I linearly interpolate among the median prices for the available maturities on each day. Unfortunately, the Market Data Express data contains data entry errors for a small number of days. On some days, either strike prices or spot prices are missing for a large number of quotes. For each day, I calculate the number of full-information call quotes available for each of my fixed maturities (by linearly interpolating among the number of call quotes available at each of the actual maturities on that day). For each fixed maturity, I drop all days with less than one thousand full-information call quotes available (note that the number of matched call quotes will be less than the number individual full-information call quotes). This process leads me to drop 86 days for the twelve-month series and 263 days for the twenty-four-month series, all out of 5277 total days from 1996-01-02 to 2016-12-22. Many of these dates (76 days) occur in the first half of 2003.

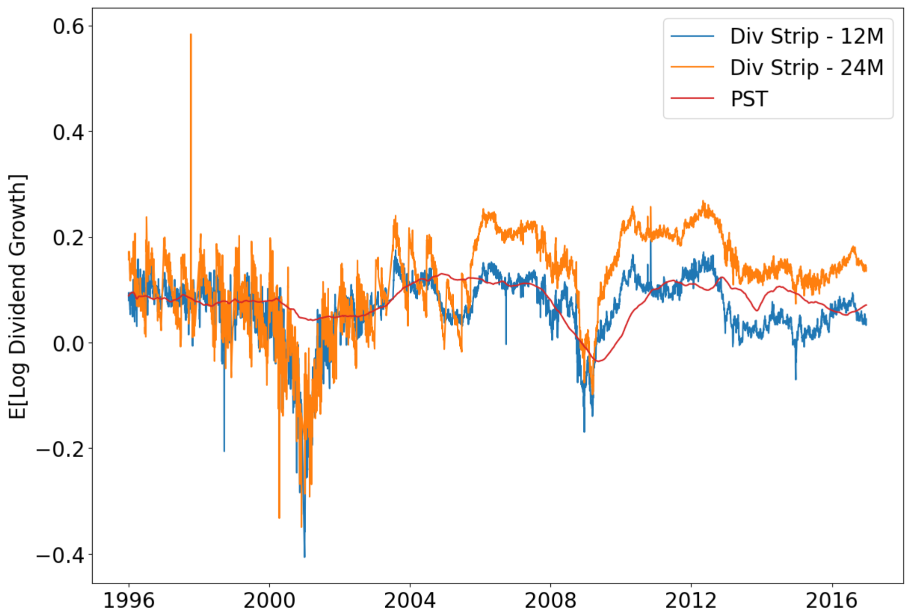
[56] As noted by Van Binsbergen, Brandt & Koijen (2012), bid-ask spreads are largest at the start and end of each day, especially the end of the day since the options exchange closes fifteen minutes after the equity exchange. Taking quotes from only the middle of the day bypasses these microstructure issues.

[57] Usually the matched call and put quotes fall within the same second and have the same quoted spot price. If the spot quotes do not match, I use the average of the two spot quotes.

Figure E.1 displays the time series of the twelve and twenty-four-month dividend strip prices as well as their implied fitted expected dividend growth series, constructed as described in Section 6.2.

Figure E.1: Time Series of Dividend Strip Prices and Fitted Expected Dividend Growth





Top: The daily time series of prices for twelve and twenty-four-month dividend strips on the S&P 500, which are extracted from S&P 500 index options using the following put-call parity relationship:

$$\mathcal{P}_{t,T} = p_{t,T} - c_{t,T} + S_t - Xe^{-r_{t,T}(T-t)},$$

where $\mathcal{P}_{t,T}$ is the price at time t for a claim to all dividends paid out from time t to T, $p_{t,T}$ and $c_{t,T}$ are time t prices on put and call options that expire at time T and have strike price X, S_t is the spot price at time t, and $r_{t,T}$ is the interest rate between time t and T. Internet Appendix E discusses the details of the construction of this series. Y-axis units are in dollars.
Bottom: The fitted expected dividend growth series $g_t^{(h)} \equiv \hat{\beta}_0^{(h)} + \hat{\beta}_1^{(h)} e_t^{(h)}$ for $h = 1$ and 2 years, as well as the baseline measure of expected dividend growth $\tilde{\mu}_{dt}$ from Pettenuzzo, Sabbatucci & Timmermann (2020) (expressed as an annual rate). Table H.6 displays the estimated coefficient values $\hat{\beta}_0^{(h)}$ and $\hat{\beta}_1^{(h)}$. Y-axis units are in absolute terms (i.e. 0.2 is an expected growth rate of 20%, not annualized).

F Internet Appendix F: Evidence from the Cross Section of Equity Returns

The main analysis in this paper concerns itself with aggregate shocks (macroeconomic uncertainty) and outcomes (returns and expected returns for the entire equity market). In this appendix I leverage cross-sectional heterogeneity to provide corroboratory evidence for my baseline results.

Heterogeneous Cash-Flow and Discount-Rate News Exposures

In this section I provide further evidence that discount rates fall on average on announcement days while expected cash flow growth does not correlate with the announcement timing by exploiting cross-sectional heterogeneity in exposures to cash-flow and discount-rate news. If on average expected returns fall and expected cash flow growth does not change on announcement days, then ceteris paribus we should see:

1. Stocks with higher (more positive) discount-rate betas experience lower average announcement-day returns than stocks with lower (more negative) discount-rate betas.

2. Average announcement-day returns should not significantly correlate with cash-flow betas.

I will not attempt to isolate exogenous variation in cash-flow and discount-rate betas and will simply use the results in this section as corroboratory suggestive evidence of the results in Sections 6.1 and 6.2.

To this end, I follow the methodology of Campbell & Vuolteenaho (2004) to construct monthly time series of cash-flow ($N_{CF,t}$) and discount-rate ($N_{DR,t}$) news. I then use these series to construct cash-flow ($\beta_{i,CF}$) and discount-rate ($\beta_{i,DR}$) betas in three-year rolling windows for all stocks i in CRSP.

To construct the monthly time series of cash-flow ($N_{CF,t}$) and discount-rate ($N_{DR,t}$) news, I begin with the following returns decomposition from Campbell (1991):

$$\underbrace{(r_{t+1}-r_{f,t+1})-E_t[r_{t+1}-r_{f,t+1}]}_{\equiv r^e_{Mt}-\mathrm{E}_{t-1}\left[r^e_{M,t}\right]}=\underbrace{(E_{t+1}-E_t)\left[\sum_{j=0}^{\infty}\rho^j\Delta d^{CF}_{t+1+j}\right]}_{\equiv N_{CF,t}}-\underbrace{(E_{t+1}-E_t)\left[\sum_{j=1}^{\infty}\rho^j r_{t+1+j}\right]}_{\equiv N_{DR,t}},$$

where r_t is the aggregate equity market return. Only realized returns are observed in this identity. To empirically estimate $N_{CF,t}$ and $N_{DR,t}$ Campbell & Vuolteenaho (2004) imposes the following VAR dynamics:

$$\mathbf{z}_{t+1} = \mathbf{a} + \mathbf{\Gamma} \mathbf{z}_t + \mathbf{u}_{t+1}, \tag{42}$$

where the vector $\mathbf{z}_t$ contains four variables:

1. Monthly realized log CRSP value-weighted market returns in excess of the log risk-free (90-day T-Bill) rate (in the first element of $\mathbf{z}_t$).

2. The term spread between yields on 10-year and 3-month U.S. Treasury notes and bills (Series GS10 and TB3MS from FRED).

3. The log S&P 500 cyclically-adjusted price-earnings ratio (CAPE) from Robert Shiller's website.[58]

4. The small-stock value spread, which is the difference in the book-to-market ratios between two value-weighted small-value and small-growth portfolios. Specifically, in June of each year I divide all stocks in CRSP into six portfolios based on whether:

   (a) Market equity is above (big) or below (small) the median market equity of all NYSE stocks as given by the breakpoint data on Ken French's website.[59]

   (b) Book-to-market ratio is below the 30th percentile (growth), between 30th and 70th percentiles, or above 70th percentile (value) of all NYSE stocks as given by the breakpoint data on Ken French's website.

   Once all stocks are partitioned into these six portfolios, take the value-weighted average book-to-market ratio of each portfolio. The small-stock value spread in June of each year t is computed as the difference in the log book-to-market ratios of the small-value and small-growth portfolios. To compute the value spread for each month until June of the next year $t+1$, simply add the cumulative log return to the small-growth portfolio since June of

[58] http://www.econ.yale.edu/~shiller/data.htm.

[59] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

year t and subtract the cumulative log return to the small-value portfolio since June of year t.

For complete details on how to construct these state variables, please refer to the online appendix of Campbell & Vuolteenaho (2004).[60]

Given the estimated VAR (42), we can construct the time series $N_{CF,t}$ and $N_{DR,t}$. Note that

$$r_{t+1} = \mathbf{e}^{'}\mathbf{z}_{t+1},$$

where $\mathbf{e}$ is a four-element vector with 1 in the first element followed by all zeros. Then note that we can write

$$(E_{t+1} - E_t)[\Delta r_{t+1+j}] = \mathbf{e}^{'}\Gamma^j \mathbf{u}_{t+1},$$

and so

$$N_{DR,t} = (E_{t+1} - E_t)\left[\sum_{j=1}^{\infty}\rho^j \Delta r_{t+1+j}\right] = \mathbf{e}^{'}\underbrace{\rho\Gamma(\mathbf{I} - \rho\Gamma)^{-1}}_{\equiv\boldsymbol{\lambda}}\mathbf{u}_{t+1}.$$

This last equation in turn implies

$$N_{CF,t} = \mathbf{e}^{'}(\mathbf{I} + \boldsymbol{\lambda})\mathbf{u}_{t+1}.$$

I then use these estimated news series to construct cash-flow ($\beta_{i,CF}$) and discount-rate ($\beta_{i,DR}$) betas in three-year rolling windows for all stocks i in CRSP as follows:

$$\beta_{i,CF} \equiv \frac{Cov(r_{i,t}, N_{CF,t})}{Var\left(r^e_{Mt} - \mathrm{E}_{t-1}\left[r^e_{M,t}\right]\right)} = \frac{Cov(r_{i,t}, N_{CF,t})}{Var(N_{CF,t} - N_{DR,t})} + \frac{Cov(r_{i,t}, N_{CF,t-1})}{Var(N_{CF,t} - N_{DR,t})}$$
$$\beta_{i,DR} \equiv \frac{Cov(r_{i,t}, N_{DR,t})}{Var\left(r^e_{Mt} - \mathrm{E}_{t-1}\left[r^e_{M,t}\right]\right)} = \frac{Cov(r_{i,t}, N_{DR,t})}{Var(N_{CF,t} - N_{DR,t})} + \frac{Cov(r_{i,t}, N_{DR,t-1})}{Var(N_{CF,t} - N_{DR,t})}.$$

For motivation behind using both the contemporaneous and first-lag covariances between returns and the news series, please refer to the online appendix of Campbell & Vuolteenaho (2004).

After constructing the cash-flow and discount-rate betas, I construct two sets of decile portfolios sorted on each type of beta. In each month t, I sort all stocks into ten decile buckets based on the

[60] https://assets.aeaweb.org/asset-server/articles-attachments/aer/contents/appendices/dec04_app_campbell.pdf.

$\beta_{i,CF}$ and $\beta_{i,DR}$ coefficients calculated in the window ending in the previous month $t-1$. I construct a value-weighted portfolio of all the stocks in each bucket and calculate daily portfolio returns for the current month t. Thus, we have daily returns for ten portfolios sorted on cash-flow betas and ten portfolios sorted on discount-rate betas that are rebalanced monthly. The first portfolio in each set contains stocks with the smallest (most negative) exposures.

I then run the following daily regression for each set of portfolios:

$$r_{d,t} = \beta_0 + \beta_1 1(t = \text{announcement}) + \sum_{j=2}^{10} \beta_{1,j} 1(j = d) 1(t = \text{announcement}) + \epsilon_{d,t},$$

where d is the portfolio decile number. Table F.1 column three illustrates that portfolios more positively exposed to discount rate news experience significantly lower average announcement-day returns than lower-exposure portfolios. On the other hand, Table F.2 demonstrates that average announcement-day returns do not vary significantly with cash-flow beta decile.[61] Both of these results prove consistent with announcement days involving significant decreases in expected returns and no significant changes in expected cash flow growth.

[61]Even the coefficient point estimates are not monotonic. For example, since $\hat{\beta}_{1,2} < 0$ the implied loading of the second portfolio on $1(t = \text{announcement})$ (i.e. $\hat{\beta}_1 + \hat{\beta}_{1,2}$) is less than the corresponding loading for the first portfolio (i.e. $\hat{\beta}_1$).

Note that the slight, insignificant positive correlation between cash-flow beta decile and average announcement-day return arises in part due to the negative correlation between cash-flow and discount-rate betas.

Table F.1: Regression Results for Discount-Rate Beta-Sorted Portfolios

	(1)	(2)	(3)
Announcement	0.147***	0.158***	0.158***
	(0.0463)	(0.0529)	(0.0529)
2^{nd} Decile × Announcement	-0.0355	-0.0489	-0.0489**
	(0.0591)	(0.0679)	(0.0208)
3^{rd} Decile × Announcement	-0.0414	-0.0606	-0.0606**
	(0.0572)	(0.0657)	(0.0242)
4^{th} Decile × Announcement	-0.0608	-0.0777	-0.0777***
	(0.0552)	(0.0635)	(0.0275)
5^{th} Decile × Announcement	-0.0685	-0.0846	-0.0846***
	(0.0539)	(0.0620)	(0.0305)
6^{th} Decile × Announcement	-0.0748	-0.0969	-0.0969***
	(0.0532)	(0.0611)	(0.0326)
7^{th} Decile × Announcement	-0.0576	-0.0715	-0.0715**
	(0.0529)	(0.0606)	(0.0343)
8^{th} Decile × Announcement	-0.0781	-0.0864	-0.0864**
	(0.0520)	(0.0597)	(0.0366)
9^{th} Decile × Announcement	-0.0786	-0.0838	-0.0838**
	(0.0521)	(0.0597)	(0.0379)
10^{th} Decile × Announcement	-0.0695	-0.0658	-0.0658*
	(0.0533)	(0.0611)	(0.0390)
const	0.0288***	0.0288***	0.0288*
	(0.00554)	(0.00554)	(0.0159)
Decile FE	N	Y	Y
Robust SE	Y	Y	N
Time-Clustered SE	N	N	Y
N	75610	75610	75610
R^2	0.000875	0.000903	0.000903

This table presents results for the following regression:

$$r_{d,t} = \beta_0 + \beta_1 1(t = \text{announcement}) + \sum_{j=2}^{10} \beta_{1,j} 1(j = d) 1(t = \text{announcement}) + \epsilon_{d,t},$$

where d is the decile number of the discount-rate-beta sorted portfolio. Each column indicates the inclusion or exclusion of fixed effects as well as the method of calculating standard errors. Units are in percentage terms (i.e. a coefficient of 1.0 represents 100 basis points). All GDP, Unemployment, CPI, PPI, Employment Cost Index, and scheduled FOMC announcements are included. The time period is 1986-11-20:2016-12-22.

Table F.2: Regression Results for Cash-Flow Beta-Sorted Portfolios

	(1)	(2)	(3)
Announcement	0.0574***	0.0656***	0.0656***
	(0.0209)	(0.0230)	(0.0230)
2^{nd} Decile × Announcement	-0.00908	-0.0168	-0.0168
	(0.0289)	(0.0330)	(0.0130)
3^{rd} Decile × Announcement	0.00210	-0.00841	-0.00841
	(0.0304)	(0.0349)	(0.0154)
4^{th} Decile × Announcement	0.0245	0.0129	0.0129
	(0.0323)	(0.0369)	(0.0190)
5^{th} Decile × Announcement	0.0167	0.00163	0.00163
	(0.0340)	(0.0390)	(0.0209)
6^{th} Decile × Announcement	0.0138	0.00633	0.00633
	(0.0357)	(0.0410)	(0.0230)
7^{th} Decile × Announcement	0.0317	0.0186	0.0186
	(0.0380)	(0.0437)	(0.0273)
8^{th} Decile × Announcement	0.0482	0.0401	0.0401
	(0.0416)	(0.0478)	(0.0324)
9^{th} Decile × Announcement	0.0676	0.0620	0.0620
	(0.0474)	(0.0543)	(0.0401)
10^{th} Decile × Announcement	0.0646	0.0619	0.0619
	(0.0533)	(0.0614)	(0.0485)
const	0.0304***	0.0304***	0.0304*
	(0.00571)	(0.00571)	(0.0159)
Decile FE	N	Y	Y
Robust SE	Y	Y	N
Time-Clustered SE	N	N	Y
N	75610	75610	75610
R^2	0.000713	0.000721	0.000721

This table presents results for the following regression:

$$r_{d,t} = \beta_0 + \beta_1 1(t = \text{announcement}) + \sum_{j=2}^{10} \beta_{1,j} 1(j = d) 1(t = \text{announcement}) + \epsilon_{d,t},$$

where d is the decile number of the cash-flow-beta sorted portfolio. Each column indicates the inclusion or exclusion of fixed effects as well as the method of calculating standard errors. Units are in percentage terms (i.e. a coefficient of 1.0 represents 100 basis points). All GDP, Unemployment, CPI, PPI, Employment Cost Index, and scheduled FOMC announcements are included. The time period is 1986-11-20:2016-12-22.

Heterogeneous Macroeconomic Uncertainty Exposures

Section 4.1 presents first-stage results demonstrating that announcement days involve significant decreases in macroeconomic uncertainty. Here I provide further evidence of this result by exploiting cross-sectional heterogeneity in exposures to macroeconomic uncertainty across stocks. If there is indeed a drop in macroeconomic uncertainty on announcement days, then ceteris paribus stocks with lower (more negative) uncertainty betas should experience greater average announcement-day returns than stocks with higher (more positive) betas. As in the previous section, I will not attempt to isolate exogenous variation in uncertainty betas and will simply use the results in this section as corroboratory suggestive evidence of the baseline results in Section 4.1.

To test this proposition, I estimate uncertainty betas by running the following monthly regression (following Bali, Brown & Tang (2017)) in three-year rolling windows for all stocks i in CRSP:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_{i,JLN} \Delta JLN_t + \epsilon_{i,t},$$

where $r_{f,t}$ is the 90-day T-Bill return and JLN_t is the original monthly Jurado, Ludvigson & Ng (2015) uncertainty index. In each month t, I then sort all stocks into ten decile buckets based on the $\beta_{i,JLN}$ coefficients calculated in the window ending in the previous month $t-1$. I construct a value-weighted portfolio of all the stocks in each bucket and calculate daily portfolio returns for the current month t. Thus, we have daily returns for ten portfolios sorted on uncertainty betas that are rebalanced monthly. Portfolio one contains stocks with the smallest (most negative) uncertainty exposures.

I then run the following daily regression:

$$r_{d,t} = \beta_0 + \beta_1 1(t = \text{announcement}) + \sum_{j=2}^{10} \beta_{1,j} 1(j = d) 1(t = \text{announcement}) + \epsilon_{d,t},$$

where d is the portfolio decile number. Table F.3 displays the results of this regression with and without decile fixed effects. In the third column, the $\beta_{1,j}$ coefficients are mostly significantly negative and decreasing. This pattern indicates that stocks with higher (more positive) uncertainty betas experience lower average returns on announcement days, which is consistent with announcement days entailing a drop in macroeconomic uncertainty.

Table F.3: Regression Results for Uncertainty Beta-Sorted Portfolios

	(1)	(2)	(3)
Announcement	0.143***	0.148***	0.148***
	(0.0432)	(0.0495)	(0.0495)
2^{nd} Decile × Announcement	-0.0194	-0.0135	-0.0135
	(0.0580)	(0.0667)	(0.0185)
3^{rd} Decile × Announcement	-0.0432	-0.0566	-0.0566**
	(0.0542)	(0.0625)	(0.0222)
4^{th} Decile × Announcement	-0.0626	-0.0720	-0.0720***
	(0.0528)	(0.0608)	(0.0258)
5^{th} Decile × Announcement	-0.0766	-0.0840	-0.0840***
	(0.0518)	(0.0596)	(0.0268)
6^{th} Decile × Announcement	-0.0725	-0.0757	-0.0757**
	(0.0506)	(0.0583)	(0.0298)
7^{th} Decile × Announcement	-0.0703	-0.0803	-0.0803**
	(0.0499)	(0.0575)	(0.0316)
8^{th} Decile × Announcement	-0.0757	-0.0845	-0.0845**
	(0.0495)	(0.0571)	(0.0333)
9^{th} Decile × Announcement	-0.0748	-0.0764	-0.0764**
	(0.0492)	(0.0567)	(0.0348)
10^{th} Decile × Announcement	-0.0728	-0.0731	-0.0731**
	(0.0510)	(0.0588)	(0.0359)
const	0.0300***	0.0300***	0.0300*
	(0.00551)	(0.00551)	(0.0159)
Decile FE	N	Y	Y
Robust SE	Y	Y	N
Time-Clustered SE	N	N	Y
N	75610	75610	75610
R^2	0.000823	0.000837	0.000837

This table presents results for the following regression:

$$r_{d,t} = \beta_0 + \beta_1 1(t = \text{announcement}) + \sum_{j=2}^{10} \beta_{1,j} 1(j = d) 1(t = \text{announcement}) + \epsilon_{d,t},$$

where d is the decile number of the uncertainty-beta sorted portfolio. Each column indicates the inclusion or exclusion of fixed effects as well as the method of calculating standard errors. Units are in percentage terms (i.e. a coefficient of 1.0 represents 100 basis points). All GDP, Unemployment, CPI, PPI, Employment Cost Index, and scheduled FOMC announcements are included. The time period is 1986-11-20:2016-12-22.

G Internet Appendix G: Robustness Check Tables

Table G.1: Two-Stage Least Squares Regression Results for Alternative Expected Return Measures

	ARU	1 STD Effect	1 Level STD Effect	% Variance Explained	Upper Bound % Variance Explained
EP Lower Bound - 1	-0.0188***	0.0884***	0.4083	42.36	95.87
	(0.0045)	(0.0228)			
EP Lower Bound - 2	-0.0162**	0.0764**	0.3528	12.42	42.57
	(0.0071)	(0.0332)			
EP Lower Bound - 3	-0.0138*	0.065*	0.3	6.91	31.81
	(0.0082)	(0.038)			
EP Lower Bound - 6	-0.0192**	0.0906**	0.4184	10.56	36.96
	(0.0087)	(0.0402)			
EP Lower Bound - 12	-0.0504***	0.2374***	1.096	29.71	72.49
	(0.0139)	(0.0681)			
LVIX - 1	-0.0327***	0.154***	0.7111	80.15	156.95
	(0.0052)	(0.0314)			
LVIX - 2	-0.0086**	0.0405**	0.1871	11.39	39.8
	(0.0038)	(0.018)			
LVIX - 3	-0.0084**	0.0396**	0.183	9.19	35.95
	(0.0043)	(0.0198)			
LVIX - 6	-0.0091*	0.0429**	0.1982	8.48	33.39
	(0.0047)	(0.0216)			
LVIX - 12	-0.0245***	0.1152***	0.5319	27.02	67.98
	(0.0071)	(0.0345)			

This table presents two-stage least squares regression and variance decomposition results for alternative expected return measures. I run the following two-stage least squares regression:

$$\Delta\sigma_t^2 = \beta_0 + \beta_1 1(t = \text{ announcement}) + \epsilon_t$$
$$\Delta\text{Expected Return}_t = \lambda_0 + \lambda_1 \widehat{\Delta\sigma_t^2} + \nu_t,$$

for two different expected return measures:

1. Equity premium lower bound of Martin (2017) over several horizons in months (Date range: 1996-01-05:2016-12-22).

2. Log equity premium lower bound of Gao & Martin (2019) (LVIX) over several horizons in months (Date range: 1996-01-05:2016-12-22).

The first stage involves a regression of the change in the daily JLN index (standardized to have standard deviation one) on an indicator for if day t is an announcement. The second stage regresses the daily change in the expected return measure on the fitted change in the daily JLN index. The first column reports the announcement resolution of uncertainty (ARU) effect, which is the estimated coefficient $\lambda_1 \cdot \beta_1$ from the regression of ΔExpected Return$_t$ on $1(t =$ announcement). The second column reports the estimated second-stage coefficient λ_1, which is the causal effect of a positive one standard deviation daily change in macroeconomic uncertainty on expected returns. The third column reports the causal effect of a positive one standard deviation change in the *level* macroeconomic uncertainty on expected returns (a simple rescaling of the second column). The fourth column reports the proportion of variance in the expected return measure explained by variation in macroeconomic uncertainty:

$$\frac{\hat{\lambda}_1^2 \text{Var}[\Delta\sigma_t^2]}{\text{Var}[\Delta ER_t]}.$$

The fifth column reports an upper bound on this variance decomposition by replacing $\hat{\lambda}_1$ in the previous equation with $\hat{\lambda}_1 + 1.96 \cdot SE_{\hat{\lambda}_1}$.

Units are in percentage terms (i.e. a coefficient of 1.0 represents 100 basis points). All GDP, Unemployment, CPI, PPI, Employment Cost Index, and scheduled FOMC announcements are included.

Table G.2: Two-Stage Least Squares Regression Results for Expected Cash Flow Growth Measures

	Reduced Form
μ_{dt}^{PST}	0.0006
	(0.0012)
μ_{dt}^{GM} - 12M (y)	-0.0188***
	(0.0061)
μ_{dt}^{GM} - 12M (dp)	-0.0154**
	(0.0061)
μ_{dt}^{GM} - 12M (y, Version 2)	-0.015**
	(0.0061)
μ_{dt}^{GM} - 12M (dp, Version 2)	-0.009
	(0.0073)
Div Strip - 12M	0.1332*
	(0.0704)
Div Strip - 24M	-0.0256
	(0.0954)

This table presents two-stage least squares regression results for expected cash flow growth measures. I run the following regression:

$$\Delta \text{Expected Cash Flow Growth}_t = \beta_0 + \beta_1 1(t = \text{ announcement}) + \epsilon_t,$$

for four different expected cash flow growth measures:

1. Long-run expected dividend growth from Pettenuzzo, Sabbatucci & Timmermann (2020) (μ_{dt}^{PST}) (Date range: 1986-11-20:2016-12-22).

2. Subjective expected log dividend growth lower bound of Gao & Martin (2019) (μ_{dt}^{GM}), calculated from $dp_t = \log(D_t/P_t)$ and $y_t = \log(1 + D_t/P_t)$ for the twelve-month horizon, constructed as discussed in Internet Appendix D (Date range: 1996-01-05:2016-12-22).

3. Subjective expected log dividend growth lower bound of Gao & Martin (2019) (μ_{dt}^{GM}), calculated from $dp_t = \log(D_t/P_t)$ and $y_t = \log(1 + D_t/P_t)$ for the twelve-month horizon, constructed using the ninety-five percent upper bound coefficient values as discussed in Internet Appendix D (Date range: 1996-01-05:2016-12-22).

4. Fitted expected dividend growth for the S&P 500 over the next X months (Div Strip - XM), constructed as discussed in Section 6.2 and Internet Appendix E (Date range: 1996-01-02:2016-12-22).

The regression regresses the daily change in the expected cash flow growth measure on an indicator for if day t is an announcement. Units are in percentage terms (i.e. a coefficient of 1.0 represents 100 basis points). All GDP, Unemployment, CPI, PPI, Employment Cost Index, and scheduled FOMC announcements are included.

Table G.3: Two-Stage Least Squares Regression Results for Alternative Macroeconomic Uncertainty Measures

	OLS	First Stage	Reduced Form	2SLS
$\sigma^2_{12,t}$	0.2986***	-0.2158***	-0.0781**	0.3619***
	(0.0326)	(0.0269)	(0.0304)	(0.138)
$\sigma^2_{1,t}$	0.2708***	-0.191***	-0.0781**	0.4088***
	(0.0304)	(0.0272)	(0.0304)	(0.1582)
$\sigma^2_{3,t}$	0.2891***	-0.197***	-0.0781**	0.3964***
	(0.0315)	(0.0272)	(0.0304)	(0.1523)
$\sigma^2_{SP500,t}$	0.4008***	-0.1918***	-0.0781**	0.4071***
	(0.037)	(0.0285)	(0.0304)	(0.1522)
$\sigma^2_{OOS,t}$	0.195***	-0.098***	-0.0908***	0.9266**
	(0.031)	(0.0296)	(0.0339)	(0.4264)

This table presents two-stage least squares regression results for alternative macroeconomic uncertainty measures. I run the following two-stage least squares regression:

$$\Delta\text{Macro Uncertainty}_t = \beta_0 + \beta_1 1(t = \text{ announcement}) + \epsilon_t$$
$$-r_t = \lambda_0 + \lambda_1 \widehat{\Delta Macro\ Uncertainty} + \nu_t.$$

for three different macroeconomic uncertainty measures:

1. 12-month (baseline), 1-month, and 3-month horizon daily JLN indices ($\sigma^2_{h,t}$) (Date range: 1986-11-20:2016-12-22).

2. Out-of-sample daily JLN index ($\sigma^2_{OOS,t}$) (Date range: 1991-11-01:2016-12-22).

3. S&P 500 implied volatility ($\sigma^2_{SP500,t}$) (Date range: 1986-11-20:2016-12-22).

The first stage involves a regression of the change in the macroeconomic uncertainty measure (all standardized to have standard deviation one) on an indicator for if day t is an announcement. The second stage regresses the negative daily log return on the fitted change in the macroeconomic uncertainty measure. The first column reports the OLS regression of the negative daily log return on the change in the macroeconomic uncertainty measure. The second column reports the first-stage results. The third column reports the reduced-form regression of the negative daily log return on $1(t = \text{ announcement})$ (i.e. the estimated coefficient is the ARU effect). The fourth column reports the estimated second stage coefficient of this two-stage least squares regression (i.e. the estimated coefficient is the effect of macroeconomic uncertainty). Units are in percentage terms (i.e. a coefficient of 1.0 represents 100 basis points). All GDP, Unemployment, CPI, PPI, Employment Cost Index, and scheduled FOMC announcements are included.

Table G.4: Heterogeneity Across Announcement Types

	OLS	First Stage	Reduced Form	2SLS
Output Announcements	0.2986***	-0.1471***	-0.0660	0.4486
(GDP and Unemployment)	(0.0326)	(0.0356)	(0.0412)	(0.2748)
Price Announcements	0.2986***	-0.2281***	-0.0434	0.1902
(CPI, PPI, and ECI)	(0.0326)	(0.0383)	(0.0423)	(0.1815)
Monetary Policy Announcements	0.2986***	-0.1512***	-0.2269***	1.5006**
(FOMC)	(0.0326)	(0.0580)	(0.0703)	(0.6724)
All but Monetary Policy Announcements	0.2986***	-0.2186***	-0.0635**	0.2906**
(GDP, Unemployment, CPI, PPI, ECI)	(0.0326)	(0.0283)	(0.0319)	(0.1424)

This table presents results for the two-stage least squares regression:

$$\Delta\sigma_t^2 = \beta_0 + \beta_1 1(t = \text{ announcement}) + \epsilon_t$$
$$-r_t = \lambda_0 + \lambda_1 \widehat{\Delta\sigma_t^2} + \nu_t.$$

The first stage involves a regression of the change in the daily JLN index (standardized to have standard deviation one) on an indicator for if day t is an announcement. The second stage regresses the negative daily log return on the fitted change in the daily JLN index. Units are in percentage terms (i.e. a coefficient of 1.0 represents 100 basis points). The first column reports the OLS regression of the negative daily log return on the change in daily JLN index. The second column reports the first-stage results. The third column reports the reduced-form regression of the negative daily log return on $1(t = \text{ announcement})$ (i.e. the estimated coefficient is the ARU effect). The fourth column reports the estimated second stage of this two-stage least squares regression (i.e. the estimated coefficient is the effect of macroeconomic uncertainty). Each row uses a different subset of all macroeconomic announcements (specified in parentheses): GDP, Unemployment, CPI, PPI, Employment Cost Index (ECI), and scheduled FOMC announcements. The time period is 1986-11-20:2016-12-22.

H Internet Appendix H: Additional Empirics Tables and Figures

Table H.1: Regression of Monthly JLN Index on Monthly Average Option Implied Volatilities

	Monthly JLN
const	0.7654***
	(0.0074)
S&P 500	0.1126***
	(0.0319)
Crude Oil	0.1057***
	(0.0177)
Gold	0.2512***
	(0.0361)
Wheat	-0.0249
	(0.0403)
10-year Note	0.2829**
	(0.1240)
Corn	-0.0919*
	(0.0520)
Soybean	0.2235***
	(0.0400)
N	362
R2	0.62

This table presents the results from estimating

$$JLN_t = \alpha + \sum_{i=1}^{N} \beta_i \overline{IV}_{it} + \epsilon_t.$$

The left-hand-side variable is the monthly macroeconomic uncertainty index from Jurado, Ludvigson & Ng (2015). The right-hand-side variables are the monthly averages of the daily implied volatilities of each set options. The time period is 1986-11-20:2016-12-22.

Table H.2: Price-Dividend Ratio Regressions

	$p_t - d_t$ (Quarterly Smooth 240)	$p_t - d_t$ (Daily Smooth 240)	$p_t - d_t$ (Daily Smooth 120)	$p_t - d_t$ (Daily Smooth 60)
const	7.726e-05***	7.823e-05***	9.185e-05***	1.056e-04***
	(8.051e-08)	(8.033e-08)	(8.072e-08)	(8.195e-08)
Announcement	2.360e-08	3.099e-08	2.945e-09	1.699e-08
	(1.718e-07)	(1.708e-07)	(1.716e-07)	(1.738e-07)
N	7561	7561	7561	7561
R^2	0.00	0.00	0.00	0.00
Date Range	1986 - 2016	1986 - 2016	1986 - 2016	1986 - 2016

This table presents results for the regression of the end-of-day daily price-dividend ratio multiplied by $(1-\rho)$ (where I use the estimated daily $\rho = 0.99998$ from Pettenuzzo, Sabbatucci & Timmermann (2020) and alternative smoothing horizons (in days) to calculate the level of dividends) on announcement timing:

$$(1-\rho)(p_t - d_t) = b_0 + b_1 1(t = \text{announcement}) + \epsilon_t.$$

All GDP, Unemployment, CPI, PPI, Employment Cost Index, and scheduled FOMC announcements are included. The time period is 1986-11-20:2016-12-22.

Table H.3: Regression Results for Response of Daily JLN Index to Announcement Timing

	$\Delta\sigma_t^2$
const	0.0774**
	(0.0333)
-5	-0.0903***
	(0.0275)
-4	0.0510*
	(0.0293)
-3	0.0095
	(0.0288)
-2	0.0578**
	(0.0286)
-1	0.0160
	(0.0289)
0	-0.2071***
	(0.0285)
1	0.0597*
	(0.0318)
2	-0.0279
	(0.0291)
3	-0.0722***
	(0.0275)
4	-0.0916***
	(0.0300)
5	-0.0544**
	(0.0273)
N	7608
R^2	0.01

This table presents results for the regression of the change in the daily JLN index on announcement timing:

$$\Delta\sigma_t^2 = \beta_0 + \sum_{j=-5}^{5} \beta_j 1(t-j = \text{announcement}) \ .$$

The right-hand-side variables are set of timing indicators representing how many days j after an announcement the current day t is. These results are displayed graphically in Figure 2. $\Delta\sigma_t^2$ is scaled to have mean zero and standard deviation one. All GDP, Unemployment, CPI, PPI, Employment Cost Index, and scheduled FOMC announcements are included. The time period is 1986-11-20:2016-12-22.

Table H.4: Correlations Among Potential Expected Return Drivers

	ILR^2	LTV	−10% Prob	1MO CP	2MO CP	3MO CP	6MO CP	12MO CP	RA	σ_t^2
ILR^2	1.000	0.115	0.083	0.053	0.032	0.059	0.070	0.025	0.341	0.152
LTV	0.115	1.000	0.148	0.055	0.085	0.104	0.065	0.028	0.183	0.117
−10% Prob	0.083	0.148	1.000	0.024	0.042	0.045	0.016	0.005	0.038	0.068
1MO CP	0.053	0.055	0.024	1.000	0.321	0.054	0.186	0.044	-0.120	0.059
2MO CP	0.032	0.085	0.042	0.321	1.000	0.531	0.204	0.109	0.110	0.042
3MO CP	0.059	0.104	0.045	0.054	0.531	1.000	0.259	0.135	0.108	0.051
6MO CP	0.070	0.065	0.016	0.186	0.204	0.259	1.000	0.146	0.067	0.090
12MO CP	0.025	0.028	0.005	0.044	0.109	0.135	0.146	1.000	0.038	0.006
RA	0.341	0.183	0.038	-0.120	0.110	0.108	0.067	0.038	1.000	0.131
σ_t^2	0.152	0.117	0.068	0.059	0.042	0.051	0.090	0.006	0.131	1.000

This table presents correlations among daily changes in the: squared intermediary leverage ratio (ILR^2) from He, Kelly & Manela (2017), options-implied risk-neutral weekly left-tail volatility (LTV) and negative ten-percent crash probability (−10% Prob) for the S&P 500 from Bollerslev, Todorov & Xu (2015), options-implied log-utility-perceived 1, 2, 3, 6, and 12 month S&P 500 negative twenty-percent crash probabilities (XMO CP) from Martin (2017), risk aversion index (RA) from Bekaert, Engstrom & Xu (2019), and daily JLN macroeconomic uncertainty index (σ_t^2). The longest available common time series between each pair of variables is used to compute each correlation.

Table H.5: Two-Stage Least Squares Regression Results for Other Assets

	ARU	1 STD Effect	1 Level STD Effect	% Variance Explained	Upper Bound % Variance Explained
TIPS Spread (5YR)	-0.0012	0.0055	0.1343	0.96	19.78
	(0.0021)	(0.0099)			
TIPS Spread (10YR)	-0.0014	0.0067	0.1653	3.56	36.04
	(0.0015)	(0.0075)			
1YR Treas	-0.0016	0.0078	0.0626	1.92	17.96
	(0.0017)	(0.0082)			
2YR Treas	-0.0042**	0.0198**	0.1594	11.01	39.77
	(0.0019)	(0.0091)			
5YR Treas	-0.0061***	0.0288***	0.2323	21.14	59.72
	(0.002)	(0.01)			
7YR Treas	-0.0063***	0.0299***	0.2411	21.75	60.22
	(0.002)	(0.0101)			
10YR Treas	-0.0063***	0.03***	0.2416	24.03	64.26
	(0.0019)	(0.0097)			
20YR Treas	-0.0059***	0.0279***	0.2246	24.74	64.82
	(0.0017)	(0.0088)			
30YR Treas	-0.0059***	0.0279***	0.2244	25.61	66.3
	(0.0017)	(0.0087)			
Treas Slope	-0.0022*	0.0102*	0.0822	5.77	26.36
	(0.0012)	(0.0059)			
Treas Curvature	-0.0008	0.0039	0.0318	3.85	21.9
	(0.0006)	(0.0028)			
AAA Corp Bond	-0.0046***	0.0238***	0.9251	23.77	67.29
	(0.0015)	(0.0083)			
BAA Corp Bond	-0.0044***	0.023***	0.8941	22.97	65.71
	(0.0014)	(0.0081)			
Credit Spread	0.0002	-0.0008	-0.031	0.14	7.75
	(0.0007)	(0.0034)			
VRP (1)	-5.2685***	25.7762**	190.732	17.24	57.49
	(1.9759)	(10.861)			
VRP (22)	-1.3785***	6.7954***	50.1419	45.01	100.53
	(0.311)	(1.7145)			
USD (Broad)	-0.0001	0.0003	0.0015	1.12	16.8
	(0.0001)	(0.0005)			
USD (Major Currencies)	-0.0	0.0002	0.0007	0.12	8.43
	(0.0001)	(0.0006)			

This table presents two-stage least squares regression and variance decomposition results for alternative assets. I run the following two-stage least squares regression:

$$\Delta\sigma_t^2 = \beta_0 + \beta_1 1(t = \text{ announcement}) + \epsilon_t$$
$$\Delta P_t = \lambda_0 + \lambda_1 \widehat{\Delta\sigma_t^2} + \nu_t,$$

where ΔP_t is some measure of change in price. TIPS Spreads are calculated as the difference in yield between maturity-matched TIPS and nominal Treasury notes. Treasury Slope and Curvature are 10 YR Yield − 2 YR Yield and 5 YR Yield − AVG(10 YR Yield,2 YR Yield), respectively. Credit spread is the difference between AAA and BAA-rated corporate bond yields. The variance risk premium is calculated as the difference between the squared VIX and the realized variance over either the past month (for VRP (22)) or day (and scaled to the monthly level for VRP (1)) calculated using five-minute returns. USD is the exchange rate between the U.S. Dollar and a trade-weighted basket of many (Broad) or only major (Major) other currencies (FRED series DTWEXB and DTWEXM, respectively).

The first stage involves a regression of the change in the daily JLN index (standardized to have mean zero and standard deviation one) on an indicator for if day t is an announcement. The second stage regresses the daily change in the price measure on the fitted change in the daily JLN index. The first column reports the announcement resolution of uncertainty (ARU) effect, which is the estimated coefficient $\lambda_1 \cdot \beta_1$ from the regression of ΔP_t on $1(t =$ announcement). The second column reports the estimated second-stage coefficient λ_1, which is the causal effect of a positive one standard deviation daily change in macroeconomic uncertainty on price. The third column reports the causal effect of a positive one standard deviation change in the *level* macroeconomic uncertainty on price (a simple rescaling of the second column). The fourth column reports the proportion of variance in the price measure explained by variation in macroeconomic uncertainty:

$$\frac{\hat{\lambda}_1^2 \mathrm{Var}[\Delta \sigma_t^2]}{\mathrm{Var}[\Delta P_t]}.$$

The fifth column reports an upper bound on this variance decomposition by replacing $\hat{\lambda}_1$ in the previous equation with $\hat{\lambda}_1 + 1.96 \cdot SE_{\hat{\lambda}_1}$.

Units are in percentage terms (i.e. a coefficient of 1.0 represents 100 basis points). All GDP, Unemployment, CPI, PPI, Employment Cost Index, and scheduled FOMC announcements are included. The time periods are: 1986-11-20:2016-12-22 for nominal treasury and corporate bonds, 1993-02-02:2014-12-30 for the variance risk premium, 1995-01-05:2016-12-22 for currencies, and 2003-01-03:2016-12-22 for TIPS spreads.

Table H.6: Dividend Growth Forecasting Regression Results

	12 Months	24 Months
$e_t^{(1.0)}$	-0.4858***	
	(0.1423)	
$e_t^{(2.0)}$		-1.0021***
		(0.1976)
const	0.0722***	0.1658***
	(0.0156)	(0.0343)
N	83	79
R^2	0.36	0.38
Date Range	1996 - 2016	1996 - 2015

This table presents the results for the following quarterly dividend forecasting regressions:

$$\Delta_{(h)} D_t = \beta_0^{(h)} + \beta_1^{(h)} e_t^{(h)} + \epsilon_t^{(h)},$$

where $\Delta_{(h)} D_t$ is dividend growth over the next h years

$$\Delta_{(h)} D_t = \frac{D_{t+4h} - D_t}{D_t},$$

$e_t^{(h)}$ is the h-year equity yield

$$e_t^{(h)} = \frac{1}{h} \ln\left(\frac{D_t}{\mathcal{P}_{t,t+4h}}\right),$$

$\mathcal{P}_{t,t+4h}$ is the h-year dividend strip price, and D_t is the current level of dividends paid. The time period is 1996-01-02:2016-12-22.

Table H.7: Returns and Expected Dividend Growth Regression Results

	Returns	Returns
$\Delta g_t^{(1)}$	0.1008***	
	(0.0117)	
$\Delta g_t^{(2)}$		0.0939***
		(0.0132)
const	0.0195	0.0194
	(0.0166)	(0.0170)
N	5155	4943
R^2	0.03	0.04

This table presents the results for the following regressions:

$$r_t = \beta_0^{(h)} + \beta_1^{(h)} \Delta g_t^{(h)} + \epsilon_t^{(h)},$$

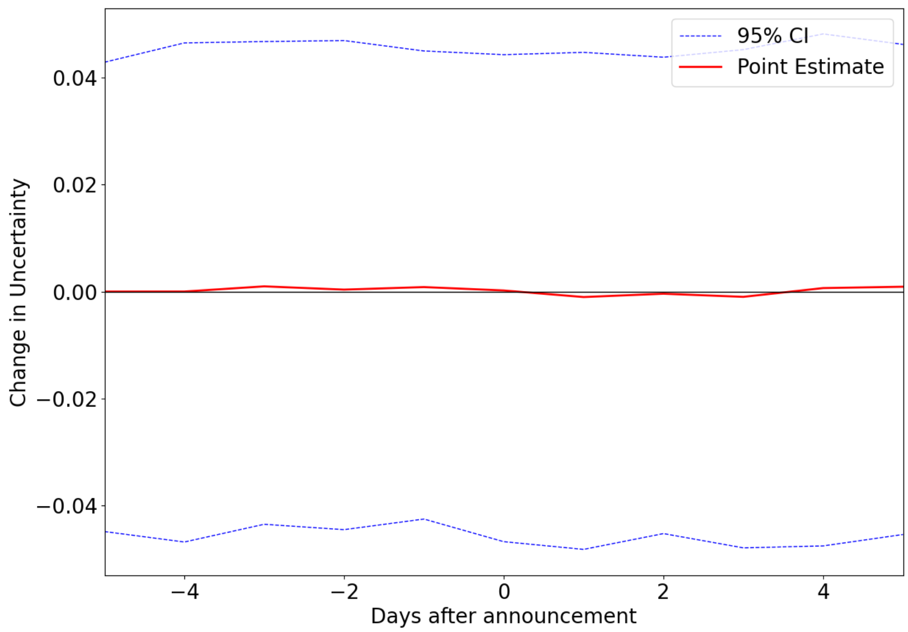
where r_t is the log return on the CRSP value-weighted market index in excess of the 30-day T-Bill rate and $\Delta g_t^{(h)}$ is the change in the fitted expected dividend growth rate for the next h years, constructed as discussed in Section 6.2. The time period is 1996-01-02:2016-12-22.

Table H.8: Summary Statistics for CME Options Data

	Num Contracts (Volume > 0)	Average Daily Volume Per Contract (Volume > 0)	Min Date	Max Date
S&P 500	1,127,646	184	1983-01-28	2016-12-30
Crude Oil	1,284,644	342	1986-11-14	2016-12-30
Gold	892,425	123	1986-01-02	2016-12-30
Wheat	542,740	128	1986-11-17	2016-12-30
10-Year Note	382,964	2,591	1985-05-01	2016-12-30
Corn	908,777	301	1985-02-27	2016-12-30
Soybean	852,017	227	1984-10-31	2016-12-30

This table presents summary statistics for CME options data.

Figure H.1: Placebo Test for First Stage

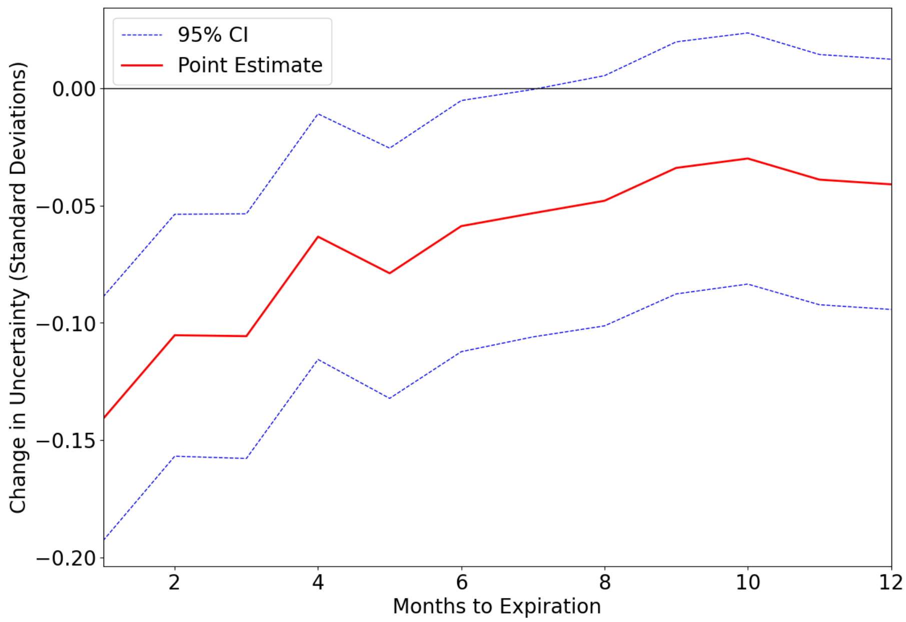


This figure presents the results for the placebo test of the regression of the change in the daily JLN index (standardized to have standard deviation one) on "pseudo-announcement" timing. For each simulation, I draw 1675 dates (since there are 1675 total announcements in the baseline time period) at random (pseudo-announcements) and run the following regression:

$$\Delta\sigma_t^2 = \beta_0 + \sum_{j=-5}^{5} \beta_j 1(t-j = \text{pseudo-announcement}) + \epsilon_t.$$

The right-hand-side variables are set of timing indicators representing how many days j after a pseudo-announcement the current day t is. I run 1000 of these simulations. The point estimates are the average regression coefficients from all simulations. The confidence intervals use the percentiles of the distributions of regression coefficients from all simulations. The time period is 1986-11-20:2016-12-22.

Figure H.2: Response of Daily JLN Index to Announcements by Horizon

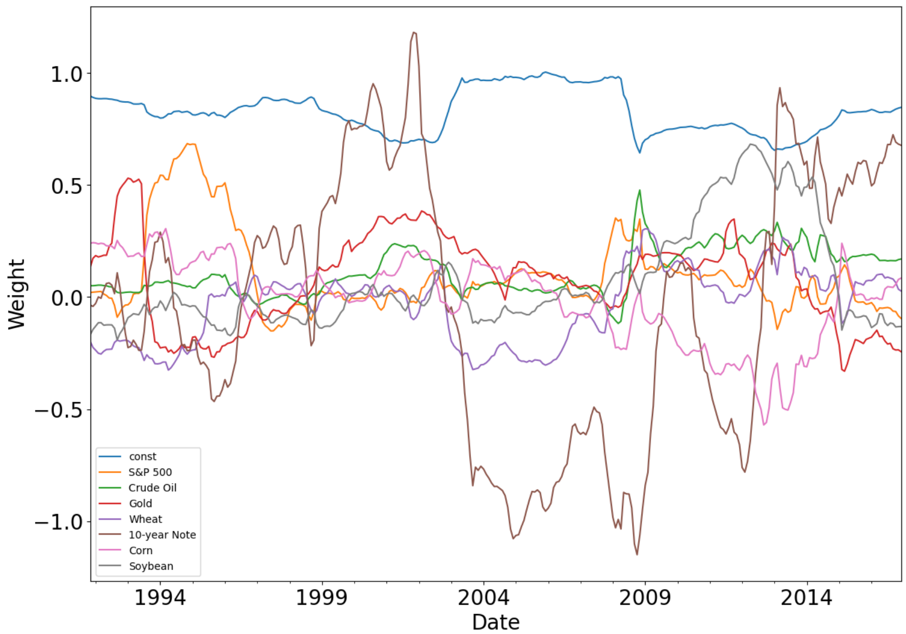


This figure displays a plot of the coefficients and 95% confidence intervals for $\beta_{h,1}$ from the regression:

$$\Delta\sigma^2_{h,t} = \beta_{h,0} + \beta_{h,1} 1(t = \text{ announcement}) + \epsilon_t.$$

The right-hand-side variable is a timing indicator for if day t is an announcement. $\Delta\sigma^2_{h,t}$ is the change in the h-month version of the daily JLN index, scaled to have mean zero and standard deviation one. To construct each $\sigma^2_{h,t}$ series, I apply the coefficients from regression (18) to the implied volatilities of subsets of options that have the same time to expiration (e.g. the subset of options for each underlying that expire one month from now). Specifically, on each day I linearly interpolate among all available times to maturity to get fixed-horizon indices. All GDP, Unemployment, CPI, PPI, Employment Cost Index, and scheduled FOMC announcements are included. The time period is 1986-11-20:2016-12-22.

Figure H.3: Time Series of Fitted Weights for Out-of-Sample Daily JLN Index



This figure displays the time-varying coefficients β_i from rolling five-year regressions of the monthly JLN index from Jurado, Ludvigson & Ng (2015) on the average monthly implied volatilities for each of the seven underlyings (corn, crude oil, gold, soybean, S&P 500, ten-year Treasury notes, and wheat):

$$JLN_t = \alpha + \sum_{i=1}^{7} \beta_i \overline{IV}_{it} + \epsilon_t.$$