A Model of Two Days: Discrete News and Asset Prices *

Jessica A. Wachter[1,2] and Yicheng Zhu[3]

[1]University of Pennsylvania
[2]NBER
[3]Hong Kong University of Science and Technology

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Empirical studies demonstrate striking patterns in stock returns related to scheduled macroeconomic announcements. A large proportion of the total equity premium is realized on days with macroeconomic announcements. The relation between market betas and expected returns is far stronger on announcement days as compared with non-announcement days. Finally, these results hold for fixed-income investments as well as for stocks. We present a model in which agents learn the probability of an adverse economic state on announcement days. We show that the model quantitatively accounts for the empirical findings. Evidence from options data provides support for the model's mechanism.

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1 Introduction

Since the work of Sharpe (1964) and Lintner (1965), the Capital Asset Pricing Model (CAPM) has been the benchmark model of the cross-section of asset returns. While the literature has explored many generalizations, the CAPM, with its simple and compelling structure and tight empirical predictions, remains the major theoretical framework for understanding the relation between risk and return. Recently, Savor and Wilson (2014) document a striking fact about the fit of the CAPM. Despite its poor performance in explaining the cross section overall, the CAPM does quite well on a subset of trading days, namely those days in which the Federal Open Market Committee (FOMC) or the Bureau of Labor Statistics (BLS) releases macroeconomic news.

Figure 1 reproduces the main result of Savor and Wilson (2014) using updated data. We sort stocks into portfolios based on market beta (the covariance with the market divided by market variance) computed using rolling windows. The figure shows the relation between portfolio beta and expected returns on announcement days and non-announcement days in the data.[1] This relation is known as the security market line. On non-announcement days (the majority), the slope is indistinguishable from zero. That is, there appears to be no relation between beta and expected returns. This result holds unconditionally, and is responsible for the widely-held view of the poor performance of the CAPM. However, on announcement days, a strong positive relation between betas and expected returns appears. Moreover, portfolios line up well against the security market line, suggesting that the relation is not only strong, but that the total explanatory power is high. Finally, these results appear even stronger for fixed-income investments than for equities.

These findings closely relate to a recent empirical literature (Lucca and Moench, 2015; Savor and Wilson, 2013) demonstrating that market returns are much higher on announcement days than non-announcement days. One potential explanation is that risk is different on announcement and non-announcement days. However in the data, market variance and covariances between stock portfolios and the market on announcement days are nearly indistinguishable from those on non-announcement days. This deepens the puzzle, ruling out a number of possible explanations.

We summarize the facts as follows:

[1] Portfolio betas are estimated using the full sample of returns. However, as we will show, betas using announcement and non-announcement day returns are very close.

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1. The equity premium is much higher on announcement days versus non-announcement days.

2. Equity volatility is not measurably higher on announcement days versus non-announcement days.

3. On announcement days, the security market line is upward-sloping. On non-announcement days, it is flat.

4. Risk-neutral equity volatility (the VIX) declines significantly immediately following announcements.

5. Fact 3 holds for Treasury bonds as well as for stocks.

In this paper, we build a frictionless model with rational investors that explains these findings. Our model is relatively simple and solved in closed form, allowing us to clearly elucidate the elements of the theory that are necessary to explain these results. Nonetheless, the model is quantitatively realistic, in that we explain not only these findings above, but also the overall risk and return of the aggregate stock market.

One important aspect of our model is that, despite the lack of frictions, investors do not have full information. Macroeconomic announcements matter for stock prices because they reveal information to investors concerning underlying shocks that have already occurred.[2] The information that is revealed matters to investors, which is why a premium is required to hold stocks on announcement days (Fact 1). In the benchmark calibration, the information concerns the likelihood of economic disaster similar to the Great Depression or what many countries suffered following the 2008 financial crisis. We assume that this latent probability follows a Markov process.

We further assume that stocks have differential exposure to macroeconomic risk. We endogenously derive the exposure on stock returns from the exposure of the underlying cash flows. We also assume, plausibly, that there is some variability in the probability of disaster that is not revealed in the macroeconomic announcements. Stocks with greater exposure have endogenously higher betas, both on announcement and non-announcement days, than those with lower exposure. They have much higher returns,

[2]Another possibility is that macroeconomic announcements themselves create the risk perhaps because they reflect on the competence of the Federal Reserve. We do not consider that possibility here.

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in line with the data, on announcement days, because that is when a disproportionate amount of information is revealed (Fact 3). Finally, the presence of disasters and of time-varying disaster risk implies that a linear relation between expected returns and betas does not hold. Stocks can have high variances, and covariances with the market, driven by time-varying disaster risk, without exposure to the actual disasters rising in proportion. This explains a part of the finding, namely why the curve is flat on non-announcement days.

In our model, learning about regime shifts break the traditional relation between risk and return. Fact 2 above states that conventional measures of risk such as variance and covariance do not appear markedly higher on announcement days. Regime shifts help to produce this finding because, on any given announcement, it is likely that investors learn that the economy is in a low-risk state. There is a small probability, however, that they will learn that risk is high. In any given sample, positive announcements could easily appear in greater proportion than they would in population. A prediction of the model, then, is that ex ante measures of risk, expecially those sensitive to tail events, should decline just after announcements. Indeed, Savor and Wilson (2013) show that the VIX declines following an announcement, an effect that we replicate in the model (Fact 4). Moreover, we also show in the data, that implied volatilities fall following announcements, and do so more for out-of-the-money than in-the-money options. This is also consistent with rare events as a mechanism. While these facts suggest that learning about rare events appears to drive the announcement premium, an alternative interpretation to disasters is that investors learn about the probability of, say, persistent recession. It is important that negative *announcements* be relatively rare; it is less clear that the news need be about a rare disaster.

Finally, an extension of the model to bonds explains Fact 5. We assume that some information that is revealed on announcements is informative about expected inflation. Bonds are exposed to announcements to a greater extent than equities. In the model, as well as in the data, betas on bonds rise dramatically on announcement days (they are near zero on non-announcement days), while equity betas do not.

While we focus on macroeconomic announcements, the techniques we employ could be used to address other types of predictable releases of discrete news (i.e. announcements). There is a vast empirical literature on announcement effects (La Porta et al., 1997; Fama, 1970), of which the literature on macro-announcements is a part. In this

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paper, we develop a set of theoretical tools to handle the fact that announcements occur at deterministic intervals, and that a finite amount of information is released over a vanishingly small period of time. In so doing, we complement and extend findings of Ai and Bansal (2018), who derive necessary conditions on a utility function for the existence of an announcement premium as well as closed-form expressions for risk premia in continuous time under the assumption of conditional lognormality. As in their work, time just before and just after the announcement is connected through intertemporal optimization conditions. We show that these conditions form a set of boundary conditions for the dynamic evolution of prices in the interval between announcements. It is this insight that allows us to compute a cross-section of stock prices in closed form.

There is a very recent literature on modeling the macroannouncement premium, focusing on the Bansal and Yaron (2004) long-run-risk setting. Savor and Wilson (2013) describe how a long-run risk model might account for a macroannouncement premium. In work contemporaneous to the present paper, Ai et al. (2018) rationalize the relative performance of the CAPM on announcement days in a production economy. In their model, total factor productivity follows an AR(1) process, about which agents receive normally distributed signals on announcement days. The fact that all shocks are normal simplifies the filtering problem. However, the evidence that daily returns exhibit no greater volatility on announcement versus non-announcement days, together with the option pricing results, is more in line with the regime-shift model that we propose. Ai et al. (2019) show that stocks whose implied volatilities change more around announcement days also have higher announcement premium, a result consistent with our model. In earlier work Andersen et al. (2003) show that foreign exchange markets respond more to negative announcements than positive ones, which is also consistent with our model. Cocoma (2018) builds a model to explain the Lucca and Moench (2015) evidence that much of the premium is realized prior to announcements.

The rest of the paper proceeds as follows. Section 2 discusses the model. Section 3 describes the data, calibration, and our simulation method. Section 4 compares the results of the simulation to the data. Section 5 compares simulation results from two alternative models: one with "small" disasters, designed to fit the VIX, and one with normally-distributed risk. We show that these alternatives do not succeed in matching at least some of the facts we describe above. Section 6 concludes.

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2 A model of asset prices with macroeconomic announcements

In the section that follows, we describe the model. Section 2.1 describes the endowment and preferences, Section 2.2 the relation between cash flows and announcements, Section 2.3 describes state prices, Section 2.4 equity prices, and Section 2.6 nominal bonds. Unless otherwise stated, proofs are contained in the Appendices.

2.1 Endowment and preferences

We assume an endowment economy with an infinitely-lived representative agent. Aggregate consumption (the endowment) follows the stochastic process

$$\frac{dC_t}{C_{t^-}} = \mu dt + \sigma dB_{Ct} + \left(e^{-Z_t} - 1\right) dN_t, \tag{1}$$

where B_{Ct} is a standard Brownian motion and where N_t is a Poisson process. The diffusion term $\mu dt + \sigma dB_{Ct}$ represents the behavior of consumption during normal times. The Poisson term $\left(e^{-Z_t} - 1\right) dN_t$ represents rare disasters. The random variable $Z_t > 0$, is the decline in log consumption, given a disaster. We assume, for tractability, that Z_t has a time-invariant distribution, which we call ν; that is, Z_t is iid over time, and independent of all other shocks. We use the notation $\mathbb{E}_\nu$ to denote expectations taken over ν.

We assume the representative agent has recursive utility with EIS equal to 1, which gives us closed-form solutions up to ordinary differential equations. We use the continuous-time characterization of Epstein and Zin (1989) derived by Duffie and Epstein (1992). The following recursion characterizes utility V_t:

$$V_t = \max \mathbb{E}_t \int_t^\infty f(C_s, V_s) ds, \tag{2}$$

where

$$f(C_t, V_t) = \beta(1-\gamma)V_t \left(\log C_t - \frac{1}{1-\gamma} \log[(1-\gamma)V_t]\right). \tag{3}$$

Here β represents the rate of time preference, and γ represents relative risk aversion. The case of $\gamma = 1$ collapses to time-additive (log) utility. When $\gamma \neq 1$, preferences

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satisfy risk-sensitivity, the characteristic that Ai and Bansal (2018) show is a necessary and sufficient condition for a nonzero announcement premium.

2.2 Scheduled announcements and the disaster probability

We assume that scheduled announcements convey information about the probability of a rare disaster (in what follows, we use the terminology probability and intensity interchangeably). The probability may also vary over time for exogenous reasons; this creates volatility in stock prices in periods that do not contain announcements.

To parsimoniously capture these features in the model, we assume the intensity of N_t is a sum of two processes, λ_{1t} and λ_{2t}.[3] The intensity λ_{1t} follows a latent Markov switching process. Following Benzoni et al. (2011), we assume two states, $\lambda_{1t} = \lambda^L$ (low) and $\lambda_{1t} = \lambda^H$ (high), with $0 \leq \lambda^L < \lambda^H$, and

$$\begin{aligned} &\text{Prob}(\lambda_{1,t+dt} = \lambda^L | \lambda_{1t} = \lambda^H) = \phi_{H\to L} dt \\ &\text{Prob}(\lambda_{1,t+dt} = \lambda^H | \lambda_{1t} = \lambda^L) = \phi_{L\to H} dt, \end{aligned} \tag{4}$$

with $\phi_{H\to L}, \phi_{L\to H} > 0$. Note that $\phi_{H\to L}$ can be interpreted as the probability (per unit of time) of a switch from the high-risk state to the low-risk state and $\phi_{L\to H}$ is similarly, the probability of a switch from the low-risk state to the high-risk state.

Announcements convey information about λ_{1t}. Let T be the length of time between announcements.[4] Define

$$\begin{aligned} \mathcal{A} &\equiv \{t : t \bmod T = 0\}, \\ \mathcal{N} &\equiv \{t : t \bmod T \neq 0\}. \end{aligned} \tag{5}$$

That is, $\mathcal{A}$ is the set of announcement times, and $\mathcal{N}$ is the set of non-announcement times. Note that $\mathcal{N}$ is an open set, so we can take derivatives of functions evaluated at times $t \in \mathcal{N}$. Note that announcements occur at an instant in time.

Let p_t denote the time-t probability that the representative agent places on $\lambda_{1t} =$

[3]Equivalently, decompose, N_t as

$$N_t = N_{1t} + N_{2t},$$

where N_{jt}, for $j = 1, 2$, has intensity λ_{jt}.

[4]In the data, announcements are periodic, but, depending on the type of announcement, the period length is not precisely the same. Our assumption of an equal period length is a convenient simplification that has little effect on our results.

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λ^H. For $t \in \mathcal{N}$, assume

$$dp_t = ((1-p_t)\phi_{L\to H} - p_t\phi_{H\to L})\,dt = (\phi_{L\to H} - p_t(\phi_{H\to L} + \phi_{L\to H}))\,dt. \tag{6}$$

This assumption implies that the agent learns only from announcements.[5] Outside of announcement periods, the agent updates based on (4). If the economy is in a low-risk state, which it is with probability $1-p_t$, the chance of a shift to a high-risk over the next instant is $\phi_{L\to H}\,dt$. If the economy is in a high-risk state, which is with probability p_t, the chance of a shift to the low-risk state over the next instant is $\phi_{H\to L}\,dt$. Define

$$\bar{\lambda}_1(p_t) \equiv p_t\lambda^H + (1-p_t)\lambda^L,$$

as the agent's posterior value of λ_{1t}. For simplicity, we assume announcements convey full information, that is, they perfectly reveal λ_{1t}.[6] Thus the process for p_t is right-continuous with left limits. In the instant just before the announcement it is governed by (6). On the announcement itself, it jumps to 0 or 1 depending on the true (latent) value of λ_{1t}. We refer to announcements revealing λ_{1t} to be λ^L as positive and those revealing it to be λ^H as negative. As we will show, this language is precise in the sense that the risk averse agent's utility rises when the announcement is positive.

It is useful to keep track of the content of the most recent announcement, because of the information it conveys about the evolution of the disaster probability. Define τ as the time elapsed since the most recent announcement:

$$\tau \equiv t \bmod T,$$

[5] Bayesian learning implies

$$dp_t = p_{t^-}\left(\frac{\lambda^H - \bar{\lambda}_1(p_{t^-})}{\bar{\lambda}_1(p_{t^-})}\right)dN_{1t} + \left(-(p_{t^-})(\lambda^H - \bar{\lambda}_1(p_{t^-})) - (p_{t^-})\phi_{H\to L} + (1-p_{t^-})\phi_{L\to H}\right)\,dt$$

(Wachter and Zhu, 2019). The first term multiplying N_{1t} corresponds to the actual effect of disasters. The term $-p(\lambda^H - \bar{\lambda}_1(p))$ in the drift corresponds to the effect of no disasters. We abstract from these effects in (6).

[6] In effect, we assume the government body issuing the announcement has better information, perhaps because of superior access to data. Stein and Sunderam (2017) model the strategic problem of the announcer and investors, and show that announcements might reveal more information than a naive interpretation would suggest.

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and define χ_t to be the probability that the announcement reveals:

$$\chi_t \equiv p_{t-\tau}. \tag{7}$$

Because announcements completely reveal the state, $\chi \in \{0,1\}$. Under these assumptions, p_t has takes a simple form.

Lemma 1. *The probability assigned to the high-risk state satisfies $p_t = p(\tau; \chi_t)$, where $\tau \in [0, T)$, $\chi \in \{0,1\}$ and*

$$p(\tau;\chi) = \chi e^{-(\phi_{H\to L}+\phi_{L\to H})\tau} + \frac{\phi_{L\to H}}{\phi_{H\to L}+\phi_{L\to H}}(1 - e^{-(\phi_{H\to L}+\phi_{L\to H})\tau}). \tag{8}$$

Proof. Equation 6 implies that p_t is deterministic between announcements. Moreover, p_t is memoryless in that it contains no information prior to the most recent announcement. Because the information revealed at the most recent announcement is summarized in χ, any solution for (6) takes the form $p_t = p(\tau;\chi)$, where $\tau = t \bmod T$ and $\chi \in \{0,1\}$. It follows directly from (6) that

$$\frac{d}{d\tau}p(\tau;\chi) = -p(\tau;\chi)(\phi_{H\to L}+\phi_{L\to H}) + \phi_{L\to H}, \qquad \tau \in [0,T). \tag{9}$$

This has a general solution:

$$p(\tau;\chi) = K_\chi e^{-(\phi_{H\to L}+\phi_{L\to H})\tau} + \frac{\phi_{L\to H}}{\phi_{H\to L}+\phi_{L\to H}}, \tag{10}$$

where K_χ is a constant that depends on χ. The boundary condition $p(0;\chi) = \chi$ determines K_χ. □

Equation 8 shows that p_t is a weighted average of χ, the probability of the high-risk state revealed in the most recent announcement, and $\frac{\phi_{L\to H}}{\phi_{L\to H}+\phi_{H\to L}}$, the unconditional probability of the high-risk state. As τ, the time elapsed since the announcement, goes from 0 to T, the agent's weight shifts from the former of these probabilities to the latter.

Agents forecast the outcome of the announcement based on p_t. The optimality conditions connecting the instant before the announcement to the instant after are crucial determinants of equilibrium. It is thus useful to define notation for p_t just

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before the announcement. Let

$$p^*_\chi = \lim_{\tau \uparrow T} p(\tau;\chi) \qquad \chi = 0,1 \tag{11}$$

Then p^*_0 is the probability that the agent assigns to a negative announcement just before the announcement is realized, if the previous announcement was positive. If the previous announcement was negative, then the agent assigns probability p^*_1. The values of p^*_0 and p^*_1 follow from (8):

$$p^*_\chi = \chi e^{-(\phi_{H\to L}+\phi_{L\to H})T} + \frac{\phi_{L\to H}}{\phi_{H\to L}+\phi_{L\to H}}(1 - e^{-(\phi_{H\to L}+\phi_{L\to H})T}). \tag{12}$$

Not surprisingly, $0 < p^*_0 < p^*_1 < 1$:

Finally, we assume investors observe λ_{2t}, which follows

$$d\lambda_{2t} = \kappa(\bar{\lambda}_2 - \lambda_{2t})dt + \sigma_\lambda \sqrt{\lambda_{2t}} dB_{\lambda t}, \tag{13}$$

with $B_{\lambda t}$ a Brownian motion independent of B_{Ct}. The process for λ_{2t} is the same as the one assumed for the disaster probability in Wachter (2013).

In what follows, all expectations should be understood to be taken with respect to the agent's posterior distribution, unless noted otherwise.

2.3 Equilibrium state prices

In what follows, we will separate quantities into a component that remains constant upon an announcement and a component that jumps. This separation allows us to focus our theoretical results on the behavior of asset prices upon an announcement.[7] This separation also implies that the results in this section could in principle be applied to any underlying model for the equity premium, provided that it is based on the revelation of latent regimes on announcement days.

We first solve for the value function of the representative agent. We then use this result to solve for the stochastic discount factor, and finally to price assets. We show that the value function depends on five state variables: consumption C_t, probability of

[7]Quantitative implications depend on the behavior of the model at all time, however, and for this reason a full solution of the model is given in the Appendix.

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the high-risk state p_t, time since the announcement τ, the previously announced state χ, and the observed component of the disaster probability λ_2. The state variable p_t is technically redundant, as it is a function of χ and τ. However, separating it out helps to gain economic intuition.

Theorem 2. *In equilibrium, the agent's continuation value $V_t = J(C_t, p_t, \lambda_{2t}, \tau; \chi_t)$, with $\tau = t \bmod T$. Continuation value takes the form:*

$$J(C_t, p_t, \lambda_{2t}, \tau; \chi_t) = \frac{1}{1-\gamma} C_t^{1-\gamma} I(p_t, \lambda_{2t}, \tau; \chi_t)^{1-\gamma}, \tag{14}$$

with

$$I(p_t, \lambda_{2t}, \tau; \chi_t) = I_{\mathcal{A}}(p_t, \tau; \chi_t) I_{\mathcal{N}}(\lambda_{2t}) \tag{15}$$

for $I_{\mathcal{N}}$ is unaffected by the announcement and

$$I_{\mathcal{A}}(p_t, \tau; \chi_t) = e^{\zeta_\chi e^{\beta\tau} + \hat{b} p_t}, \tag{16}$$

where

$$\hat{b} = \frac{(\lambda^H - \lambda^L)\mathbb{E}_\nu \left[e^{(\gamma-1)Z_t} - 1 \right]}{(1-\gamma)(\beta + \phi_{H\to L} + \phi_{L\to H})}, \tag{17}$$

and where ζ_χ, $\chi = 0, 1$ satisfy

$$e^{(1-\gamma)(\zeta_\chi e^{\beta T} + \hat{b} p^*_\chi)} = p^*_\chi e^{(1-\gamma)(\zeta_1 + \hat{b})} + (1 - p^*_\chi) e^{(1-\gamma)\zeta_0}, \tag{18}$$

with probabilities p^* satisfying (12).

The value function J is a product of the usual CRRA utility term $(1-\gamma)^{-1} C_t^{1-\gamma}$ and a term that depends on the stationary state variables. We are most interested in $I_{\mathcal{A}}$, which represents that aspect of utility affected by by announcements. The coefficient $\hat{b}$ in (17) determines how the agent's utility responds to changes in the posterior probability of a high risk state. This term depends on the difference between the disaster probability in the two states and the expected outcome for utility should a disaster occur. It also depends on $\beta + \phi_{H\to L} + \phi_{L\to H}$, which captures the persistence of effect. The more patient the investor (the lower is β), and the more persistent the states (the lower the transition probabilities), the greater the effect.

The value function also depends on the announced state and the time since the last announcement. The recursion (18) derives from the condition that the value function

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prior to the announcement must equal its expected value following the announcement.

Using the analytical expressions in Theorem 2, we can show that the agent is always worse off should the high-risk state prevail. The proof follows from the condition (18), and the result that $\zeta_0 > \zeta_1 + \hat{b}$ (which we prove in the Appendix).

Corollary 3. *For all risk averse agents, utility increases for positive announcements and decreases for negative ones. That is, for $\gamma > 0$, $I_{\mathcal{A}}$ increases when the announcement is positive and decreases when it is negative:*

$$I_{\mathcal{A}}(1, 0; 1) < \lim_{\tau \uparrow T} I_{\mathcal{A}}(p^*_{\chi}, \tau; \chi) < I_{\mathcal{A}}(0, 0; 0) \qquad \chi = 0, 1.$$

Duffie and Skiadas (1994) link the equilibrium value function to the state-price density:

$$\pi_t = \exp\left\{\int_0^t \frac{\partial}{\partial V} f(C_s, V_s) ds\right\} \frac{\partial}{\partial C} f(C_t, V_t). \tag{19}$$

We can think of π_t as the process for marginal utility. Standard calculations (see Lemma A.3) imply that

$$\pi_t = \beta \exp\left\{\int_0^t \frac{\partial}{\partial V} f(C_s, V_s) ds\right\} C_t^{-\gamma} I(p_t, \lambda_{2t}, \tau; \chi_t)^{1-\gamma}, \tag{20}$$

Appendix A derives the process for the state-price density π_t. Our present focus is on the change in π_t over announcements, namely π_t/π_{t^-}, for $t \in \mathcal{A}$. It turns out that many terms drop out, and the change in π_t over announcements only depends on the previously-announced probability and the just-announced probability.[8] That is, we can define a function of the last announcement χ_- and the current announcement χ:

$$M(\chi, \chi_-) \equiv \left(\frac{\exp\{\zeta_\chi + \hat{b}\chi\}}{\exp\{e^{\beta T}\zeta_{\chi_-} + \hat{b} p^*_{\chi_-}\}}\right)^{1-\gamma} \tag{21}$$

The next theorem states that M is indeed the change in the state-price density.

$$M(\chi_t, \chi_{t^-}) = \frac{\pi_t}{\pi_{t^-}}. \tag{22}$$

[8] There is a theoretical possibility of a disaster co-occurring with an announcement, in which case (22) would not hold. Because announcements occur on a set of measure zero, this is a zero probability event, and we can ignore it when calculating expectations and therefore prices and returns.

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Following Ai and Bansal (2018), we refer to the change in π_t upon the announcement as the announcement stochastic discount factor, or the announcement SDF.

Theorem 4 (Announcement SDF)**.** *The change in state-price density upon the announcement equals*

$$M(\chi, \chi_-) = \left(\frac{\exp\{\zeta_\chi + \hat{b}\chi\}}{\exp\{e^{\beta T}\zeta_{\chi_-} + \hat{b}p^*_{\chi_-}\}} \right)^{1-\gamma}, \tag{23}$$

where (17) defines $\hat{b}$ and where ζ satisfies (18). We refer to $M(\chi, \chi_-)$ as the announcement SDF.

Negative announcements decrease utility for all risk averse agents. However, negative announcements only affect *marginal utility*, and hence the SDF, for agents with a preference for the timing of the resolution of uncertainty.:

Corollary 5. *The announcement SDF is > 1 for negative announcements and < 1 for positive ones, if $\gamma > 1$. If $\gamma < 1$, the inequalities reverse.*

A preference for early or late resolution of uncertainty is a special case of risk-sensitivity, as defined by Ai and Bansal (2018). In their setting, as in ours, risk-sensitivity is a necessary and sufficient condition for a nonzero announcement premium.

Using the announcement SDF, we can define risk-neutral probabilities of negative announcements, just before the announcement occurs.

$$\tilde{p}^*_\chi \equiv M(1, \chi)p^*_\chi \qquad \chi = 0, 1 \tag{24}$$

These are the risk-neutral counterparts of (11). When $\chi = 0$, (24) is the risk-neutral probability of a negative announcement, given that the previous announcement was positive. when $\chi = 1$, (24) is the risk-neutral probability of a negative announcement given that the previous announcement was negative.

Provided that $\gamma > 1$, risk-neutral probabilities of a negative announcements are higher than physical probabilities because of the effect of the announcement on state prices. Perhaps less obvious is the fact that, regardless of the value of γ, the risk-neutral probability of a negative announcement following a previous negative announcement is higher than the risk-neutral probability of a negative announcement following a positive

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one. This means that a negative announcement is bad news in a dynamic sense: it affects not only dividends that are about to be realized, but also the agents' beliefs about future cash flows. This insight is important for equity pricing.

Theorem 6. *Let $\tilde{p}_1^*$ be the risk-neutral probability of a negative announcement, just prior to the announcement occurring, provided that the previous announcement was negative, and $\tilde{p}_0^*$ be the analogous quantity, provided that the previous announcement was positive. Then*

$$\tilde{p}_1^* > \tilde{p}_0^*.$$

This section shows that the stochastic discount factor undergoes a discrete change at the instant of an announcement, provided that there is a preference for the timing of the resolution of uncertainty. As we will show, any asset whose price undergoes a discrete change at the instant of an announcement will carry an announcement premium: investors must be compensated for the risk of holding the asset over any interval containing the announcement. If the price change is in the opposite direction as the SDF change, then the announcement premium is positive. Unlike the risk premium due to diffusion or Poisson risk, the announcement premium does not scale with the length of time over which the premium is measured. Even though the announcement occurs at an infinitesimal point in time, the premium is bounded away from zero.

Savor and Wilson (2014) document announcement premia, as measured by the slope of the security market line, for equities and bonds. In what follows, these are the focus of our analysis. We endogenously derive the price change for equities and for nominal bonds upon announcements and show that the magnitude of the effect matches the Savor and Wilson evidence. Savor and Wilson also document an announcement premium in foreign exchange markets. When currencies are sorted into portfolios based on interest rate differentials, higher beta portfolios have higher returns on announcement days, but there is no relation (or a negative relation) on non-announcement days. While a full explanation of this finding is outside the scope of our paper, the above reasoning suggests that if high interest rate differential portfolios are those exposed to macroeconomic disasters (as captured in the $\lambda_1(t)$ regime) then these would have high announcement day returns, with little or no relation between risk and return on non-announcement days.

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2.4 Equities

In this section, we derive properties of claims to dividends (that is, equity claims). Dividends follow a process that is similar to that of consumption:

$$\frac{dD_t}{D_{t^-}} = \mu_D dt + \sigma dB_{Ct} + (e^{-\varphi Z_t} - 1)dN_t. \tag{25}$$

To reduce the number of free parameters, we assume dividends have the same loading on Brownian risk as does consumption.[9] We allow dividends to display additional disaster sensitivity, where the parameter φ determines the degree of this sensitivity.[10] We will define a cross-section of stocks by varying the parameter φ.

We first consider the price of an equity strip (a claim that pays a dividend at a fixed point in time). Let Φ denote the ratio of the price of this claim to the current dividend. By the Markov property,

$$\Phi(p_t, \lambda_{2t}, \tau, s; \chi_t) = \mathbb{E}_t \left[\frac{\pi_{t+s}}{\pi_t} \frac{D_{t+s}}{D_t} \right]. \tag{26}$$

Theorem 7. *The price of an s-period equity strip, scaled by the current dividend, equals*

$$\Phi(p_t, \lambda_{2t}, \tau, s; \chi_t) = \Phi_{\mathcal{A}}(p_t, \tau, s; \chi_t)\Phi_{\mathcal{N}}(\lambda_{2t}, s), \tag{27}$$

where $\Phi_{\mathcal{N}}$ is unaffected by the announcement, and where

$$\Phi_{\mathcal{A}}(p_t, \tau, s; \chi_t) = \exp\{a(\tau + s; \chi_t) + b(s)p_t\}, \tag{28}$$

with

$$b(s) = \frac{(\lambda^H - \lambda^L)\mathbb{E}_\nu \left[e^{\gamma Z_t}(e^{-\varphi Z_t} - e^{-Z_t}) \right]}{\phi_{H\to L} + \phi_{L\to H}} \left(1 - e^{-(\phi_{H\to L} + \phi_{L\to H})s}\right). \tag{29}$$

[9]This specification does imply that dividends in the model will, during normal times, feature the same volatility as consumption. In the data, dividends are more volatile than consumption, but the normal-times correlation between dividends and consumption is low. Adding unpriced dividend risk would make it easier to explain the volatility of dividend growth and of returns but would leave the results otherwise unchanged.

[10] Longstaff and Piazzesi (2004) show that earnings were far more affected than consumption during the Great Depression. Bianchi (2015), Bai et al. (2019) and Lu and Murray (2017) find that disaster sensitivity is an important determinant of risk and return in the cross-section.

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The function $a : \mathbb{R}_+ \times \{0,1\} \to \mathbb{R}$ *is the unique solution to the system of equations*

$$e^{a(u;\chi)+b(u-T)p^*_\chi} = \tilde{p}^*_\chi e^{a(u-T;1)+b(u-T)} + (1-\tilde{p}^*_\chi)e^{a(u-T;0)} \tag{30}$$

with boundary condition $a(u;\cdot) = 0$, $u \in [0,T)$, *for risk neutral probabilities* $\tilde{p}^*_\chi$, $\chi \in \{0,1\}$, *which are functions of the primitive parameters.*

Theorem 7 decomposes the price of an equity strip into a component affected by the announcement, and a component that is unaffected (which we describe in the Appendix). The component affected by the announcement depends on the probability of a high-risk state, the time since the announcement, the maturity of the strip, and the previous announcement. When an announcement occurs, the time since the last announcement jumps from T back to 0, the probability of a high risk state jumps to either 0 or 1, and the content of the previous announcement is updated to the content of the current announcement.

We can gain some intuition from the form of prices in Theorem 7. First, provided that $\varphi > 1$, $-\varphi Z_t < -Z_t$, implying that $b(s)$ is strictly negative and decreasing in s. The greater is the probability that the economy is in the high-risk state, the lower is the price, and the longer the maturity of the claim, the more pronounced the effect. Dividing this term is the sum of the transition probabilities; thus, the more persistent the state, the greater the effect on the price.

Second, consider (30). This equation arises from the fact that the price just prior to the announcement must be the expected value of the price just after the announcement, under the risk-neutral probabilities. The function a depends on the number of announcements until maturity, and the most recent announcement.[11] It keeps track of the cumulative effects of anticipated future announcements on the price.

Corollary 8. *Assume* $\varphi > 1$. *Then the price of an equity strip with positive maturity on the announcement date increases when the announcement is positive and decreases when the announcement is negative. That is*

$$\Phi_{\mathcal{A}}(1,0,s;1) < \lim_{\tau \uparrow T} \Phi_{\mathcal{A}}(p_\chi, \tau, s; \chi) < \Phi_{\mathcal{A}}(0,0,s;0) \qquad \chi = 0, 1,$$

[11] The fact that a depends on the sum $s+\tau$ rather than s and τ by themselves indicates that it does not matter how far away in time the next announcement is. As time goes by, τ increases, s decreases, so that $s+\tau$ remains constant until (upon the announcement) τ jumps back to zero.

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for $s > 0$.

First consider the equity strip with one announcement prior to maturity. By standard reasoning (for this equity strip, we do not have to worry about the future announcements), this asset will fall in price if the announcement is negative and rise if it is positive. Recall that $\tilde{p}_1^* > \tilde{p}_0^*$, in other words, the risk-neutral probability of a negative announcement is higher if the previous announcement was negative than if it was positive. The value of the equity strip with one announcement to maturity will reflect the current risk-neutral probability of a negative announcement, and this value will be higher if the previous announcement was negative.

Now consider the effect of an announcement on an equity strip with two announcements prior to maturity. Consider the effect of the first announcement. After this announcement has passed, it becomes a strip with one announcement prior to maturity, and so the reasoning in the above paragraph applies. If this first announcement is negative, then $\tilde{p}_1^*$ is the risk-neutral probability of the next announcement being negative, and the claim with one announcement prior to maturity now has a lower value than if the announcement had been positive. Thus the strip with two announcements prior to maturity falls in price if the announcement is negative. Iteratively applying this reasoning (see Appendix B for details) leads to the result above.

This result tells us immediately that there must be an announcement premium, because the price moves in opposite direction to marginal utility. Consider the return on the equity strip of maturity s:

$$r_{\mathcal{A}}(\chi, \chi_-, s) \equiv \frac{\Phi_{\mathcal{A}}(\chi, 0, s; \chi)}{\lim_{\tau \uparrow T} \Phi_{\mathcal{A}}(p^*_{\chi_-}, \tau, s; \chi_-)} = \frac{e^{a(s;\chi)+b(s)\chi}}{e^{a(T+s;\chi_-)+b(s)p^*_{\chi_-}}} \tag{31}$$

Just prior to the announcement $\tau = T$, its maximum value. The notation χ_- represents the most recently announced probability. The notation $p^*_{\chi_-}$ represents the current posterior, given the most recent announcement. At the announcement, τ goes from T to 0, and both χ_- and $p^*_{\chi_-}$ becomes χ, the announced probability. All other terms are unaffected by the announcement, and hence drop out of the equity valuation.[12]

We can use (31) to derive an intuitive expression for the announcement premium. Equations 30 and 31 together imply the natural conclusion that the expected (gross)

[12] As mentioned previously (31) holds almost surely, because there is a theoretical probability that a disaster could coincide with an announcement.

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announcement return under the risk-neutral probability must equal 1:

$$\tilde{p}^*_{\chi_-} r_{\mathcal{A}}(1, \chi_-, s) + (1 - \tilde{p}^*_{\chi_-}) r_{\mathcal{A}}(0, \chi_-, s) = 1. \tag{32}$$

Now consider the expected announcement return under the physical probability:

$$\bar{r}_{\mathcal{A}}(\chi_-, s) \equiv p^*_{\chi_-} r_{\mathcal{A}}(1, \chi_-, s) + (1 - p^*_{\chi_-}) r_{\mathcal{A}}(0, \chi_-, s) \tag{33}$$

Subtracting (33) from (32) implies the following form for the announcement premium:

$$\begin{aligned} \bar{r}_{\mathcal{A}}(\chi_-, s) - 1 &= (\tilde{p}^*_{\chi_-} - p^*_{\chi_-})(r_{\mathcal{A}}(0, \chi_-, s) - r_{\mathcal{A}}(1, \chi_-, s)) \\ &= (\tilde{p}^*_{\chi_-} - p^*_{\chi_-}) \frac{e^{a(s;0)} - e^{a(s;1)+b(s)}}{e^{a(T+s;\chi_-)+b(s)p^*_{\chi_-}}}, \end{aligned} \tag{34}$$

where (34) follows from (31). As long as the risk-neutral probability of a negative announcement is greater than the physical probability, the announcement premium is positive. Corollary 5 and (24) show that this will be the case as long as $\gamma > 1$ (namely, if the agent has a preference for early resolution of uncertainty). This corresponds to the finding, in Ai and Bansal (2018), that risk-sensitive preferences are a necessary and sufficient condition for a nonzero announcement premium.

Another way to write the announcement premium is in terms of the co-movement of the price with the SDF around announcements:

Corollary 9. *The announcement premium on the s-period equity strip equals*

$$\begin{aligned} \mathbb{E}_{t^-}\left[r_{\mathcal{A}}(\chi_t, \chi_{t^-}, s) - 1\right] &= -\mathbb{E}_{t^-}\left[\left(r_{\mathcal{A}}(\chi_t, \chi_{t^-}, s) - 1\right)\left(M(\chi_t, \chi_{t^-}) - 1\right)\right] \\ &= -\mathrm{Cov}_{t^-}(r_{\mathcal{A}}(\chi_t, \chi_{t^-}, s), M(\chi_t, \chi_{t^-})). \end{aligned} \tag{35}$$

Moreover, provided $s > T - \tau$,

1. *The announcement premium is strictly positive if $\varphi > 1$ and $\gamma > 1$, or if $\varphi < 1$ and $\gamma < 1$.*

2. *The announcement premium is strictly negative if $\varphi < 1$ and $\gamma > 1$, or if $\varphi > 1$ and $\gamma < 1$.*

3. *The announcement premium is equal ot zero if either γ or φ equals 1.*

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It may first appear that Corollary 9 and (34) refer merely to the existence of an announcement premium; it appears to say nothing of the magnitude. However, implicit in Corollary 9 is a strong statement about the magnitude of the announcement premium. Equation 35 gives an absolute number; it does not scale with the size of the interval containing the announcement. By contrast, the risk premium on the equity strip (or on any other asset) at a non-announcement time is proportional to the time interval, and is infinitesimal over infinitesimal intervals. The key difference between the announcement day and the non-announcement day is that the announcement day provides a discrete amount of news: the agent anticipates receiving news on this day with probability 1. At any other day, there is either a tiny amount of news for sure (in the case of Brownian risk), or a large amount of news with a tiny probability (in the case of Poisson risk). The Brownian and Poisson shocks provide risk that is continuous, whereas announcement news is discrete.

Because of the discrete quantity of news released on the announcement day, the daily return on an announcement day can easily be an order of magnitude higher than on a non-announcement day. Our numerical evaluation in the next section makes this statement precise. In this numerical evaluation, we will consider claims to continuous streams of dividends. These will represent stock prices; we will consider a cross-section with varying parameters φ. For the remainder of this section, we specify how pricing works for a fixed φ, and postpone discussion of the cross-section until Section 3. No-arbitrage gives us the value of the stock:

$$S_t = \mathbb{E}_t \int_t^\infty \frac{\pi_s}{\pi_t} D_s \, ds = \int_t^\infty \mathbb{E}_t \frac{\pi_s}{\pi_t} D_s \, ds. \tag{36}$$

Clearly, the price of the stock is an integral of the prices of the underlying strips.

Lemma 10. *Let S_t be the time-t price of an asset paying the dividend process (25). Then*

$$S\big(D_t, p_t, \lambda_{2t}, \tau; \chi_t\big) = \int_0^\infty D_t \Phi(p_t, \lambda_{2t}, \tau, s; \chi_t) ds, \tag{37}$$

Proof. The result follows directly from Theorem 7 and the no-arbitrage condition (36). □

The stock price moves in the same direction as the underlying strips, given an announcement:

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Corollary 11. *Assume that $\varphi > 1$. Then $S\big(D_t, p_t, \lambda_{2t}, \tau; \chi_t\big)$ increases when the announcement is positive and decreases when the announcement is negative. That is,*

$$S(D, 1, \lambda_2, 0; 1) < \lim_{\tau \uparrow T} S(D, p_{t^-}, \lambda_2, \tau; \chi_{t^-}) < S(D, 0, \lambda_2, 0; 0).$$

Proof. The result follows directly from Corollary 8 and from Lemma 10. □

The expression for announcement premium on the stock is necessarily more complicated than the announcement premium on the equity strip. However, the sign of the premium is clearly the same.

Corollary 12. *Consider an asset paying dividends given by (25),*

1. *The announcement premium is strictly positive if $\varphi > 1$ and $\gamma > 1$, or if $\varphi < 1$ and $\gamma < 1$.*
2. *The announcement premium is strictly negative if $\varphi < 1$ and $\gamma > 1$, or if $\varphi > 1$ and $\gamma < 1$.*
3. *The announcement premium is equal ot zero if either γ or φ equals 1.*

Proof. Corollaries 5 and 11 show that increases in S coincide with $M(\chi, \chi_-) < 1$ in case 1, whereas increases in S coincide with $M(\chi, \chi_-) > 1$ in case 2. Finally, in case 3, either $M(\chi, \chi_-) = 1$ or S does not change given an announcement. □

2.5 Implications for the VIX

Since 1993, the VIX, which is reported by the Chicago Board Options Exchange (Cboe), has been a popular way to measure uncertainty.[13] Following Carr and Wu (2009), we define the VIX as the square root of expected quadratic variation of the equity index under the risk-neutral measure. For quadratic variation calculated between t and $t+v$, the the VIX is defined so that

$$\mathrm{VIX}_t^2 = \frac{1}{v}\mathbb{E}_t^Q \left[\int_t^{t+v} d[\log S, \log S]_u \right],$$

[13] See the Cboe White Paper https://www.cboe.com/micro/vix/vixwhite.pdf.

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where, for ease of interpretation, we follow the Cboe in scaling the expected quadratic variation by the length of the interval over which it is calculated.

For the same reason that expected returns over any non-announcement interval go to zero as that interval becomes infinitesimally small, the change in VIX also goes to zero. However, announcement times are different: our model predicts a discrete fall in the VIX before and after the announcement. The reason is that the announcement is a non-infinitesimal source of variance that disappears after the announcement has passed.[14] We test this prediction of the model in Section 4.

The analytical results that we have thus far easily translate into the change in VIX. Intuitively, the change in VIX is simply the negative of the expected variance of the announcement.

Theorem 13 (VIX change on announcements)**.** *In expectation, the VIX falls on the instant of an announcement. The expected announcement decline, under the risk neutral measure, equals:*

$$\begin{aligned}\mathbb{E}^{Q}_{t^-}[\mathrm{VIX}^2_t - \mathrm{VIX}^2_{t^-}] &= -\frac{1}{\nu}\mathbb{E}^{Q}_{t^-}\left[\left(a(s;\chi_t) + b(s)\chi_t - \left(a(T+s;\chi_{t^-}) + b(s)p^*_{\chi_{t^-}}\right)\right)^2\right] \\ &= -\frac{1}{v}\mathbb{E}^{Q}_{t^-}\left[\left(\log r_{\mathcal{A}}(\chi_t, \chi_{t^-}, s)\right)^2\right],\end{aligned}$$

where VIX^2 *is expected quadratic variation measured over an interval of length* v*.*

While the formula in Theorem 13 shows the change under the risk-neutral measure, the equivalence of the risk-neutral and physical measure on sets of zero probability imply that in expectation the VIX undergoes a non-infinitesimal change under the physical measure as well.

Theorem 13 connects between the model's predictions for the announcement premium and the model's predictions for the VIX. The announcement premium is the covariance between the announcement return and the announcement SDF, or equivalently, the difference in the return under the risk neutral and physical probability. The change in the VIX under the risk-neutral measure is the expected squared announce-

[14]This discussion assumes that the interval over which the VIX is calculated is not shifted to include a new announcement. This assumption is accurate given that the VIX is calculated using options of a fixed maturity. Thus as time moves forward, the window length v shrinks until a specific day on which the options used to calculate the VIX "roll." See the Supplemental Appendix for more detail.

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ment return. That said, they are not equivalent: we will see it is possible for a model to explain one but not the other.

2.6 Nominal bonds

The pricing of nominal bonds requires an assumption on inflation. For simplicity, in event of disaster we assume that inflation rises by the same amount – in percentage terms – that consumption declines. Thus, in event of disaster, bonds will suffer a loss equal to the percent decline in consumption. The price level Π_t follows

$$\frac{d\Pi_t}{\Pi_{t^-}} = q_t dt + \sigma_p dB_{Pt} + \left(e^{Z_t} - 1\right) dN_t. \tag{38}$$

Expected normal-times inflation, q_t, follows a mean-reverting process:

$$dq_t = \kappa_q(\bar{q}_t - q_t)dt + \sigma_q dB_{qt}, \tag{39}$$

where B_{Pt} and B_{qt} are independent Brownian motion processes that are also independent of B_{Ct} and $B_{\lambda t}$, and where $\kappa_q > 0$.

Equation 39 implies that expected inflation mean-reverts to a time-varying $\bar{q}_t$, which follows a Markov-switching process. Consistent with the data (Dergunov et al., 2018), we assume that high risk to consumption and elevated expected inflation co-occur. That is, $\bar{q}_t = \bar{q}^H$ when $\lambda_{1t} = \lambda^H$ and $\bar{q}_t = \bar{q}^L$ when $\lambda_{1t} = \lambda^L$, with $\bar{q}^H > \bar{q}^L$. This implies that the macro-announcements, which reveal the latent disaster-probability state, also reveal expected inflation. Given that macro-announcements are often ostensibly about inflation, this seems reasonable.[15]

The nominal state-price density, which prices payoffs written in nominal terms, equals

$$\pi_t^{\$} = \frac{\pi_t}{\Pi_t}. \tag{40}$$

Thus if $\Phi^{\$}(p_t, q_t, \tau, s; \chi_t)$ denotes the price of a default-free nominal bond with s years

[15] We continue to assume that the agent infers the state only from announcements, and not from inflation observations.

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to maturity and a face value of 1, no-arbitrage implies

$$\Phi^{\$}(p_t, q_t, \tau, s; \chi_t) = \mathbb{E}_t \left[\frac{\pi^{\$}_{t+s}}{\pi^{\$}_t} \right]. \tag{41}$$

Note that realized inflation stays constant upon an announcement, so the nominal announcement SDF equals the real announcement SDF.

Theorem 14. *The nominal price of an s-period nominal bond satisfies the following decomposition*

$$\Phi^{\$}\big(p_t, q_t, \tau, s; \chi_t\big) = \Phi^{\$}_{\mathcal{A}}(p_t, \tau, s; \chi_t)\Phi^{\$}_{\mathcal{N}}(q_t, s) \tag{42}$$

where $\Phi^{\$}_{\mathcal{N}}$ is constant upon an announcement, and where

$$\Phi^{\$}_{\mathcal{A}}(p_t, \tau, s; \chi_t) = \exp\left\{a^{\$}(\tau + s; \chi_t) + b^{\$}(s)p_t\right\} \tag{43}$$

with $b^{\$}$ satisfying

$$\frac{d}{ds}b^{\$}(s) = -(\phi_{H\to L} + \phi_{L\to H})b^{\$}(s) + \left(\bar{q}^H - \bar{q}^L\right)\left(e^{-\kappa_q s} - 1\right), \tag{44}$$

with boundary condition $b^{\$}(0) = 0$. The function $a^{\$} : \mathbb{R}_+ \times \{0,1\}$ is the unique solution to the system of equations

$$e^{a^{\$}(u;\chi) + b^{\$}_p(u-T)p^*_\chi} = \tilde{p}^*_\chi e^{a^{\$}(u-T;1) + b^{\$}_p(u-T)} + (1 - \tilde{p}^*_\chi)e^{a^{\$}(u-T;0)}, \tag{45}$$

with boundary condition $a^{\$}(u;\cdot) = 0$, $u \in [0,T)$, for risk neutral probabilities $\tilde{p}^*_\chi$ satisfying (24).

An increase in risk coincides with an increase in inflation. For this reason, bond prices fall when the announcement is negative and rise when it is positive:

Corollary 15. *The price of a zero-coupon bond with positive maturity on the announcement date increases when the announcement is positive and decreases when the announcement is negative. That is*

$$\Phi^{\$}_{\mathcal{A}}(1,0,s;1) < \lim_{\tau\uparrow T}\Phi^{\$}_{\mathcal{A}}(p_\chi, \tau, s; \chi) < \Phi^{\$}_{\mathcal{A}}(0,0,s;0) \qquad \chi = 0, 1,$$

for $s > 0$.

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Because bond prices fall when the announcement is negative, bonds have an announcement premium, provided that there is a preference for early resolution of uncertainty. Define the announcement return on the s-period bond as:

$$r^{\$}_{\mathcal{A}}(\chi, \chi_-, s) = \frac{\Phi^{\$}_{\mathcal{A}}(p^*_{\chi}, 0, s; \chi)}{\lim_{\tau \uparrow T} \Phi^{\$}_{\mathcal{A}}(p^*_{\chi_-}, \tau, s; \chi_-)}$$

Note that, with probability 1, realized inflation is constant upon an announcement, and therefore the nominal announcement SDF can be treated as if it were identical to the announcement SDF defined in (23). The remainder of the analysis proceeds in a manner analogous to that of equities.

Corollary 16. *The announcement premium on the s-period nominal bond equals*

$$\begin{aligned} \mathbb{E}_{t^-}\left[r^{\$}_{\mathcal{A}}(\chi_t, \chi_{t^-}, s) - 1\right] &= -\mathbb{E}_{t^-}\left[\left(r^{\$}_{\mathcal{A}}(\chi_t, \chi_{t^-}, s) - 1\right)\left(M(\chi_t, \chi_{t^-}) - 1\right)\right] \\ &= -\mathrm{Cov}_t(r^{\$}_{\mathcal{A}}(\chi_t, \chi_{t^-}, s), M(\chi_t, \chi_{t^-})) \end{aligned} \tag{46}$$

Moreover, provided $s > T - \tau$, the bond announcement premium is positive if $\gamma > 1$, negative if $\gamma < 1$, and zero if $\gamma = 1$.

3 Data and Methods

This section describes our data and methods. Section 3.1 describes the data sources. Section 3.2 describes the calibration and Section 3.3 the simulation method.

3.1 Data

We obtain daily stock and bond returns returns from the Center for Research in Security Prices (CRSP). We consider individual stocks traded on NYSE, AMEX, NASDAQ and ARCA from January 1961 to September 2016. In addition, we also use the daily market excess returns and risk-free rate provided by Kenneth French. Data for bond returns comes from the CRSP fixed-term indices file. Each month, for each target maturity, we choose a Treasury bond with a maturity closest to the target maturity and compute daily returns on this bond. The scheduled announcement dates before 2010 are provided by Savor and Wilson (2014). Following their approach, we add target-

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rate announcements of the FOMC and inflation and employment announcements of the BLS for the remaining dates.

For annual riskfree returns, we use the CRSP US Treasury and Inflation indices. For daily riskfree returns, we use the Federal Funds Rate available from the St. Louis Federal Reserve. For VIX, we use the CBOE S&P 500 Volatility Index. The CBOE provides intra-day real time VIX, while the open, close, high and low-of-the-day values are available. Data on the volatility surface comes from OptionMetrics. OptionMetrics reports implied volatilities as functions of option deltas. Because OptionMetrics calculations are based on the Black and Scholes (1973) model, we use this model to translate from option Delta to moneyness, namely the ratio of the strike price to the forward price of the security.

We define the daily excess return to be the daily (level) return of a stock (or bond) in excess of the daily return on the 1-month Treasury bill. We estimate covariances on individual stock returns with the market return using daily data and 12-month rolling windows. We include stocks which are available for trading on 90% or more of the trading days. At the start of each trading month, we sort stocks by estimated betas, and create deciles. We then form value-weighted portfolios of the stocks in each deciles, and compute daily excess returns.

Table 1 reports summary statistics on the ten beta-sorted portfolios. For each portfolio j, $j = 1, \dots, 10$, we use the notation $E[RX^j]$ to denote the mean excess return, σ^j the volatility of the excess return, and β^j the covariance with the value-weighted market portfolio divided by the variance of the market portfolio. Table 1 shows statistics for daily returns computed over the full sample, over announcement days, and over non-announcement days.[16] There is a weak positive relation between full-sample returns and market betas. On non-announcement days, there is virtually no relation between betas and expected returns. However, on announcement days, there is a strong relation between beta and expected returns.[17]

Table 2 reports summary statistics for Treasury bonds. On non-announcement days, the beta on Treasury bond returns with respect to the market is negative, and

[16] Betas and volatilities are computed in the standard way, as central second moments. An announcement-day volatility therefore is computed as the mean squared difference between the announcement return and the mean announcement return. Announcement-day betas are computed analogously.

[17] Units for excess returns in this table are basis points (bps) per day. An excess return of 1.53 basis points is, implies that the asset earned 0.000153 more than the riskfree rate over that day.

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there is no discernable relation between risk and return. However, this beta is positive, and, like the expected return, increases with maturity.

3.2 Fitting the model to the data

We now describe how we fit the model in Section 2. We choose preference parameters, normal-times consumption parameters, the mean reversion for λ_{2t} (κ), and the volatility parameter (σ_λ) as in Wachter (2013). For simplicity, we assume that, when the economy is in the low-risk state, the intensity λ_{1t} is zero, that is $\lambda^L = 0$. The magnitude of the announcement premium is determined by the size of informational friction. In our model, this is captured by, $\phi_{H\to L}$, $\phi_{L\to H}$, and the unconditional jump intensity explained by announcements, $\lambda^H \frac{\phi_{L\to H}}{\phi_{L\to H}+\phi_{H\to L}}$. We calibrate λ^H, $\bar{\lambda}_2$, $\phi_{L\to H}$, $\phi_{H\to L}$ and μ_D by conducting a grid search. The parameters are picked based on a least-squares criterion to match 1) the empirical announcement premium 2) change in VIX on announcement days and 3) the empirical price-dividend ratio of the equity asset. In addition, the parameters are picked such that the average disaster probability is 3.6% per annum, as in Barro and Ursúa (2008).

The unconditional probability of the high-risk state in our calibration is $\phi_{L\to H}/(\phi_{L\to H}+\phi_{H\to L}) = 5.3\%$. $\bar{\lambda}_2 = 2.1\%$ and $\lambda^H = 29.3\%$. The regime switch process (namely λ_{1t}) is responsible for 40% of disasters. We assume a multinomial distribution for the outcomes Z_t. This multinomial distribution, which also comes from Barro and Ursúa (2008), is the same as in Wachter (2013).

We choose the disaster sensitivities φ_j to obtain a reasonable spread in betas, and so that the average exposure to disasters is three times the consumption claim (this is a standard calibration, see, e.g. Bansal and Yaron (2004)). We use the fact that betas depend primarily on the exposure to $\lambda_2(t)$, which, as we show in Appendix B, is approximately proportional to $\mathbb{E}_\nu\left[e^{\gamma Z}(e^{-\varphi Z} - e^{-Z})\right]$.[18] We solve for φ_j such that

$$\frac{\mathbb{E}_\nu\left[e^{\gamma Z_t}(e^{-\varphi_j Z_t} - e^{-Z_t})\right]}{\mathbb{E}_\nu\left[e^{\gamma Z}(e^{-3Z_t} - e^{-Z_t})\right]} = k, \qquad k \in \{0.2, 0.35, \ldots, 1.85\}.$$

[18]Note that $\mathbb{E}_\nu\left[e^{\gamma Z_t}(e^{-\varphi Z_t} - e^{-Z_t})\right]$ is the last term in the ordinary differential equation (B.11) for the sensitivity $b_{\varphi\lambda}(s)$. It therefore determines the magnitude of this sensitivity as φ varies.

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This yields 12 firm types, and a spread in betas that is sufficiently wide to compare model with data.

Our identifying assumption is normal-times betas line up with downside risk in disasters. Recent events provide an opportunity to test this assumption. Figure 2 plots the realized excess returns of the beta-sorted portfolios in March 2020 against the portfolios' corresponding CAPM betas. The figure clearly shows that the realized returns in March 2020, the month during with the US equity market was hit the hardest, line up very closely with CAPM beta, with a t-statistic from a linear regression of -6.89.

Normal-times inflation parameters, σ_q, σ_P, and κ_q, are as in Tsai (2016). These roughly determine the volatility of inflation, the persistence, and the volatility and persistence of the nominal interest rate. Given these parameters, we choose expected inflation in each regime to match normal-times expected inflation in the data. Table 3 reports parameter choices.

3.3 Simulation method

To evaluate the fit of the model, we simulate 500 artificial histories, each of length 50 years (240×50 days). We assume that announcements occur every 10 trading days. For each history, we simulate a burn-in period, so that we start the history from a draw from the stationary distribution of the state variables. We simulate the model using the true (as opposed to the agents') distribution. We report statistics for the full set of sample paths.

While time is continuous in our analytical model, it is necessarily discrete in our simulations. We simulate the model at a daily frequency to match the frequency of the data. We compute end-of-day prices, and assume the announcement occurs in the middle of a trading day. We will use the notation a and n to denote announcement and non-announcement days respectively.

Given a series of state variables and of shocks, we compute returns as follows. For each asset j, define the price-dividend ratio

$$\Gamma^j(p_t, \lambda_{2t}, \tau; \chi_t) = \frac{S^j(D_t, p_t, \lambda_{2t}, \tau; \chi_t)}{D_t^j} = \int_0^\infty \Phi^j(p_t, \lambda_{2t}, \tau, s; \chi_t)\, ds$$

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We approximate the daily return as

$$
\begin{aligned}
R^j_{t,t+\Delta t} &\approx \frac{S^j_{t+\Delta t} + D^j_{t+\Delta t}\Delta t}{S^j_t} \\
&= \frac{D^j_{t+\Delta t}\Phi^j_{t+\Delta t} + D^j_{t+\Delta t}\Delta t}{D^j_t \Phi^j_t} \\
&= \frac{D^j_{t+\Delta t}}{D^j_t}\frac{\Gamma^j_{t+\Delta t} + \Delta t}{\Phi^j_t} \\
&\approx \exp\left\{\mu_D \Delta t - \frac{1}{2}\sigma^2\Delta t + \sigma(B_{C,t+\Delta t} - B_{C,t}) + \phi Z(N_{t+\Delta t} - N_t)\right\}\frac{\Gamma^j_{t+\Delta t} + \Delta t}{\Gamma^j_t},
\end{aligned}
\tag{47}
$$

where Z is drawn from the specified multinomial distribution, $\Delta t = 1/240$, and where $N_{t+\Delta t} - N_t = 1$ with probability $(\lambda_{1t} + \lambda_{2t})\Delta t$ and zero otherwise. The risk free rate is approximated by

$$
R_{ft} = \exp\{r_{ft}\Delta t\}. \tag{48}
$$

The daily excess return of asset j is then

$$
RX^j_{t,t+\Delta t} = R^j_{t,t+\Delta t} - R_{ft}. \tag{49}
$$

We define the value-weighted market return just as in the data, namely we take a value-weighted portfolio of returns. We assume that the assets have the same value at the beginning of the sample. Because the assets all have the same loading on the Brownian shock and the same drift, and conditional on a history not containing rare events, the model implies a stationary distribution of portfolio weights. Given a time series of excess returns on firms (which, because we have no idiosyncratic risk, we take as analogous to portfolios), and a time series of excess returns on the market, we compute statistics exactly as in the data.

Before discussing the implications of our model for returns around announcement days, we confirm that the model replicates the main findings in Wachter (2013): namely that it can match the equity premium, the average riskfree rate, and the predictability in stock returns. We show these and their data equivalents in Table 4. When it comes to these moments, the main difference between this model and the earlier one is that this model produces negative return skewness, as in the data. One might ask whether this difference comes from the imperfect information or from the regime-switching process,

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since these are both ways in which the current model differs from that of Wachter (2013). Under our calibration, it comes from the regime-switching process. Figures 5 and 6 of the Supplental Appendix show that results for full-sample moments do not change in the limit as the model approaches full information.[19]

4 Results

In this section, we compare the data to the simulation. Section 4.1 discusses the equity premium and equity volatility. Section 4.2 discusses the security market line for stocks and for bonds. Section 4.3 discusses implied volatilities and the VIX. Section 4.4 discusses the results for Treasury bonds.

4.1 The equity premium and volatility on announcement and non-announcement days

The model captures the time series result that most of the equity premium is realized on announcement days (Savor and Wilson, 2013; Lucca and Moench, 2015).[20] Table 5 shows that the average market return is far higher on announcement days versus non-announcement days, both in the model and in the data. On the other hand, the increase in volatility is small. The standard deviation of returns is about 1 percentage point on both announcement and non-announcement days. While the median increase in volatility is greater in the model than in the data, the data is well-within the 90 percent confidence intervals, reflecting the fact that a substantial fraction of the samples feature no increase in volatility on non-announcement days at all. The fact that announcement-day volatility does not increase is a key feature, along with options evidence to be presented in Section 4.3, that distinguishes our model from competing explanations, as we discuss in greater detail in Sections 4.3 and 5.

[19]The empirical R^2 for return predictability are smaller than those reported in Wachter (2013). The sample that we look at (motivated by availability of announcement data) happens to be one with little predictability.

[20]Lucca and Moench (2015) focus on a later sample period and on scheduled FOMC announcements. They show that the premium is realized on the announcement day, but before the actual announcement. While outside the scope of our model, this finding could be rationalized in a similar model in which information about the disaster regime leaks with some probability in the interval prior to the announcement, and then is fully realized on the announcement itself.

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Savor and Wilson (2013) also show that riskfree interest rates are lower on announcement days as compared with non-announcement days. Our model can account for the sign and magnitude of this result. The interest rate in the model equals:

$$r_t = \beta + \mu - \gamma\sigma^2 + \left(\bar{\lambda}_1(p_t) + \lambda_{2t}\right)\mathbb{E}_\nu\left[e^{\gamma Z_t}(e^{-Z_t} - 1)\right].$$

and is a decreasing function of the disaster probability. Bonds of non-infinitesimal maturity are a hedge against disaster risk (because they go up in price when the interest rate declines (see Section 3.3 of the Supplemental Appendix). They therefore feature a negative risk premium that, through the same mechanism as equities, is greater in magnitude on announcement days as compared with non-announcement days. The difference in the 30-day yield between announcements and non-announcements is 40 basis points in the model, as compared with 80 basis points in the data. To summarize: short-term interest rates decline in the model, as in the data, and the declines are of similar magnitude.[21]

4.2 The cross-section of beta-sorted portfolios on announcement and non-announcement days

Figure 3 shows our main result: the model's ability to match the differential beta-return relation on announcement days. We overlay the simulated statistics on the empirical statistics from Figure 1. Each dot on the figure represents a statistic for one firm, for one simulated sample. Blue dots show pairs of average excess returns and betas on announcement days, while grey dots show pairs on non-announcement days. The figure shows that average returns on announcement days in the model are much higher than on non-announcement days. Furthermore, average returns vary with beta on announcement days in the model, whereas they do not on non-announcement days.

Figure 4 further clarifies the relation between the announcement and non-announcement days in the model by showing medians and interquartile ranges from the full set of simulated samples. Median returns closely match the data, whereas interquartile ranges show that the vast majority of samples with announcements can be clearly distinguished from those of non-announcements.

[21] We ignore, for simplicity, the effect of inflation uncertainty on a short-term Treasury bill. The presence of an average inflation term would not affect this calculation.

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How is it that the model can explain these findings? Announcements convey important news about the distribution of future outcomes in the economy. On that day, it is possible that a high-risk state of the economy could be revealed. If the high-risk state is realized, not only will asset values be affected, but the marginal utility of economic agents will rise. Thus investors require a premium to hold assets over the risky announcement period.

In our model, some assets have cash flows that are more sensitive than others. The sensitivity parameter φ_j, while not the same as the beta, is closely related. Assets with high φ_j have a greater dividend response to disasters. Their prices thus move more with changes in the disaster probability, and in particular with λ_{1t} and λ_{2t}. The value-weighted market portfolio also moves with the disaster probability, and thus the higher is φ_j (over the relevant range), the higher is the return beta with the market, both on non-announcement days (which reveal information about λ_{2t}, and on announcement days, which reveal additional information about λ_{1t}.

Panel A of Table 6 shows the security market line for equities on announcement and non-announcement days. We run the regression

$$\hat{E}[RX_t^j \,|\, t \in i] = \delta_i \beta_i^j + \text{error}, \tag{50}$$

where $i = a$ (announcement days) or n (non-announcement days). The regression slope δ_i is the slope of the security market line. It is simultaneously a measure of risk and return, and a measure of the daily market risk premium. Table 6 shows an economically significant difference between the slope on announcement and non-announcement days in the data, a difference that is matched in the model.[22] Thus the model predicts a relation between risk and return on both announcement and non-announcement days, but because the risk is so much greater on announcement days, the premium, and therefore the spread in expected returns between low and high-sensitivity assets, will also be much greater.

Thus one reason for the differential slope in the SML is the difference in the an-

[22] One concern is that there might be a positive correlation between the slope difference and the volatility difference (Table 5 shows that the volatility difference is within a 90% confidence interval implied by the model) in data simulated from the data. If this were true, samples with a large difference in SML slopes would also be those with a (counterfactually) high difference in volatility. In fact, there is almost no correlation between these statistics, and a joint test (see Figure 3 of the Supplemental Appendix) shows that the data has a p-value of greater than 0.5.

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nouncement premium. There is another reason for the difference in the slope, however. Table 6 shows that the slope of the security market line for equities predicted by the model is about half the size of the equity premium on non-announcement days. That is, while the model predicts that the premium is far lower on non-announcement days, as compared with announcement days, it also implies that the slope of the security market line is below even the premium on non-announcement days. Furthermore, consider Figure 4. The relation between beta and expected return implied by the model is linear on announcement days, but concave on non-announcement days, just as in the data.

The reason is that, on announcement days, there is a single source of variation driving both the risk premium and the covariance. This is variation due to the disaster probability p_t. The greater the response to a change in p_t, the greater the covariance and the greater the risk premium. This relation is approximately linear. However, on non-announcement days, there are two sources of covariance: the disaster probability and disasters themselves. It is exposure to disasters themselves that explain most of the risk premium, but it is covariation with the disaster probability that determines the beta. The resulting error-in-variables problem leads to a flattened beta-return relation, both in non-announcement periods, and in the full sample, thus partially explaining the beta anomaly.[23] It also implies that a conditional CAPM does not hold on non-announcement days.

4.3 The volatility surface and VIX around announcements

Our explanation for announcement day anomalies is based on resolution of uncertainty upon the announcement. Direct evidence for resolution of uncertainty can come from put options prices.

The price of a put option with strike price X is the risk-neutral expectation of (discounted) $\max(0, X - S)$, where S is the price of the underlying. Thus put options are insurance against adverse states, and their prices are the prices of such insurance. The greater the likelihood that an adverse state will realize, the higher the put option price. Moreover, the greater the risk price attached to the adverse state (determined by the SDF), the more valuable the insurance and the higher the price. Our model predicts

[23]Figure 4 in the Supplemental Appendix shows the unconditional security market line in the model and in the data.

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both greater likelihood of tail events, and a higher price of those events, relative to the Black and Scholes (1973) model.

Negative announcements are priced in the model; Section 2.4 discusses how this is necessary to explain the announcement premium. Similarly, this is necessary to explain an average decline in put option prices. While put options should follow a martingale under the risk-neutral measure, they need not follow a martingale under the physical measure: as the announcement is realized, the difference between the physical and risk-neutral measure implies that, on average, put option prices fall. Figure 5 shows implied volatility of index put options at the close on announcement days, and at the close of the day prior to the announcement day. Implied volatilities are reported as functions strike price over underlying price (moneyness); the lower the moneyness, the further out-of-the-money are the put options that go into the implied volatility calculation. Options with low moneyness best represent insurance against low-probability crash events. Implied volatility is a convenient normalization of the option price (analogous to looking at yield to maturity on bonds). The greater the implied volatility, the higher the option price.

Figure 5 (Panel A) shows implied volatilities at the close following the announcement and at the close the previous day. Panel B shows the change. The left panel reports results from the data whereas the right panel reports results from the model. Put option prices are clearly lower following the announcement, with the difference being greatest for the most out-of-the-money options. Table 9 shows that the decline in the slope is statistically significant. This is evidence that investors seek to insure the risk of a market crash around announcements; that the price falls following the announcement is evidence of a difference in the risk-neutral and physical expectation consistent with our model.

Panel B shows implied volatilities in the model. Unlike the VIX, discussed below, option prices and hence implied volatilities are not available in closed form. To compute the price of an option, we must simulate from the risk neutral distribution for each value of the state variables, and then take an unconditional average to obtain values comparable to the data. Because of rare events, obtaining the risk neutral distribution at each state is difficult and prone to inaccuracies. Given that the focus of this paper is not option prices, we encourage the reader to take the model-simulated option data with a grain of salt. With these caveats, Panel B shows that the model offers a reasonable

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fit to the data. On average, the slope of implied volatilities is steeper in the model; a known problem with models calibrated to rare events (Backus et al., 2011). Though there is some non-monotonicity (most likely due to numerical error), the model also implies that further out-of-the-money options fall by more following the announcement, with a change of similar magnitude to that in the data.

A second option-implied measure of announcement uncertainty is the VIX. Unlike implied volatilities, the VIX is itself the (square root) of the risk-neutral moment and thus has an analytical solution (see Section 2.5 of the Supplemental Appendix). The formula for a VIX decline following an announcement takes a particularly simple form, and is closely linked to the announcement return (Theorem 13). A value for the VIX that is on average higher prior to the announcement than following the announcement indicates investors expecting that uncertainty will be resolved. Thus one hypothesis, which is that the average announcement return reflects purely reflects an institutionally-driven aversion to holding equities over the announcement interval, is rendered very unlikely the decline in VIX. Another hypothesis is that the announcement return reflects a different price of risk on announcement days but no change in volatility – as we discuss in Section 5, this too is rendered unlikely. Investors expect uncertainty to be resolved on macro-announcement days.

Table 5 shows that indeed the VIX declines sharply following announcements: on average the post-announcement VIX is -0.30 units lower than the pre-announcement VIX (the decline, also reported by Savor and Wilson (2013), is highly statistically significant). The model implies a decline that is slightly larger (-0.60). Note that the VIX itself is on the order of 20, so the difference between model and data is less than 2% of the VIX itself. The model generates 90% standard error bars of $[-0.69, -0.48]$, the top of which is close to the data. As we discuss In Section 5, there is a tension in precisely fitting this value and the lack of change in the standard deviation.

The statistically significant decline in the VIX, together with the similarity in return volatility across announcement and non-announcement days, suggests the presence of negatively skewed news on announcements. Most announcements confirm positive expectations, implying that there need not be a large increase in return volatility on announcement days. However ex ante there is always the possibility of a negative announcement, which is priced into the pre-announcement VIX. The average decline in the VIX, and the high realized return represent the resolution of this uncertainty.

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The fact that the VIX is a risk-neutral measure implies that negative announcements receive disproportionately high weight, further contributing to its decline.

Table 5 also reports average values of the VIX, assuming, pre-announcement, that there are two announcements within the VIX window (in the data, the VIX covers approximately one month, and announcements appear approximately twice a month). As a risk-neutral moment of log returns, which are unbounded from below, the VIX is particularly sensitive to the probability of very low returns. Such low returns (predicted the disaster model) do not appear in monthly US data even during disasters, suggesting some force outside of the model prevents their occurence (recently, Ghaderi et al. (2019) show that information frictions and learning act as such a mechanism). We follow Seo and Wachter (2019) in assuming large declines are spread out over a series of months (see the Supplemental Appendix for further detail). With this adjustment, the model succeeds in matching the level of the VIX. A recent literature highlights how reconciling the VIX with the equity premium proves challenging for a wide class of models (Martin, 2017; Dew-Becker et al., 2017; Beason and Schreindorfer, 2020). A full reconciliation of the average level of the VIX and the average level of the equity premium is an interesting topic for further research.

4.4 Bond returns on announcement and non-announcement days

We now consider the results for bonds. Table 6 repeats the regression (50) for bonds with various maturities. For bonds, the data reveal a slightly negative slope on non-announcement days. The slope on announcement days is strongly positive.

Unlike equities, bonds are not, in aggregate exposed to stock market risk. For bonds, this need not be the case. Indeed, Table 2 shows that betas on bonds are close to zero on average. It is well-known that the covariances between Treasury bonds and stocks are unstable (Campbell et al., 2017), suggesting that the the beta does not reveal much about the risk in bonds. This makes it all the more striking that bonds exhibit positive betas on announcement days, and that these betas line up with the expected returns. [24]

[24] For further discussion of the properties of bond returns around announcements, see Jones et al. (1998) and Balduzzi and Moneta (2017).

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What does the model have to say about these findings? Section 2 shows that, on non-announcement days, the true instantaneous covariance between bonds and stocks is equal to zero. This implies that the true security market line is undefined on non-announcement days. Thus the model is consistent both with negative observed betas on non-announcement days, and the fact that these betas exhibit no relation with expected returns. On the other hand, macro-announcements directly reveal news about bond cash flows, because they are informative about inflation. In our model, news of higher inflation is interpreted as indicating macroeconomic instability. Losses on bonds therefore coincide with losses on the stock market. Thus the model predicts both positive betas on bonds on announcement days, and a strong risk-return relation. Table 8 shows that, indeed, bonds have much higher betas on announcement days in simulated data. In contrast, equity betas can increase or decrease, with confidence intervals generally containing zero.

Because betas on announcement days are higher in the model than in the data, the model does not succeed in capturing the full magnitude of the announcement-day slope. The model does succeed, however, in capturing the fact that bond returns contain substantial market risk on announcement days, and no measurable market risk on non-announcement days. In the model, news about disaster directly correlates with that of expected inflation. Stated differently, the announcements are concerned with inflation; investors perhaps infer that information concerning inflation also is informative about disasters. Moreover, because inflation tends to rise when the probability of a disaster rises, news about inflation is priced. The greater the bond maturity, the greater the impact of this news, and the greater is the expected return.

5 Alternative models

In this section, we contrast our findings with two alternative models, one with "small" disasters and one with normally distributed news, and one with "small" disasters. While these models can qualitatively capture some of the facts, they fall short in important ways. The results in this section highlight the characteristics a model needs to have in order to match the data.[25]

[25]In both cases, the proposed models do not match some other aspects of the data, such as excess volatility and return predictability. We are not undertaking a formal statistical comparison of these models and ours.

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5.1 Minor Poisson events

Backus et al. (2011) argue that rare disasters are inconsistent with evidence on index options. Using option data, they back out the features the consumption data need to have to jointly match options evidence, the equity premium, and equity volatility. They argue that the data are more consistent with Poisson events that are frequent and minor, as compared with large rare disasters.[26] In the spirit of their model, we apply the model in Section 2 to a setting in which Poisson events are frequent and minor, basing the calibration on their preferred model to match the options data, implying risk aversion $\gamma = 8.7$, a jump distribution $Z \sim N(-0.0074, 0.191^2)$, and a jump intensity of 1.4. Furthermore, following Backus et al. we assume $\beta = 0.012$, $\mu = 3.06$, $\sigma = 2.53\%$, $\varphi = 5.1$. Thus the jump sizes in their model are 0.74%, to be contrasted with roughly 30% in our benchmark calibration, whereas the jump intensity is 1.4, as opposed to 0.04. We calibrate the remaining parameters (μ_D, λ_H, $\phi_{H\to L}$, $\phi_{L\to H}$) following the same strategy as in our benchmark calibration: namely, we seek to match the announcement premium, the average change in the VIX, and the average price-dividend ratio.

This model differs in two important respects from the original model of Backus et al. (2011). There is significant time-variation in the event probability, whereas their model is iid. Second, for the reasons explained in Section 2.4, we require a preference for early resolution of uncertainty. In an iid model, early versus late verus no preference for early resolution are all observationally equivalent. That is not the case in the model with time-varying event probabilities. Thus an important source of the unconditional equity premium in this model, unlike in the model of Backus et al. (2011), is due to time-variation in λ_{1t}.

Not surprisingly, restricting the event size to be small implies that the intensity must be much larger to match the announcement premium. We find $\lambda^H = 8.73$. Probability of regime shifts are slightly higher in both directions, but this difference is not large. Overall, Poisson events occur about once a year, as opposed to twice in a century, consistent with the original model of Backus et al. (2011). Table 10 reports the parameter values.

Table 11 shows that the model indeed can account for the announcement premium.[27] It also can account for the change in VIX (indeed, the change in VIX is inside

[26] Seo and Wachter (2018) argue that time-varying disaster risk improves the fit to the options data.
[27] In the Supplemental Appendix, we show that the model can partially account for the different

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the standard error bars, so this model outperforms the benchmark along this dimension). There are two drawbacks. First, the announcements in Backus et al. (2011) are sufficiently "normal" to produce a noticeable difference between the volatility on announcement and non-announcement days. Recall that a major distinguishing feature between models is whether they can match the lack of change in second moment. The small-disasters model is unable to match this lack of change. Second, and related, the model attributes all normal-times variation in stock market prices to cash flows. This implies cash flows that are far too volatile (Figure 6).[28] One could argue that this is not a failing of the announcement part of the model, and indeed one could have a different driving force for normal-times volatility, while still having announcements deliver information about the frequency of small jumps rather than large. Comparing the results of Tables 5 and 11 suggest this is a valid interpretation in that both models match key aspects of the data, but neither match every aspect. Note that the analytical results in Section 2 apply equally to both models, and indeed the economic interpretations are not very different: in either case the negative announcement is a rare event for which the agent receives compensation in the form of a premium.

5.2 Normally-distributed news

One alternative to a rare events model is one in which the equity premium arises from Bansal and Yaron (2004) long-run risk. That is, there is a small, persistent expected growth term as part of consumption. The agent receives a signal about this term on announcements. Ai and Bansal (2018) formalize such a model. For simplicity, however, we consider the version presented in Savor and Wilson (2013).[29]

slopes around announcement days.

[28]The baseline model implies cash flows that are arguably not volatile enough. This could easily be remedied by adding idiosyncratic volatility to the dividend process in (25) without altering any other conclusions.

[29]The difference is that Savor and Wilson simply assume that the volatility of the long-run risk term rises on announcement days, whereas Ai and Bansal (2018) endogenize this result in a model with learning. In our model, a similar distinction might be assuming that that the risk of a regime change is greater on announcement days, rather than one learns about the regime. It is preferable, from a modeling perspective, to endogenize the arrival of new information; otherwise it is as if the announcement itself causes the risk. However, the quantitative implications of the two approaches are similar.

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5.2.1 The model

Consider a discrete-time model with conditionally homoskedastic consumption growth. Let $\Delta c_{t+1} = \log C_{t+1} - \log C_t$, and assume

$$\Delta c_{t+1} = \mu_t + \varepsilon_{c,t+1} \tag{51}$$

$$\mu_{t+1} = \bar{\mu} + \rho(\mu_t - \bar{\mu}) + \varepsilon_{\mu,t+1}. \tag{52}$$

Even though time is discrete, we can still use the notation (5) to whether a day is an "announcement day" or not. The shocks $\varepsilon_{c,t+1}$ and $\varepsilon_{\mu,t+1}$ are mean zero, normal random variables. Conditional on whether $t+1$ is an announcement day, they are independent. Their standard deviations change deterministically, depending on whether the day is an announcement day or not. With some abuse of notation, define

$$\mathrm{Var}_t(\varepsilon_{c,t}) = \sigma^2_{c,t} = \begin{cases} \sigma^2_{c,a} & t \in \mathcal{A} \\ \sigma^2_{c,n} & t \in \mathcal{N} \end{cases}$$

and

$$\mathrm{Var}_t(\varepsilon_{\mu,t}) = \sigma^2_{\mu,t} = \begin{cases} \sigma^2_{\mu,a} & t \in \mathcal{A} \\ \sigma^2_{\mu,n} & t \in \mathcal{N} \end{cases}$$

Note that the announcement status of date $t+1$ is deterministic, and therefore is known at time t. The representative agent's preference is characterized by Epstein and Zin (1989) utility:

$$U_t = \left((1-\beta) C_t^{1-1/\psi} + \beta \left(\mathbb{E}_t \left[U_{t+1}^{1-\gamma} \right] \right)^{\frac{1-1/\psi}{1-\gamma}} \right)^{\frac{1}{1-1/\psi}}, \tag{53}$$

where, as above, β is the time discount factor and γ is risk aversion. The new parameter relative to the previous model is ψ, the elasticity of intertemporal substitution.

Savor and Wilson (2013) conjecture a solution in which the price-dividend ratio is approximately log-linear in the state variable μ_t, and solve the model using Campbell and Shiller (1988) log-linearization. We follow their approach.[30] Let $\kappa_1 =$

[30] Because $\psi \neq 1$, there will not be a closed-form solution, even in continuous time. In the limit as ψ approaches 1, the price-consumption ratio approaches a constant. The announcement premium on the consumption claim approaches zero. One could write down an alternative model in which dividends are more exposed to μ_t than to consumption. With $\psi = 1$, such a model would have a closed-form solution, which could be found using the method outlined in Section 2. Such a model would likely

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$(1+e^{\mathbb{E}\log(C_t/S_t)})^{-1}$ and $\kappa_0 = -\log\kappa_1 + (1-\kappa_1)\log(1/\kappa_1 - 1)$. The price-dividend ratio is a function of μ_t and τ: $S_t/C_t = \Gamma(\mu,\tau)$, such that

$$\Gamma(\tau,\mu) \approx A_0(\tau) + \frac{1-1/\psi}{1-\kappa_1\rho}\mu_t, \tag{54}$$

for a constant $A_0(\tau)$ satisfying

$$\begin{aligned} A_0(\tau) &= \kappa_1 A_0(\tau+1) + \log\beta + \kappa_0 + \kappa_1\frac{1-1/\psi}{1-\kappa_1\rho}(1-\rho)\bar{\mu} \\ &\quad + \frac{1}{2}(1-\gamma)(1-1/\psi)\sigma^2_{c,n} + \frac{1}{2}(1-\gamma)(1-1/\psi)\left(\frac{\kappa_1}{1-\kappa_1\rho}\right)^2\sigma^2_{\mu,n}, \end{aligned}$$

for $\tau = 0,1,\ldots,T-2$, with boundary condition

$$\begin{aligned} A_0(T-1) &= \kappa_1 A_0(0) + \log\beta + \kappa_0 + \kappa_1\frac{1-1/\psi}{1-\kappa_1\rho}(1-\rho)\bar{\mu} \\ &\quad + \frac{1}{2}(1-\gamma)(1-1/\psi)\sigma^2_{c,n} + \frac{1}{2}(1-\gamma)(1-1/\psi)\left(\frac{\kappa_1}{1-\kappa_1\rho}\right)^2\sigma^2_{\mu,n}. \end{aligned}$$

The approximate expression for the riskfree rate $r_{f,t+1} = \log(1+R_{f,t+1})$ between times t and $t+1$ is:

$$\begin{aligned} r_{f,t+1} &\approx -\log\beta + \frac{\mu_t}{\psi} + \frac{1}{2\psi}\sigma^2_{c,t+1} - \frac{1}{2}\gamma\left(1+\frac{1}{\psi}\right)\sigma^2_{c,t+1} \\ &\quad - \frac{1}{2}\left(\gamma - \frac{1}{\psi}\right)\left(1-\frac{1}{\psi}\right)\left(\frac{\kappa_1}{1-\kappa_1\rho}\right)^2\sigma^2_{\mu,t+1}. \end{aligned} \tag{55}$$

We can approximate the equity premium by

$$\log\mathbb{E}_t\left[\frac{1+R^{\text{mkt}}_{t+1}}{1+R_{f,t+1}}\right] \approx \gamma\sigma^2_{c,t+1} + \left(1-\frac{1}{\psi}\right)\left(\gamma-\frac{1}{\psi}\right)\left(\frac{\kappa_1}{1-\kappa_1\rho}\right)^2\sigma^2_{\mu,t+1}, \tag{56}$$

and the variance of the log stock return $r_{\text{mkt},t+1} = \log(1+R^{\text{mkt}}_{t+1})$ by

$$\text{Var}_t(r_{\text{mkt},t+1}) \approx \sigma^2_{c,t+1} + \left(1-\frac{1}{\psi}\right)^2\left(\frac{\kappa_1}{1-\kappa_1\rho}\right)^2\sigma^2_{\mu,t+1}. \tag{57}$$

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have very similar implications to the one presented here.

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In this conditionally lognormal model, The VIX will simply capture the number of announcement versus non-announcement days. As in the previous section, we assume that there are two announcements within the VIX window. Directly applying (57) implies that just prior to the announcement:

$$\mathrm{VIX}_t^2 = \frac{2T-2}{2T}\sigma_{c,n}^2 + \frac{2}{2T}\sigma_{c,a}^2 + \left(\frac{\kappa_1(1-1/\psi)}{1-\kappa_1\rho}\right)^2 \left(\frac{2T-2}{2T}\sigma_{\mu,n}^2 + \frac{2}{2T}\sigma_{\mu,a}^2\right). \quad t+1 \in \mathcal{A}$$

After the announcement, there is one fewer announcement day:

$$\mathrm{VIX}_t^2 = \frac{2T-2}{2T-1}\sigma_{c,n}^2 + \frac{1}{2T-1}\sigma_{c,a}^2 + \left(\frac{\kappa_1(1-1/\psi)}{1-\kappa_1\rho}\right)^2 \left(\frac{2T-2}{2T-1}\sigma_{\mu,n}^2 + \frac{1}{2T-1}\sigma_{\mu,a}^2\right). \quad t \in \mathcal{A}.$$

5.2.2 Quantitative results

To calibrate the model, we use the same preference parameters as Savor and Wilson (2013). That is, $\beta = 0.97^{1/240}$, $\gamma = 1.2$, and $\psi = 1.001$. We also keep their choice of the persistence parameter: $\rho = 0.836^{1/240}$. We set $\kappa_1 = 0.965^{1/240}$, consistent with the parameter choice in Bansal and Yaron (2004). We use our own choice of $\bar{\mu} = 2.5$. Because of a possible (small) difference in $\bar{\mu}$ and κ, as well as in our data, we follow their calibration strategy (but do not use their exact values), in choosing the remaining moments.[31] We choose $\sigma_{c,a}, \sigma_{c,n}, \sigma_{\mu,a}$, and $\sigma_{\mu,n}$ to match the equity premium and the equity volatility on announcement days and non-announcement days, using (56) and (57).We find parameters similar to Savor and Wilson (2013), which we report in Table 12 .[32]

Table 13 compares data simulated from the model with historical data. the model can account for the announcement premium, and lack of change in volatility.[33] This success comes at a cost, however. The calibration implies $\sigma_{\mu,a} = 3.2\%$ per annum,

[31] Savor and Wilson (2013) do not report $\bar{\mu}$ or κ_1.

[32] The model frequency is daily. For ease of interpretation, we report annual moments in Table 12. These should be converted as follows: $\bar{\mu} = 0.025/240$, $\sigma_{c,a} = 0.1515/\sqrt{240}$, $\sigma_{\mu,a} = 0.0321/\sqrt{240}$, and similarly for non-announcement moments.

[33] The minor differences between model and data in Table 13 are due to the fact that we fit the log version of the moments, but simulate and report from the levels.

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or $0.032/\sqrt{240} = 0.002$ per day. In comparison, Bansal and Yaron (2004) assume a monthly volatility of the conditional mean of 0.008. At first glance, the results appear consistent if one assumes that most of the volatility in expected consumption growth occurs on announcement days. However, in the model of Bansal and Yaron μ_t refers to a monthly growth rate. Here μ_t is a daily growth rate of consumption. Shocks to μ_t are persistent, and each has a permanent effect on consumption growth through (51). A one-standard-deviation shock (0.002) has cumulative effect over the next month (20 days) of $\sum_{t=0}^{20} \rho^t(0.0002) = 0.04$, translating into a 4 percentage point change in expected consumption growth and (therefore) the riskfree rate. Even if such as shock realized only once a month, it would imply greater volatility of consumption and interest rates as compared with the Bansal and Yaron (2004) model (0.04 versus 0.008); but there are multiple announcements in a month.[34] Equation 55 gives the formula for the daily interest rate. The unconditional variance of this value, which we report in Table 13, mainly arises from the unconditional variance in μ_t and is 150 basis points per day. This is larger than the volatility of daily stock returns.

Is this an accident of the calibration, or is it true more generally? To understand the link between the riskfree rate volatility and the equity premium in this model, consider the mechanism by which this model must match the means and standard deviations of equity returns. The model has two shocks: the shock to realized expected growth and the shock to expected consumption growth. If the goal of the calibration is to keep the volatility the same between announcement and non-announcement days, then it must be the case that the price of risk is higher on announcement days versus non-announcement days. There is little scope to do this for the realized consumption growth shocks. This is because the price of risk is $\gamma\sigma_{c,t}$, whereas the volatility is $\sigma_{c,t}$. Raising the price of risk through $\sigma_{c,t}$ will simply raise the volatility. The situation is different with shocks to expected consumption growth. Here, the price of risk is $(\gamma - 1/\psi)\left(\frac{\kappa_1}{1-\kappa_1\rho}\right)\sigma_{\mu,t}$, whereas the volatility is $(1 - 1/\psi)\left(\frac{\kappa_1}{1-\kappa_1\rho}\right)\sigma_{\mu,t}$. By making ψ very close to 1 (so that the cash flow and interest rate effects nearly cancel out), one can raise the price of risk on announcement days with only minimal effects on the volatility, by raising $\sigma_{\mu,t}$. But a higher $\sigma_{\mu,t}$ also raises interest rate volatility.

A second problem with this model concerns its implications for the VIX. The model matches the approximate level of stock return volatility because the volatility of unex-

[34]This effect is relatively greater in the Savor and Wilson (2013) model, considering that a higher ψ dampens the effect of μ_t on interest rates in the Bansal and Yaron (2004) model.

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pected shocks to consumption, at 15% per annum, is unrealistically high (the fact that the EIS is very close to one implies that the impact of expected consumption growth shocks on stock returns is minimal). Because the VIX in their model essentially just reflects the volatility of stock returns (this is a standard result for models without skewness), the VIX is also 15%, which is counterfactually low.[35] Moreover, because the volatility is essentially the same on announcement versus non-announcement days, the decline in the VIX will be an order of magnitude smaller than in the in the data. The model can explain the lack of change in realized volatility by assuming that there is no uncertainty about stock returns actually being realized. Data on the VIX suggest otherwise.

6 Conclusion

The Capital Asset Pricing Model has been a major focus of research in financial economics, and the benchmark model in financial practice for over fifty years. Despite its pre-eminent status, years of empirical research has found little support for the CAPM. That is, until quite recently. The CAPM predicts a tight relation between market beta and expected return, known as the security market line. Recent research has shown that this security market line, seemingly absent on most days, appears on days with macro-economic announcements (Savor and Wilson, 2014).

This paper builds a general equilibrium model to explain why the security market line appears on macroeconomic announcement days, but is hard to discern on others. The model derives the result from underlying economic principles in a frictionless environment. For this reason, we can explain why the relation between risk and return is not asset-class specific. It holds for both bonds and equities. Days with scheduled announcements provide a discrete amount of news, leading to a risk premium that does not, unlike a risk premium for Brownian or Poisson risk, does not scale with the time interval. This risk premium can be an order of magnitude greater than the risk premium realized on other days.

Our model also makes use of a preference for early resolution of uncertainty, implying risk sensitive preferences (Ai and Bansal, 2018). Because investors have a preference

[35] Table 13 does not report standard errors, there is no uncertainty about the conditional volatility in the model.

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for early resolution of uncertainty, they require a risk premium for bearing assets that fall in price on adverse economic news (as opposed to simply adverse economic events themselves, as would be the case with time-additive utility). Quantitatively matching the model to the data also appears to require an asymmetry in the release of bad versus good economic news. In the data, volatility in equity returns appears about the same on announcement and non-announcement days. Our model explains this finding through the result that the release of bad news is relatively unusual; most of the time, investors learn what they expect, which is that economic fundamentals are sound. Occasionally, they learn that the economy is facing higher risk; this possibility is sufficient to produce a risk premium, even if the risk does not always realize. A decline in implied volatilities, especially pronounced for out-of-the-money put options, as well as a decline in the VIX post-announcement offers further evidence for a risk-based explanation of the annoucement premium. We show that the model offers a good quantitative fit to the options data as well.

While our focus in this paper is on macro-announcements, the methodology can be applied to scheduled announcements more generally, and understanding the rich array of empirical facts that the announcement literature has uncovered.

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A The value function and the state-price density

For the remainder of the Appendix, define the vector Brownian motion

$$dB_t \equiv [dB_{Ct}, dB_{\lambda t}]^\top. \tag{A.1}$$

Lemma A.1. *In equilibrium, the representative agent's continuation value takes the form*

$$J(C_t, p_t, \lambda_{2t}, \tau; \chi_t) = \frac{1}{1-\gamma} C_t^{1-\gamma} I(p_t, \lambda_{2t}, \tau; \chi_t)^{1-\gamma}, \tag{A.2}$$

with

$$I(p_t, \lambda_{2t}, \tau; \chi_t) = e^{\hat{a}(\tau;\chi_t) + \hat{b}p_t + \hat{b}_\lambda \lambda_{2t}}, \tag{A.3}$$

and

$$\hat{b} = \frac{(\lambda^H - \lambda^L)\mathbb{E}_\nu\left[e^{(\gamma-1)Z_t} - 1\right]}{(1-\gamma)(\beta + \phi_{H\to L} + \phi_{L\to H})}, \tag{A.4}$$

$$\hat{b}_\lambda = \frac{1}{(1-\gamma)\sigma_\lambda^2}\left(\beta + \kappa - \sqrt{(\beta+\kappa)^2 - 2\sigma_\lambda^2 \mathbb{E}_\nu[e^{(\gamma-1)Z_t} - 1]}\right). \tag{A.5}$$

for a function $\hat{a} : [0, T) \times \{0, 1\} \to \mathbb{R}$ satisfying

$$\hat{a}(\tau; \chi_t) = \zeta_{\chi_t} e^{\beta\tau} + \frac{1}{\beta}\left(\mu - \frac{1}{2}\gamma\sigma^2 + \hat{b}\phi_{L\to H} + \hat{b}_\lambda \kappa \bar{\lambda}_2 + \frac{\lambda^L}{1-\gamma}\mathbb{E}_\nu\left[e^{(\gamma-1)Z_t} - 1\right]\right), \tag{A.6}$$

for scalars ζ_0, ζ_1 solving a system of two equations in two unknowns.

Proof. Along the optimal path, and over intervals not containing announcements, the value function must satisfy the usual Hamilton-Jacobi-Bellman equation. That is:

$$\begin{aligned} f(C_t, J_t) + \frac{\partial J}{\partial \tau} + \frac{\partial J}{\partial C} C_t \mu + \frac{\partial J}{\partial p}(\phi_{L\to H} - p_t(\phi_{H\to L} + \phi_{L\to H})) - \frac{\partial J}{\partial \lambda}\kappa(\lambda_{2t} - \bar{\lambda}_2) \\ + \frac{1}{2}\frac{\partial^2 J}{\partial C^2} C_t^2 \sigma^2 + \frac{1}{2}\frac{\partial^2 J}{\partial \lambda^2}\lambda_{2t}\sigma_\lambda^2 \\ + \left(p_t \lambda^H + (1-p_t)\lambda^L + \lambda_{2t}\right) J\, \mathbb{E}_\nu\left[\frac{J(Ce^{-Z}, \cdot) - J(C, \cdot)}{J(C, \cdot)}\right] = 0. \end{aligned} \tag{A.7}$$

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Given the conjecture (A.2),

$$\frac{1}{J}(J(Ce^{-Z},\cdot) - J(C,\cdot)) = e^{(\gamma-1)Z} - 1. \tag{A.8}$$

Further conjecturing (A.3), and using (3) and (A.8), we find

$$\begin{aligned}
&- \beta\hat{a}(1-\gamma)(\hat{a}(\tau;\chi_t) + \hat{b}p_t + \hat{b}_\lambda\lambda_{2t}) \\
&+ (1-\gamma)\frac{da}{d\tau} + (1-\gamma)\mu + (1-\gamma)(\phi_{L\to H} - p_t(\phi_{H\to L} + \phi_{L\to H}))\hat{b} - (1-\gamma)\hat{b}_\lambda\kappa(\lambda_{2t} - \bar{\lambda}_2) \\
&\qquad - \frac{1}{2}\gamma(1-\gamma)\sigma^2 + \frac{1}{2}(1-\gamma)^2\hat{b}_\lambda^2\sigma_\lambda^2\lambda_{2t} \\
&+ p_t(\lambda^H - \lambda^L)\mathbb{E}_\nu\left[e^{(\gamma-1)Z_t} - 1\right] + \lambda^L\mathbb{E}_\nu\left[e^{(\gamma-1)Z_t} - 1\right] + \lambda_{2t}\mathbb{E}_\nu\left[e^{(\gamma-1)Z_t} - 1\right] = 0.
\end{aligned} \tag{A.9}$$

Matching coefficients on λ_{2t}, p_t, and on the constant term implies:

$$-\beta(1-\gamma)\hat{b}_\lambda - (1-\gamma)\hat{b}_\lambda\kappa + \frac{1}{2}(1-\gamma)^2\hat{b}_\lambda^2\sigma_\lambda^2 + \mathbb{E}_\nu\left[e^{(\gamma-1)Z_t} - 1\right] = 0 \tag{A.10}$$

$$-\beta(1-\gamma)\hat{b} - (1-\gamma)(\phi_{H\to L} + \phi_{L\to H})\hat{b} + (\lambda^H - \lambda^L)\mathbb{E}_\nu\left[e^{(\gamma-1)Z_t} - 1\right] = 0, \tag{A.11}$$

and

$$\frac{d\hat{a}}{d\tau} = \beta\hat{a}(\tau;\chi_t) - \mu + \frac{1}{2}\gamma\sigma^2 - \hat{b}\phi_{L\to H} - \hat{b}_\lambda\kappa\bar{\lambda}_2 - \frac{\lambda^L}{1-\gamma}\mathbb{E}_\nu\left[e^{(\gamma-1)Z_t} - 1\right]. \tag{A.12}$$

This verifies the conjecture (A.3) over non-announcement intervals. Furthermore, (A.5–A.6) solve (A.10–A.12).[36]

It remains to verify (A.3) over announcement intervals. Along the optimal path, continuation value must satisfy

$$\begin{aligned}
V_{t^-} &= \mathbb{E}_{t^-}\left[\int_t^\infty f(C_s, V_s)ds\right] \\
&= \mathbb{E}_{t^-}[V_t].
\end{aligned} \tag{A.13}$$

[36]Equation A.10 as two solutions. Equation A.5 represents the economically reasonable one in that zero disaster risk implies zero impact of disasters on the value function.

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Applying (A.13) for $t \in \mathcal{A}$, we obtain

$$\lim_{\tau \uparrow T} J(C_{t^-}, p_{t^-}, \lambda_{2,t^-}, \tau; \chi_{t^-}) = \mathbb{E}_{t^-}\left[J(C_t, p_t, \lambda_{2t}, 0; \chi_t)\right]. \tag{A.14}$$

That is, the value function on the instant before the announcement must equal the expectation of its value just after the announcement. Furthermore, because C_t and λ_{2t} are continuous at t with probability 1,

$$\lim_{\tau \uparrow T} J(C_t, p_{t^-}, \lambda_{2t}, \tau; \chi_{t^-}) = \mathbb{E}_{t^-}\left[J(C_t, p_t, \lambda_{2t}, 0; \chi_t)\right]. \tag{A.15}$$

A solution of the form (A.2) will satisfy (A.13) provided that

$$\lim_{\tau \uparrow T} I(p_{t^-}, \lambda_{2t}, \tau; \chi_{t^-}) = \mathbb{E}_{t^-}\left[I(p_t, \lambda_{2t}, 0; \chi_t)\right]. \tag{A.16}$$

because, almost surely, C_t does not change on announcements or on any other specific time t. Moreover, (A.3) and (A.16) imply a set of two equations in the two unknowns ζ_0 and ζ_1, verifying (A.2) and (A.3) over announcement intervals. $\square$

Proof of Theorem 2. Define the function $I_{\mathcal{A}} : [0,1] \times [0,T) \times \{0,1\} \to \mathbb{R}$ as follows:

$$I_{\mathcal{A}}(p_t, \tau; \chi_t) = e^{\zeta_{\chi_t} e^{\beta\tau} + \hat{b} p_t}. \tag{A.17}$$

The form of the function I (Equation A.3) then implies the multiplicative decomposition:

$$I(p_t, \lambda_{2t}, \tau; \chi_t) = I_{\mathcal{A}}(p_t, \tau; \chi_t) I_{\mathcal{N}}(\lambda_{2t}), \tag{A.18}$$

for $I_{\mathcal{N}}(\cdot)$ a function of λ_{2t}. Substituting (A.2), (A.3) and (A.17) into (A.15) leads to

$$\lim_{\tau \uparrow T} I_{\mathcal{A}}(p_{t^-}, \tau; \chi_{t^-}) = \mathbb{E}_{t^-}\left[I_{\mathcal{A}}(p_t, 0; \chi_t)\right]. \tag{A.19}$$

Equation 18 then follows from substituting (A.17) into (A.19), using the definition of p^*. $\square$

Lemma A.2. *Define ζ_0, ζ_1, and $\hat{b}$ as in Theorem 2. Then $\hat{b} < 0$ and*

$$\zeta_0 > \zeta_1 + \hat{b}. \tag{A.20}$$

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Proof. Suppose by contradiction that

$$\zeta_0 \leq \zeta_1 + \hat{b}. \tag{A.21}$$

Recall the following pair of equations which determine ζ_0 and ζ_1:

$$\begin{aligned} e^{(1-\gamma)\left(\zeta_0 e^{\beta T}+\hat{b}p_0^*\right)} &= p_0^* e^{(1-\gamma)(\zeta_1+\hat{b})} + (1-p_0^*)e^{(1-\gamma)\zeta_0} \\ e^{(1-\gamma)\left(\zeta_1 e^{\beta T}+\hat{b}p_1^*\right)} &= p_1^* e^{(1-\gamma)(\zeta_1+\hat{b})} + (1-p_1^*)e^{(1-\gamma)\zeta_0}, \end{aligned} \tag{A.22}$$

The expressions on the left hand side of (A.22) are weighted averages of $e^{(1-\gamma)(\zeta_1+\hat{b})}$ and $e^{(1-\gamma)\zeta_0}$ with weights between 0 and 1. Thus they must lie between these two terms. Because the exponential function is strictly increasing, it follows that

$$\begin{aligned} \zeta_0 &\leq \zeta_0 e^{\beta T} + \hat{b}p_0^* \\ \zeta_1 e^{\beta T} + \hat{b}p_1^* &\leq \zeta_1 + \hat{b}. \end{aligned} \tag{A.23}$$

However, (A.23) implies

$$\begin{aligned} &\zeta_0(1-e^{\beta T}) \leq \hat{b}p_0^* < 0 \\ &\zeta_1(e^{\beta T}-1) \leq \hat{b}(1-p_1^*) < 0, \end{aligned}$$

because $\hat{b} < 0$. Therefore $\zeta_0 > 0$ and $\zeta_1 < 0$, contradicting (A.21).

□

Proof of Corollary 3. Utility prior to the announcement must equal its expectation just after the announcement (see Equation A.19). That is:

$$\lim_{\tau \uparrow T} I_{\mathcal{A}}(p_\chi^*, \tau; \chi) = p_\chi^* I_{\mathcal{A}}(1,0;1) + (1-p_\chi^*) I_{\mathcal{A}}(0,0;0), \tag{A.24}$$

for $\chi = 0, 1$, where p_χ^* is the probability of a negative announcement for the previous announcement being positive ($\chi = 0$) or negative ($\chi = 1$). It follows from Lemma A.2 and the form of $I_{\mathcal{A}}$ that

$$I_{\mathcal{A}}(1,0;1) < I_{\mathcal{A}}(0,0;0),$$

namely, utility is lower for a negative announcement than for a positive one. Utility just before the announcement is a weighted average of the utility for the announcement

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outcomes as (A.24) shows. Thus it must lie strictly between the two. It follows that utility falls when the announcement is negative and rises when it is positive.

□

Lemma A.3. *The state-price density π_t takes the form*

$$\pi_t = \beta \exp\left\{\int_0^t \frac{\partial}{\partial V} f(C_s, V_s) ds\right\} C_t^{-\gamma} I(p_t, \lambda_{2t}, \tau; \chi_t)^{1-\gamma}, \tag{A.25}$$

with $I(p_t, \lambda_{2t}, \tau; \chi_t)$ equal to (A.3).

Proof. Duffie and Skiadas (1994) show that

$$\pi_t = \exp\left\{\int_0^t \frac{\partial}{\partial V} f(C_s, V_s) ds\right\} \frac{\partial}{\partial C} f(C_t, V_t). \tag{A.26}$$

The form of f implies

$$\begin{aligned}
\frac{\partial}{\partial C} f(C_t, V_t) &= \beta(1-\gamma)\frac{V_t}{C_t} \\
&= \beta(1-\gamma)(1-\gamma)^{-1} C_t^{-\gamma} I(p_t, \lambda_{2t}, \tau; \chi_t)^{1-\gamma} \\
&= \beta C_t^{-\gamma} I(p_t, \lambda_{2t}, \tau; \chi_t)^{1-\gamma}.
\end{aligned} \tag{A.27}$$

Combining (A.26) and (A.27) implies

$$\pi_t = \beta \exp\left\{\int_0^t \frac{\partial}{\partial V} f(C_s, V_s) ds\right\} C_t^{-\gamma} I(p_t, \lambda_{2t}, \tau; \chi_t)^{1-\gamma}.$$

□

Proof of Theorem 4. We compute the instantaneous change in π_t over an infinitesimal interval containing an announcement. With probability 1, a disaster does not coincide with an announcement. Therefore, it follows from (A.25) that

$$\frac{\pi_t}{\pi_{t^-}} = \lim_{\tau \uparrow T} \frac{I_{\mathcal{A}}(p_t, 0; \chi_t)}{I_{\mathcal{A}}(p_{t^-}, \tau; \chi_{t^-})} = \lim_{\tau \uparrow T} \frac{I_{\mathcal{A}}(\chi_t, 0; \chi_t)}{I_{\mathcal{A}}(p^*_{\chi_{t^-}}, \tau; \chi_{t^-})}, \quad t \in \mathcal{A}. \tag{A.28}$$

The second equality follows from the definition of p^* and of χ_t. We substitute in for

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$I_{\mathcal{A}}$ using (A.17) to find

$$\lim_{\tau \uparrow T} \frac{I_{\mathcal{A}}(\chi_t, 0; \chi_t)}{I_{\mathcal{A}}(p^*_{\chi_{t^-}}, \tau; \chi_{t^-})} = \frac{e^{(1-\gamma)(\zeta_{\chi_t} + \hat{b}\chi_t)}}{e^{(1-\gamma)(\zeta_{\chi_{t^-}} e^{\beta T} + \hat{b} p^*_{\chi_{t^-}})}}. \tag{A.29}$$

This shows that the change in the state-price density equals the right hand side of (23). Finally (23) follows from the definition of M as the change in the state-price density around announcements. □

Proof of Corollary 5. The result follows directly from Lemma A.2 and the fact that the denominator of (23) is a weighted average of two terms, with weights strictly between 0 and 1, as given in (18). □

Proof of Theorem 6. We show the result for $\gamma > 1$. The proof for $\gamma < 1$ is similar and easier. Recall that $M(\chi, \chi_-)$ is the announcement SDF for previously announced probability χ_- and current announcement χ. It follows from (23) that

$$\frac{M(1,1)}{M(0,1)} = \frac{M(1,0)}{M(0,0)}. \tag{A.30}$$

Define

$$x = \frac{M(0,0)}{M(1,0) - M(0,0)} = \frac{M(0,1)}{M(1,1) - M(0,1)}.$$

It follows from

$$p^*_\chi M(1,\chi) + (1 - p^*_\chi) M(0,\chi) = 1$$

and (A.30) that

$$\frac{M(1,0)}{M(1,1)} = \frac{p^*_1 + x}{p^*_0 + x} < \frac{p^*_1}{p^*_0}.$$

The second inequality follows from the fact that $\frac{p^*_1 + x}{p^*_0 + x}$ is decreasing in x for $p^*_1 > p^*_0$. Therefore,

$$\tilde{p}^*_1 = p^*_1 M(1,1) > p^*_0 M(1,0) = \tilde{p}^*_0.$$

□

Lemma A.4. *Over non-announcement intervals ($t \in \mathcal{N}$), the state-price density π_t*

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follows the stochastic process

$$\frac{d\pi_t}{\pi_{t^-}} = -(r_{ft} + \left(\bar{\lambda}_1(p_t) + \lambda_{2t}\right) \mathbb{E}_\nu \left[e^{\gamma Z_t} - 1\right])dt \\ - \gamma\sigma dB_{Ct} + (1-\gamma)\hat{b}_\lambda \sigma_\lambda \sqrt{\lambda_{2t}} dB_{\lambda t} + (e^{\gamma Z_t} - 1)dN_t, \quad \text{(A.31)}$$

where $\hat{b}_\lambda$ is given by (A.5) and where r_{ft} is the instantaneous riskless interest rate:

$$r_{ft} = \beta + \mu - \gamma\sigma^2 + \left(\bar{\lambda}_1(p_t) + \lambda_{2t}\right) \mathbb{E}_\nu \left[e^{\gamma Z_t}(e^{-Z_t} - 1)\right]. \quad \text{(A.32)}$$

Proof. Consider $t \in \mathcal{N}$. Ito's Lemma and Lemma A.3 imply

$$\frac{d\pi_t}{\pi_{t^-}} = \mu_{\pi t}\, dt + \sigma_{\pi t}\, dB_t + \frac{\pi_t - \pi_{t^-}}{\pi_{t^-}} dN_t, \quad \text{(A.33)}$$

for a scalar process $\mu_{\pi t}$ and a 1×2 vector process $\sigma_{\pi t}$.[37] It follows from (A.25) and Ito's Lemma that

$$\sigma_{\pi t} = [-\gamma\sigma, (1-\gamma)\hat{b}_\lambda \sigma_\lambda \sqrt{\lambda_{2t}}], \quad \text{(A.34)}$$

and that, for $t_i = \inf\{t | N_t = i\}$,

$$\frac{\pi_{t_i} - \pi_{t_i^-}}{\pi_{t_i^-}} = e^{\gamma Z_{t_i}} - 1. \quad \text{(A.35)}$$

It follows from no-arbitrage that

$$\mathbb{E}_{t^-}\left[\frac{d\pi_t}{\pi_{t^-}}\right] = -r_{ft^-} dt.$$

It follows from (A.33) and (A.35) that

$$\mathbb{E}_{t^-}\left[\frac{d\pi_t}{\pi_{t^-}}\right] = \mu_{\pi t} + \left(\bar{\lambda}_1(p_t) + \lambda_{2t}\right) \mathbb{E}_\nu[e^{\gamma Z_t} - 1],$$

implying

$$\mu_{\pi t} = -r_{ft} - \left(\bar{\lambda}_1(p_t) + \lambda_{2t}\right) \mathbb{E}_\nu[e^{\gamma Z_t} - 1], \quad \text{(A.36)}$$

where $r_{ft} = r_{ft^-}$ because $\mu_{\pi t}$, and λ_{2t} are continuous.

[37] Lemma A.3 also implies the continuity of $\mu_{\pi t}$ and $\sigma_{\pi t}$ on non-announcement dates. This allows us to use t rather than t^- to subscript these variables in (A.33) and elsewhere.

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Finally, we show (A.32). Note that

$$\begin{aligned}\frac{\partial}{\partial V}f(C_t,V_t) &= \frac{\partial}{\partial V}\Big(\beta(1-\gamma)V_t\log C_t - \beta V_t\log[(1-\gamma)V_t]\Big)\\ &= \beta(1-\gamma)\log C_t - \beta\log[(1-\gamma)V_t]-\beta \\ &= -\beta\left(1+(1-\gamma)[\hat{a}(\tau;\chi_t)+\hat{b}p+\hat{b}_\lambda\lambda_{2t}]\right).\end{aligned} \tag{A.37}$$

It follows from (A.25) and Ito's Lemma that

$$\begin{aligned}\mu_{\pi t} = &\left(-\beta\Big[1+(1-\gamma)\hat{a}\big(\tau;\chi_t\big)+(1-\gamma)\hat{b}p_t+(1-\gamma)\hat{b}_\lambda\lambda_{2t}\Big]+(1-\gamma)\frac{\partial\hat{a}}{\partial\tau}\right)\\ &-\gamma\mu+(1-\gamma)\hat{b}\left[-p_t\phi_{H\to L}+(1-p_t)\phi_{L\to H}\right]-(1-\gamma)\hat{b}_\lambda\kappa(\lambda_{2t}-\bar{\lambda}_2)\\ &+\frac{1}{2}\gamma(\gamma+1)\sigma^2+\frac{1}{2}(1-\gamma)^2\hat{b}_\lambda^2\sigma_\lambda^2\lambda_{2t}.\end{aligned}$$

Collecting terms and substituting in for $\hat{a}\big(\tau;\chi_t\big)$, $\hat{b}$, and $\hat{b}_\lambda$ using (A.4–A.6) implies

$$\mu_{\pi t} = -\left(\beta+\mu-\gamma\sigma^2+\left(\bar{\lambda}_1(p_t)+\lambda_{2t}\right)\mathbb{E}_\nu\left[e^{(\gamma-1)Z_t}-1\right]\right). \tag{A.38}$$

The result then follows from (A.36).

□

B Equity prices

Lemma B.1. *The price of an equity strip of maturity s satisfies:*

$$\Psi(D_t,p_t,\lambda_{2t},\tau,s;\chi_t) = \mathbb{E}_t\left[\frac{\pi_{t+s}}{\pi_t}D_{t+s}\right], \tag{B.1}$$

where

$$\Psi(D_t,p_t,\lambda_{2t},\tau,s;\chi_t) = D_t\Phi(p_t,\lambda_{2t},\tau,s;\chi_t), \tag{B.2}$$

and

$$\Phi(p_t,\lambda_{2t},\tau,s;\chi_t) = \mathbb{E}_t\left[\frac{\pi_{t+s}}{\pi_t}\frac{D_{t+s}}{D_t}\right]. \tag{B.3}$$

Proof. The validity of (B.1) follows from the Markov property for π_t and D_t. That (B.1) represents the price of an equity strip follows from the absence of arbitrage.

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Finally (B.2) again follows from the Markov property, and (B.3) is by definition, given (26). $\square$

Lemma B.2. *Let $\Psi_t = \Psi(D_t, p_t, \lambda_{2t}, \tau, \bar{t} - t; \chi_t)$ be the time-t price of the equity strip maturing at date $\bar{t}$. Then, for $t \in \mathcal{N}$, Ψ_t satisfies*

$$\frac{d\Psi_t}{\Psi_{t^-}} = \mu_{\Psi t} dt + \sigma_{\Psi t} dB_t + (e^{-\varphi Z_t} - 1) dN_t, \tag{B.4}$$

with scalar $\mu_{\Psi t}$ and (row) vector $\sigma_{\Psi t}$ satisfying

$$\mu_{\Psi t} + \mu_{\pi t} + \sigma_{\Psi t}\sigma_{\pi t}^\top + \left(\bar{\lambda}_1(p_t) + \lambda_{2t}\right) \mathbb{E}_\nu \left[e^{(\gamma-\varphi)Z_t} - 1\right] = 0, \tag{B.5}$$

with μ_π as in (A.38) and σ_π as in (A.34).

Proof. It follows from (B.2) and (25) that

$$\frac{1}{\Psi}(\Psi(De^{-\varphi Z}, \cdot) - \Psi(D, \cdot)) = e^{-\varphi Z_t} - 1. \tag{B.6}$$

Then (B.4) follows from Ito's Lemma.

Equation B.1 implies that $\pi_t \Psi_t$ is a martingale. Consider $t \in \mathcal{N}$ and chose Δt sufficiently small so that the interval $[t, t + \Delta t]$ does not contain an announcement. It follows from (B.4) that

$$\begin{aligned}\Psi_{t+\Delta t}\pi_{t+\Delta t} = \Psi_t \pi_t + \int_t^{t+\Delta t} \pi_u \Psi_u (\mu_{\Psi u} + \mu_{\pi u} + \sigma_{\Psi u}\sigma_{\pi u}^\top) du + \int_t^{t+\Delta t} \pi_u \Psi_u (\sigma_{\Psi u} + \sigma_{\pi u}) dB_u \\ + \sum_{t < u_i \leq t+\Delta t} (\pi_{u_i}\Psi_{u_i} - \pi_{u_{i^-}}\Psi_{u_{i^-}}),\end{aligned} \tag{B.7}$$

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where $u_i = \inf\{u : N_u = i\}$. Rewriting, we have:

$$\Psi_{t+\Delta t}\pi_{t+\Delta t} = \Psi_t\pi_t + \underbrace{\int_t^{t+\Delta t} \pi_u\Psi_u \left(\mu_{\Psi u} + \mu_{\pi u} + \sigma_{\Psi u}\sigma_{\pi u}^\top + \left(\bar{\lambda}_1(p_u) + \lambda_{2u}\right)\mathbb{E}_\nu\left[e^{(\gamma-\varphi)Z} - 1\right]\right) du}_{(1)}$$
$$+ \underbrace{\int_t^{t+\Delta t} \pi_u\Psi_u(\sigma_{\Psi u} + \sigma_{\pi u})dB_u}_{(2)}$$
$$+ \underbrace{\sum_{t<u_i\le t+\Delta t} (\pi_{u_i}\Psi_{u_i} - \pi_{u_{i-}}\Psi_{u_{i-}}) - \int_t^{t+\Delta t} \pi_u\Psi_u \left(\bar{\lambda}_1(p_u) + \lambda_{2u}\right)\mathbb{E}_\nu\left[e^{(\gamma-\varphi)Z} - 1\right] du}_{(3)}. \tag{B.8}$$

Since $\Psi_t\pi_t$ is a martingale, the time-t expectation of $\Psi_{t+\Delta t}\pi_{t+\Delta t}$ must be $\Psi_t\pi_t$. In (B.8), (2) and (3) equal zero in expectation, so that the integrand in (1) must be zero.[38] We obtain (B.5). □

Corollary B.3. *The price-dividend ratio of an equity strip with maturity s satisfies (B.2) with*

$$\Phi(p_t, \lambda_{2t}, \tau, s; \chi_t) = \exp\left\{a_0(s) + a\big(\tau + s; \chi_t\big) + b(s)p_t + b_\lambda(s)\lambda_{2t}\right\}, \tag{B.9}$$

for some function $a : [0, T) \times \{0, 1\} \to \mathbb{R}$, where

$$b(s) = \frac{(\lambda^H - \lambda^L)\mathbb{E}_\nu\left[e^{\gamma Z_t}(e^{-\varphi Z_t} - e^{-Z_t})\right]}{\phi_{H\to L} + \phi_{L\to H}}\left(1 - e^{-(\phi_{H\to L}+\phi_{L\to H})s}\right), \tag{B.10}$$

where $b_\lambda(s)$ solves

$$\frac{db_\lambda}{ds} = \frac{1}{2}\sigma_\lambda^2 b_\lambda(s)^2 + \Big((1-\gamma)\hat{b}_\lambda\sigma_\lambda^2 - \kappa\Big)b_\lambda(s) + \mathbb{E}_\nu\left[e^{\gamma Z_t}(e^{-\varphi Z_t} - e^{-Z_t})\right], \tag{B.11}$$

[38] Note that $\pi_t\Psi_t$ follows a jump diffusion with intensity $\bar{\lambda}_1(p_t) + \lambda_{2t}$ and jump size

$$\frac{\pi_{u_i}\Psi_{u_i} - \pi_{u_i^-}\Psi_{u_i^-}}{\pi_{u_i^-}\Psi_{u_i^-}} = e^{(\gamma-\varphi)Z_{u_i}} - 1.$$

It follows that the term (3) in (B.8) equals zero.

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with boundary condition $b_\lambda(0) = 0$*, and where*

$$a_0(s) = \int_0^s \left(-\beta + \mu_D - \mu + \lambda^L \mathbb{E}_\nu\Big[e^{\gamma Z_t}(e^{-\varphi Z_t} - e^{-Z_t})\Big] + \kappa\bar{\lambda}_2 b_\lambda(u) + \phi_{L\to H} b(u)\right) du.$$

Proof. No-arbitrage applied to the zero-maturity claim implies the following boundary condition:

$$\Psi(D, p, \lambda_2, \tau, 0; \chi) = D.$$

Thus

$$a_0(0) = b(0) = b_\lambda(0) = 0. \tag{B.12}$$

Define $\mu_{\Psi t}$ and $\sigma_{\Psi t}$ as in Lemma B.2. Applying Ito's Lemma to the conjecture (B.2) and (B.9) implies

$$\begin{aligned}\mu_{\Psi t} = \mu_D &- \frac{da_0}{ds} + b(s)\phi_{L\to H} + b_\lambda(s)\kappa\bar{\lambda}_2 \\ &+ \left(-\frac{db}{ds} - b(s)(\phi_{H\to L} + \phi_{L\to H})\right) p_t + \left(-\frac{db_\lambda}{ds} + \frac{1}{2} b_\lambda(s)^2 \sigma_\lambda^2 - \kappa b_\lambda(s)\right) \lambda_{2t},\end{aligned} \tag{B.13}$$

and

$$\sigma_{\Psi t} = \left[\sigma, b_\lambda(s)\sigma_\lambda\sqrt{\lambda_{2t}}\right]. \tag{B.14}$$

Substituting (B.13), (B.14), (A.34), and (A.38) into (B.5) and matching coefficients implies

$$-\frac{db}{ds} - (\phi_{H\to L} + \phi_{L\to H})b(s) + (\lambda^H - \lambda^L)\mathbb{E}_\nu\left[e^{\gamma Z_t}(e^{-\varphi Z_t} - e^{-Z_t})\right] = 0 \tag{B.15}$$

$$-\frac{db_\lambda}{ds} + \frac{1}{2}\sigma_\lambda^2 b_\lambda(s)^2 + \left((1-\gamma)\hat{b}_\lambda\sigma_\lambda^2 - \kappa\right) b_\lambda(s) + \mathbb{E}_\nu\left(e^{\gamma Z_t}(e^{-\varphi Z_t} - e^{-Z_t})\right] = 0, \tag{B.16}$$

and

$$-\frac{da_0}{ds} = \beta + \mu - \mu_D + \lambda^L \mathbb{E}_\nu\left[e^{\gamma Z_t}(e^{-\varphi Z_t} - e^{-Z_t})\right] - \kappa\bar{\lambda}_2 b_\lambda(s) - \phi_{L\to H} b(s). \tag{B.17}$$

Then (B.10) uniquely solves (B.15) together with the boundary condition (B.12). □

Proof of Theorem 7. Corollary B.3 implies that there exists a decomposition (27),

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where $\Phi_{\mathcal{A}} : [0,1] \times [0,T) \times \mathbb{R}^+ \times \{0,1\} \to \mathbb{R}^+$ takes the form

$$\Phi_{\mathcal{A}}(p_t, \tau, s; \chi_t) = \exp\{a(\tau + s; \chi_t) + b(s)p_t\},$$

with $b(s)$ in (B.10), and with $a : \mathbb{R}_+ \times \{0,1\} \to \mathbb{R}$. Note that

$$\Psi(D_t, p_t, \lambda_{2t}, \tau, s; \chi_t) = D_t \Phi_{\mathcal{A}}(p_t, \tau, s; \chi_t)\Phi_{\mathcal{N}}(\lambda_2). \tag{B.18}$$

We now show (30). We apply (B.1) over an interval containing an announcement:[39]

$$\lim_{\tau \uparrow T} \Psi(D_{t^-}, p_{t^-}, \lambda_{2t}, \tau, s; \chi_{t^-}) = \mathbb{E}_{t^-}\left[\frac{\pi_t}{\pi_{t^-}} \Psi(D_t, p_t, \lambda_{2t}, 0, s; \chi_t)\right]. \tag{B.19}$$

for $t \in \mathcal{A}$. Almost surely, D_t does not change over a sufficiently short announcement interval. We substitute (B.18) into (B.19) to obtain

$$\lim_{\tau \uparrow T} \Phi_{\mathcal{A}}(p_{t^-}, \tau, s; \chi_{t^-}) = \mathbb{E}_{t^-}\left[\frac{\pi_t}{\pi_{t^-}} \Phi_{\mathcal{A}}(p_t, 0, s; \chi_t)\right], \qquad t \in \mathcal{A}.$$

We use Theorem 4 to substitute in for the change in the state-price density:

$$\lim_{\tau \uparrow T} \Phi_{\mathcal{A}}(p^*_{\chi_{t^-}}, \tau, s; \chi_{t^-}) = \mathbb{E}_{t^-}\left[M(\chi_t, \chi_{t^-})\Phi_{\mathcal{A}}(\chi_t, 0, s; \chi_t)\right], \tag{B.20}$$

where we have also applied the definition of p^* and χ_t. Substituting in for $\Phi_{\mathcal{A}}$ using (28) yields

$$e^{a(\tau+s;\chi_{t^-}) + b(s)p^*_{\chi_{t^-}}} = \mathbb{E}_{t^-}\left[M(\chi_t, \chi_{t^-})e^{a(s;\chi_t)+b(s)\chi_t}\right].$$

Then (30) follows from the definition of $\tilde{p}^*$.

We now show that (30) uniquely characterizes a. In the process, we provide a recursive algorithm for computing g. Define $u = s + \tau$. For $u < T$, $a(u, \cdot) = 0$ uniquely solves (30). Let

$$n = \left\lfloor \frac{u}{T} \right\rfloor$$

equal the number of announcements prior to maturity. We prove uniqueness by induc-

[39] Note that

$$\Psi(D_t, p_t, \lambda_{2t}, \tau, s; \chi_t) = \mathbb{E}_t\left[\frac{\pi_u}{\pi_t}\Psi(D_u, p_u, \lambda_{2u}, \tau + t - u, s - (t-u); \chi_u)\right]$$

for $u \geq t$.

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tion on n. Assume g is unique for $u \in [(n-1)T, nT)$. Note that (30) defines $a(u, \cdot)$ in terms of $a(u-T, \chi)$, $\chi = 0, 1$. Consider $u \in [n, (n+1)T)$. Then $u-T \in [(n-1)T, nT)$. It follows that the right hand side of (30) is unique. Therefore, for each $u \in [nT, (n+1)T)$, (30), applied at $\chi = 0, 1$, gives the value of $a(u, \chi)$ on the left hand side. Thus $a(u, \cdot)$ is unique for $u \in [n, (n+1)T)$, and hence for all $u > 0$. □

Proof of Corollary 8. It follows from Theorem 7 that the equity strip price just prior to an announcement is a weighted average of its possible values just after the announcement, with the weights given by the risk-neutral probabilities (which are strictly between zero and one). Thus the value prior to the announcement must lie between the post-announcement values. It therefore suffices to show that the equity strip price is higher when the announcement is positive as compared to when it is negative. That is, we need to show:

$$a(s; 0) > a(s; 1) + b(s) \tag{B.21}$$

for $s > 0$.

When $s < T$, (B.21) follows from $a(s; 1) = a(s; 0) = 0$ and $b(s) < 0$ (recall that we assume $\varphi > 1$). We now show (B.21) for general $s \geq T$ using induction on the number of announcements prior to maturity:

$$n = \left\lfloor \frac{u}{T} \right\rfloor.$$

Assume for $s \in [(n-1)T, nT)$, a weaker condition holds:

$$a(s; 0) \geq a(s; 1) + b(s).$$

Consider $s \in [nT, (n+1)T)$. It is helpful to write (30) out more explicitly:

$$e^{a(s;0)+b(s-T)p_0^*} = \tilde{p}_0^* e^{a(s-T;1)+b_{\varphi p}(s-T)} + (1 - \tilde{p}_0^*) e^{a(s-T;0)} \tag{B.22}$$

$$e^{a(s;1)+b(s-T)p_1^*} = \tilde{p}_1^* e^{a(s-T;1)+b_{\varphi p}(s-T)} + (1 - \tilde{p}_1^*) e^{a(s-T;0)}. \tag{B.23}$$

By Theorem 6, $\tilde{p}_1^* > \tilde{p}_0^*$. That is, under the risk-neutral measure, when the previous announcement was negative, the probability that the high-risk state will prevail in the next period is higher. However, by the induction step, we know that the equity price,

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in the next period, is (weakly) lower, if the high-risk state occurs. That is,

$$a(s-T;0) \geq a(s-T;1) + b(s-T).$$

Because the right hand side of (B.22) puts greater weight on the state with higher prices, as compared with (B.23), the left hand side of (B.22) is bigger than the left hand side of (B.23). That is,

$$a(s;0) + b(s-T)p_0^* \geq a(s;1) + b(s-T)p_1^*.$$

Finally,

$$\begin{aligned} a(s;0) &\geq a(s;0) + b(s-T)p_0^* \\ &\geq a(s;1) + b(s-T)p_1^* \\ &\geq a(s;1) + b(s-T) \\ &> a(s;1) + b(s). \end{aligned}$$

The last inequality follows because b is a strictly decreasing function. Thus (B.21) holds for $s \in [nT, (n+1)T)$, and therefore for all $s > 0$, completing the proof. □

Proof of Corollary 9. It follows from the definition of the announcement return (31), and the instantaneous Euler equation for the price around announcements (B.20) that

$$\mathbb{E}_{t^-}\left[M(\chi_t, \chi_{t^-}) r_{\mathcal{A}}(\chi_t, \chi_{t^-}, s)\right] = 1. \tag{B.24}$$

Moreover, it follows from (A.19), and (A.28) that

$$\mathbb{E}_{t^-}\left[M(\chi_t, \chi_{t^-})\right] = 1 \tag{B.25}$$

Then, (35) follows from (B.24), (B.25), and algebraic manipulation.

Statement 1 of the corollary follows from the fact that, under the stated conditions, the announcement return and the announcement SDF are in opposite positions relative to 1 (see Corollaries 5 and 8). Statement 2 follows from the fact that, under the stated conditions, they are in the same position relative to 1. Statement 3 follows from the fact that, under the stated conditions, either M or $r_{\mathcal{A}}$ equal 1. □

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C The VIX

Lemma C.1 (Characterization of the VIX). *Expected quadratic variation for an equity strip of fixed maturity s equals*

$$v\mathrm{VIX}_t^2 = v\sigma^2 + \varphi^2 \mathbb{E}_t^Q \left[\int_t^{t+v} Z_u^2 dN_u\right] + \mathbb{E}_t^Q \left[b_\lambda(s)^2 \sigma_\lambda^2 \int_t^{t+v} \lambda_{2u} ds\right] + \sum_{\{u: t<u\leq t+v, u \bmod T=0\}} \mathbb{E}_t^Q \left[\left(a(s;\chi_u) + b(s)p_u - a(T+s;\chi_{u^-}) - b(s)p_{u^-}\right)^2\right] \quad \text{(C.1)}$$

Proof. By definition,

$$v\mathrm{VIX}_t^2 \equiv \mathbb{E}_t^Q \int_t^{t+v} d[\log\Psi, \log\Psi]_u \quad \text{(C.2)}$$

Apply Lemma B.1 and Corollary B.3 to obtain

$$\log\Psi(D, p, \lambda_2, \tau, s; \chi) = \log D_t + a_0(s) + a\big(\tau + s; \chi_t\big) + b(s)p_t + b_\lambda(s)\lambda_{2t}.$$

It follows from the process for dividends (25) and the definition of the Poisson process N_t that

$$\mathbb{E}_t^Q \int_t^{t+v} d[\log D, \log D]_u = v\sigma^2 + \varphi^2 \mathbb{E}_t^Q \left[\int_t^{t+v} Z_u^2 dN_u.\right],$$

The process for λ_{2t} (13) implies that

$$\mathbb{E}_t^Q \int_t^{t+v} d[\lambda_2, \lambda_2]_u = \sigma_\lambda^2 \mathbb{E}_t^Q \int_t^{t+v} \lambda_{2u} ds.$$

Finally, $a\big(\tau + s; \chi_t\big) + b(s)p_t$ is deterministic except on days u with $u \bmod T = 0$. On those days, which have $\tau = T$ just prior to the announcement and $\tau = 0$ just after,

$$d[a\big((u \bmod T) + s; \chi_u\big) + b(u)p_u, a\big((u \bmod T) + s; \chi_u\big) + b(u)p_u] = \mathbb{E}_t^Q \left[\left(a(s;\chi_u) + b(s)p_u - a(T+s;\chi_{u^-}) - b(s)p_{u^-}\right)^2\right]$$

□

Proof of Theorem 13. Consider an interval Δt. It follows the definition (C.2) from

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the law of iterated expectations that

$$\mathbb{E}_t^Q\left[(v-\Delta t)\mathrm{VIX}_{t+\Delta t}^2 - v\mathrm{VIX}_t^2\right] = -\mathbb{E}_t^Q \int_t^{t+\Delta t} d[\log\Psi, \log\Psi]_u. \tag{C.3}$$

Now assume t is an announcement date, u is a date prior to the announcement, and $\bar{t}$ is the date that the VIX matures. Apply (C.3) to the interval $t-u$:

$$\mathbb{E}_u^Q\left[(\bar{t}-t)\mathrm{VIX}_t^2 - (\bar{t}-u)\mathrm{VIX}_u^2\right] = -\mathbb{E}_u^Q \int_u^t d[\log\Psi, \log\Psi]_w.$$

Note that

$$\begin{aligned} \lim_{u\uparrow t} \mathbb{E}_u^Q \int_u^t d[\log D, \log D]_w &= 0 \\ \lim_{u\uparrow t} \mathbb{E}_t^Q \int_u^t d[\lambda_2, \lambda_2]_w &= 0 \end{aligned}$$

It follows from Lemma C.1 that:

$$\lim_{u\uparrow t} \mathbb{E}_u^Q\left[(\bar{t}-t)\mathrm{VIX}_t^2 - (\bar{t}-u)\mathrm{VIX}_u^2\right] = -\mathbb{E}_{t^-}^Q\left[\left(a(s;\chi_t) + b(s)p_t - a(T+s;\chi_{t^-}) - b(s)p_{t^-}\right)^2\right]$$

because the interval $(u, \bar{t}]$ contains one more announcement relative to $(t, \bar{t}]$. The result follows from $\lim_{u\uparrow t} \frac{t-u}{\bar{t}-t}\mathrm{VIX}_u = 0$. □

D Nominal bond prices

Define the vector Brownian motion

$$dB_t^{\$} = [dB_t^\top, dB_t^\Pi, dB_{qt}]^\top,$$

with dB_t defined in (A.1).

We first show the validity of the nominal stochastic discount factor.

Lemma D.1. *Let Π_t denote a process for the price level, and let $\Phi_t^{\$}$ denote a time-t nominal price of a non-dividend paying asset. Then absence of arbitrage implies that*

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there exists a nominal state-price density $\pi^\$_t = \pi_t/\Pi_t$, such that

$$\pi^\$_t \Phi^\$_t = \mathbb{E}_t \left[\pi^\$_u \Phi^\$_u \right], \qquad u \geq t. \tag{D.1}$$

Proof. The time-t real price of the asset equals $\Phi^\$_t/\Pi_t$. Absence of arbitrage implies that

$$\pi_t \frac{\Phi^\$_t}{\Pi_t} = \mathbb{E}_t \left[\pi_u \frac{\Phi^\$_u}{\Pi_u} \right], \qquad u \geq t. \tag{D.2}$$

Define $\pi^\$_t = \pi_t/\Pi_t$, then (D.2) is equivalent to (D.1), implying that $\pi^\$_t$ is the nominal stochastic discount factor process. □

Corollary D.2. *For $t \in \mathcal{N}$, the nominal state-price density $\pi^\$_t$ evolves according to*

$$\begin{aligned} \frac{d\pi^\$_t}{\pi^\$_{t^-}} = -(r^\$_{ft} + \left(\bar{\lambda}_1(p_t) + \lambda_{2t}\right) E_\nu \left[e^{(\gamma-1)Z_t} - 1 \right])dt \\ - \gamma\sigma dB_{Ct} + (1-\gamma)\hat{b}_\lambda \sigma_\lambda \sqrt{\lambda_{2t}} dB_{\lambda t} - \sigma_\Pi dB^\Pi_t \\ + (e^{(\gamma-1)Z_t} - 1) dN_t, \end{aligned} \tag{D.3}$$

where $r^\$_{ft}$, the nominal riskless rate, equals

$$r^\$_{ft} = r_{ft} + q_t - \sigma^2_\Pi - (\bar{\lambda}_{1t} + \lambda_{2t}) \mathbb{E}_\nu \left[e^{-\gamma Z_t} (e^{Z_t} - 1) \right], \tag{D.4}$$

for r_{ft} the real riskless rate in (A.32), and where $\hat{b}_\lambda$ equals (A.5).[40]

Proof. Applying Itô's Lemma to

$$\pi^\$_t = \frac{\pi_t}{\Pi_t} \tag{D.5}$$

implies that there exists a (scalar) process $\mu^\$_{\pi t}$ and (row vector) process $\sigma^\$_{\pi t}$ such that

$$\frac{d\pi^\$_t}{\pi^\$_{t^-}} = \mu^\$_{\pi t}\, dt + \sigma^\$_{\pi t}\, dB^\$_t + \frac{\pi^\$_t - \pi^\$_{t^-}}{\pi^\$_{t^-}} dN_t. \tag{D.6}$$

Given (A.34) and (38), it follows that

$$\sigma^\$_{\pi t} = [-\gamma\sigma, (1-\gamma)\hat{b}_\lambda \sigma_\lambda \sqrt{\lambda_{2t}}, -\sigma_\Pi, 0]. \tag{D.7}$$

[40] The nominal riskless interest rate is the nominal return on the asset that is instantaneously riskfree when payoffs are expressed in nominal terms.

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Furthermore, (A.35) and (38) together imply that, for $t_i = \inf\{t|N_t = i\}$,

$$\frac{\pi^{\$}_{t_i} - \pi^{\$}_{t_i^-}}{\pi^{\$}_{t_i^-}} = e^{(\gamma-1)Z_{t_i}} - 1. \tag{D.8}$$

Finally, the drift of $\pi^{\$}_t$, together with (D.4), arise from (A.36) and the drift of Π_t given in (38). Substituting in for r_{ft} using (A.32) implies

$$\mu^{\$}_{\pi t} = -\beta - \mu + \gamma\sigma^2 - q_t + \sigma^2_{\Pi} - \left(\bar{\lambda}_1(p_t) + \lambda_{2t}\right) \mathbb{E}_\nu \left[e^{(\gamma-1)Z_t} - 1\right]. \tag{D.9}$$

□

Lemma D.3. *Define the function*

$$\Phi^{\$}(p_t, q_t, \lambda_{2t}, \tau, s; \chi_t) = \mathbb{E}_t \left[\frac{\pi^{\$}_{t+s}}{\pi^{\$}_t}\right]. \tag{D.10}$$

Then $\Phi^{\$}$ represents the nominal price of a nominal bond with maturity s.

Proof. The validity of (D.10) follows from the Markov property of $\pi^{\$}_t$. The fact that (D.10) equals the nominal bond price follows from the absense of arbitrage. □

Lemma D.4. *Define $\Phi^{\$}_t = \Phi^{\$}(p_t, q_t, \lambda_{2t}, \tau, \bar{t} - t; \chi_t)$, so that $\Phi^{\$}_t$ is the time-t nominal price of the nominal bond maturing at date $\bar{t}$. Then, for $t \in \mathcal{N}$, $\Phi^{\$}_t$ satisfies*

$$\frac{d\Phi^{\$}_t}{\Phi^{\$}_{t^-}} = \mu^{\$}_{Pt}\, dt + \sigma^{\$}_{Pt}\, dB^{\$}_t, \tag{D.11}$$

with scalar $\mu^{\$}_{Pt}$ and (row) vector $\sigma^{\$}_{Pt}$ satisfying

$$\mu^{\$}_{\pi t} + \mu^{\$}_{Pt} + \sigma^{\$}_{\pi t}(\sigma^{\$}_{Pt})^\top + (\bar{\lambda}_1(p_t) + \lambda_{2t})\mathbb{E}_\nu \left[e^{(\gamma-1)Z_t} - 1\right] = 0, \tag{D.12}$$

with $\mu^{\$}_{\pi t}$ as in (D.9) and $\sigma^{\$}_{\pi t}$ as in (D.7)

Proof. Equation D.11 follows from Ito's Lemma. Equation D.10 implies that $\pi^{\$}_t \Phi^{\$}_t$ is a martingale. Moreover, it follows from (D.3) that for $t_i = \inf\{t|N_t = i\}$,

$$\frac{\pi^{\$}_{t_i}\Phi^{\$}_{t_i} - \pi^{\$}_{t_i^-}\Phi^{\$}_{t_i^-}}{\pi^{\$}_{t_i^-}\Phi^{\$}_{t_i^-}} = \frac{\pi^{\$}_{t_i} - \pi^{\$}_{t_i^-}}{\pi^{\$}_{t_i^-}} = e^{(\gamma-1)Z_{t_i}} - 1.$$

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The remainder of the proof follows that of Lemma B.2.

$\square$

Corollary D.5. *The time-t nominal price of a nominal zero-coupon bond with maturity s equals*

$$\Phi^{\$}\big(p_t, q_t, \tau, s; \chi_t\big) = \exp\left\{a_0^{\$}(s) + a^{\$}(\tau;\chi) + b^{\$}(s)p_t + b_q^{\$}(s)q_t\right\}, \tag{D.13}$$

for some function $a^{\$} : [0,T) \times \{0,1\} \to \mathbb{R}$*, where*

$$b_q^{\$}(s) = \frac{1}{\kappa_q}(e^{-\kappa_q s} - 1), \tag{D.14}$$

$b^{\$}(s)$ *solves*

$$\frac{db^{\$}}{ds} = -(\phi_{H\to L} + \phi_{L\to H})b^{\$}(s) + b_q^{\$}(s)\kappa_q\left(\bar{q}^H - \bar{q}^L\right) \tag{D.15}$$

with boundary condition $b^{\$}(0) = 0$*, and where*

$$a_0^{\$}(s) = \int_0^s(-\beta - \mu + \gamma\sigma^2 + \sigma_\Pi^2 + b_q^{\$}(u)\kappa_q\bar{q}^L + b^{\$}(u)\phi_{L\to H} + \frac{1}{2}b_q^{\$}(u)^2\sigma_q^2)du. \tag{D.16}$$

Proof. No-arbitrage applied to the zero-maturity claim implies the following boundary condition

$$a_0^{\$}(0) = b^{\$}(0) = b_q^{\$}(0) = 0. \tag{D.17}$$

Define $\mu_{Pt}^{\$}$ and $\sigma_{Pt}^{\$}$ as in Lemma D.4. Applying Ito's Lemma to the conjecture (D.13) implies

$$\begin{aligned}\mu_{Pt}^{\$} = &-\frac{da_0^{\$}}{ds} + b^{\$}(s)\phi_{L\to H} + b_q^{\$}(s)\kappa_q\bar{q}^L \\ &+ \left(-\frac{db^{\$}}{ds} - (\phi_{H\to L} + \phi_{L\to H})b_p^{\$}(s)\right)p_t + \left(-\frac{db_q^{\$}}{ds} - \kappa_q b_q^{\$}(s)\right)q_t,\end{aligned} \tag{D.18}$$

and

$$\sigma_{Pt}^{\$} = \left[\sigma, 0, 0, b_q^{\$}(s)\sigma_q\right]. \tag{D.19}$$

Substituting (D.18), (D.19), (D.9) and (D.7) into (D.12) and matching coefficients

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implies

$$0 = -\frac{da_0^\$}{ds} + b^\$(s)\phi_{L\to H} + b_q^\$(s)\kappa_q \bar{q}^L + \frac{1}{2} b_q^\$(s)^2 \sigma_q^2 - \beta - \mu + \gamma\sigma^2 + \sigma_\Pi^2 \tag{D.20}$$

$$0 = -\frac{db^\$}{ds} - (\phi_{H\to L} + \phi_{L\to H}) b^\$(s) + b_q^\$(s)\kappa_q \left(\bar{q}^H - \bar{q}^L\right) \tag{D.21}$$

$$0 = -\frac{db_q^\$}{ds} - b_q^\$(s)\kappa_q - 1. \tag{D.22}$$

Then (D.14) uniquely solves (D.22) together with the boundary condition (D.17). Moreover, (D.20) and (D.17) ensure that that $a_0^\$$ takes the form (D.16). □

Proof of Theorem 14. Given the foregoing results, this proof follows closely along the lines of that of Theorem 7. □

Lemma D.6. *$b^\$(s) < 0$, and $db^\$/ds < 0$, for $s > 0$.*

Proof. Substituting the boundary conditions (D.17) into (D.21) yields

$$\left.\frac{db^\$}{ds}\right|_{s=0} = 0. \tag{D.23}$$

In addition, (D.14) implies

$$\kappa_q(\bar{q}^H - \bar{q}^L) b_q^\$(s) < 0, \ \ s > 0. \tag{D.24}$$

It follows that there is a sufficiently small but positive s_1, such that

$$b^\$(s_1) < 0.$$

Suppose by contradiction that there exists $s_2 > 0$, such that $b^\$(s_2) \geq 0$. Then there must exist $s^* \in [s_1, s_2]$, such that $b^\$(s^*) = 0$ (because of continuity).

Consider the function $b_*^\$(s)$ such that $b_*^\$(s^*) = 0$, and

$$\frac{db_*^\$}{ds} = -(\phi_{H\to L} + \phi_{L\to H}) b_*^\$(s) + b_q^\$(s^*)\kappa_q \left(\bar{q}^H - \bar{q}^L\right)$$

Note that this function is strictly negative for $s > s^*$, and moreover, $b^\$(s) < b_*^\$(s)$ for $s > s^*$. Therefore, we cannot have $b^\$(s_2) > 0$. Given that $b^\$(s) \leq 0$, it follows that $db^\$/ds > 0$, and from there, it follows that $b^\$(s) < 0$. □

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Proof of Corollary 15. Using (D.13) and the almost-sure continuity of all variables around announcements, with the exception of p_t and χ_t, it suffices to show that nominal zero-coupon bond price is higher when the announcement is positive as compared to when it is negative. That is, we need to show:

$$a^{\$}(s;0) > a^{\$}(s;1) + b^{\$}(s) \tag{D.25}$$

for $s > 0$.

When $s < T$, (D.25) follows from $a^{\$}(s;0) = a^{\$}(s;1) = 0$ and $b^{\$}(s) < 0$ from Lemma D.6.

We now show (D.25) holds for $s \geq T$. We prove this by using induction on the number of announcements prior to maturity:

$$n = \left\lfloor \frac{u}{T} \right\rfloor .$$

Assume for $s \in [(n-1)T, nT)$, $n = 1, 2, 3, \ldots$, the following weaker condition holds:

$$a^{\$}(s;0) \geq a^{\$}(s;1) + b^{\$}(s). \tag{D.26}$$

Equation 45 suggests

$$\begin{aligned} e^{a^{\$}(s;0)+b^{\$}(s-T)p_0^*} &= \tilde{p}_0^* e^{a^{\$}(s-T;1)+b^{\$}(s-T)} + (1-\tilde{p}_0^*)e^{a^{\$}(s-T;0)} \\ e^{a^{\$}(s;1)+b^{\$}(s-T)p_1^*} &= \tilde{p}_1^* e^{a^{\$}(s-T;1)+b^{\$}(s-T)} + (1-\tilde{p}_1^*)e^{a^{\$}(s-T;0)}. \end{aligned}$$

Theorem 6 shows that $\tilde{p}_1^* > \tilde{p}_0^*$. However, by the induction step, we know that the equity price, in the next period, is (weakly) lower, if the high-risk state occurs. That is,

$$a^{\$}(s-T;0) \geq a^{\$}(s-T;1) + b^{\$}(s-T).$$

Therefore, it follows that

$$a^{\$}(s;0) + b^{\$}(s-T)p_0^* \geq a^{\$}(s;1) + b^{\$}(s-T)p_1^*.$$

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Finally,

$$\begin{aligned} a^{\$}(s;0) &\geq a^{\$}(s;0) + b^{\$}(s-T)p_0^* \\ &\geq a^{\$}(s;1) + b^{\$}(s-T)p_1^* \\ &\geq a^{\$}(s;1) + b^{\$}(s-T) \\ &> a^{\$}(s;1) + b^{\$}(s). \end{aligned}$$

The last inequality follows because $b^{\$}(s)$ is strictly decreasing from Lemma D.6. Thus (D.25) holds for $s \in [nT, (n+1)T]$, and therefore for all $s > 0$, completing the proof. $\square$

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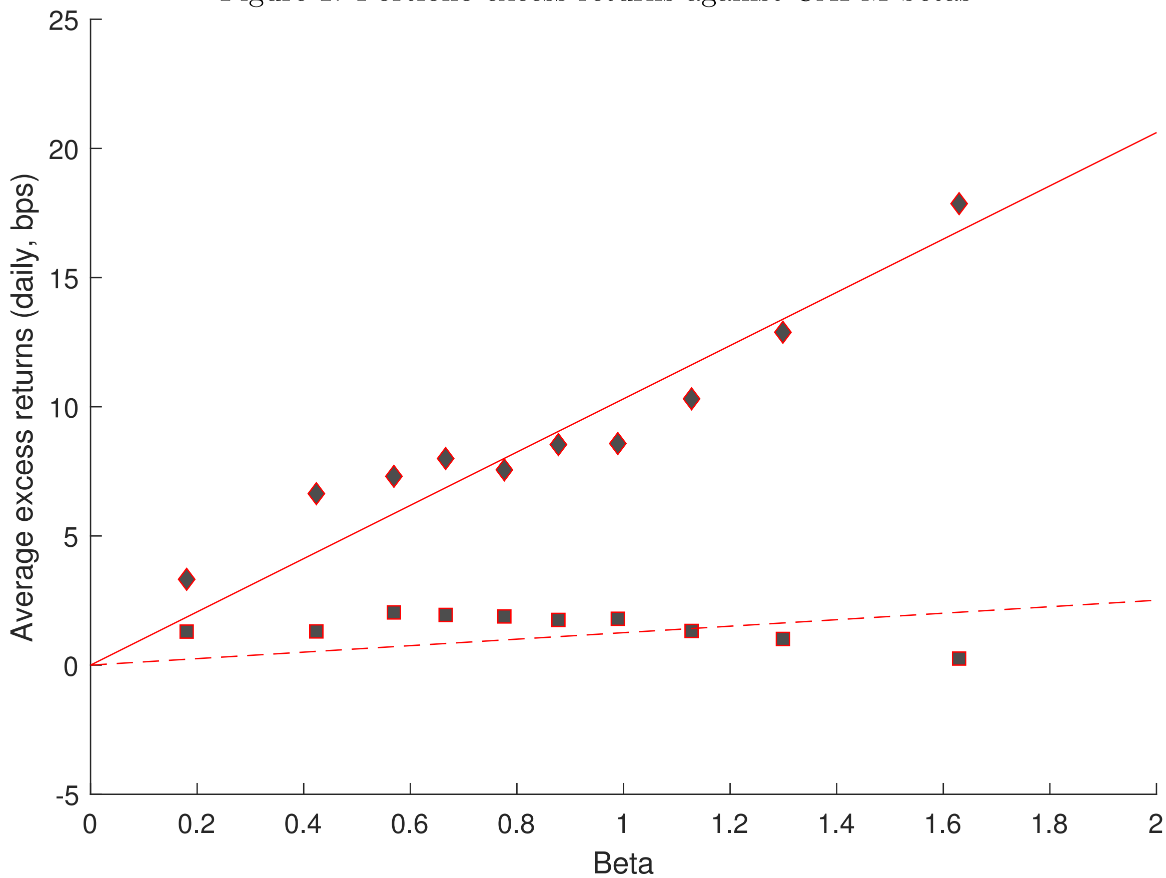
Figure 1: Portfolio excess returns against CAPM betas



Notes: The figure shows average excess returns on announcement days (diamonds) and non-announcement days (squares) on beta-sorted portfolios in daily data from 1961.01-2016.09. On the horizontal axis is CAPM beta, estimated using the full sample. Also shown are estimated regression lines for announcement day returns against beta (solid red) and non-announcement day returns against beta (dashed red).

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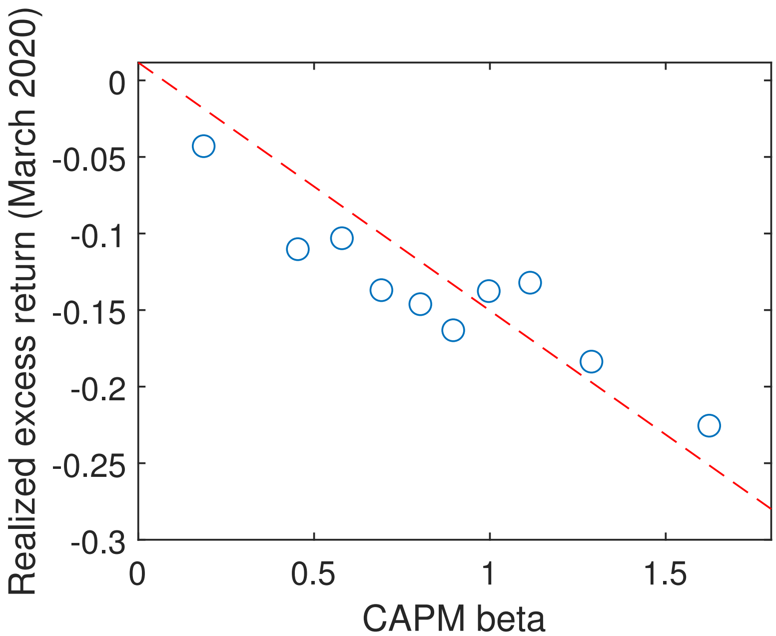
Figure 2: Unconditional betas and returns in a disaster



Notes: We extend our data to March 2020 and construct the beta-sorted portfolios with data from 1961.01 to 2020.03. We then compute the realized excess returns and CAPM beta of the beta-sorted portfolios of the month March 2020. The figure shows the realized excess returns and the unconditional CAPM beta of the beta-sorted portfolios. The red dashed line is the fitted line for the regression of March 2020 realized excess return against CAPM beta.

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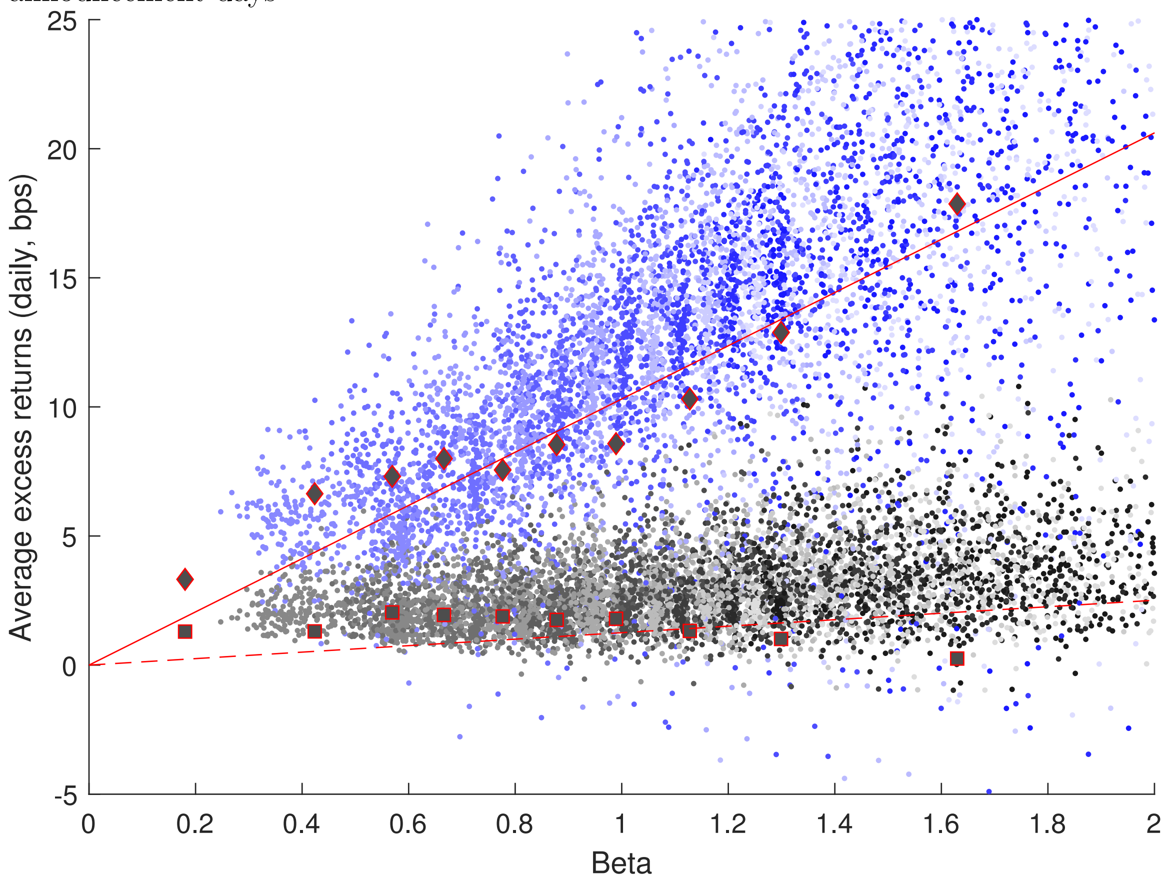
Figure 3: Portfolio excess returns against CAPM betas on announcement and non-announcement days



Notes: The figure shows average excess returns on announcement days (diamonds) and non-announcement days (squares) on beta-sorted portfolios in daily data from 1961.01-2016.09 as a function of the CAPM beta. Also shown are estimated regression lines for announcement day returns against beta (solid red) and non-announcement day returns against beta (dashed red). We simulate 500 samples of artificial data from the model, each containing a cross-section of firms. The blue and grey dots show average announcement day and non-announcement day returns for each sample as a function of beta, respectively.

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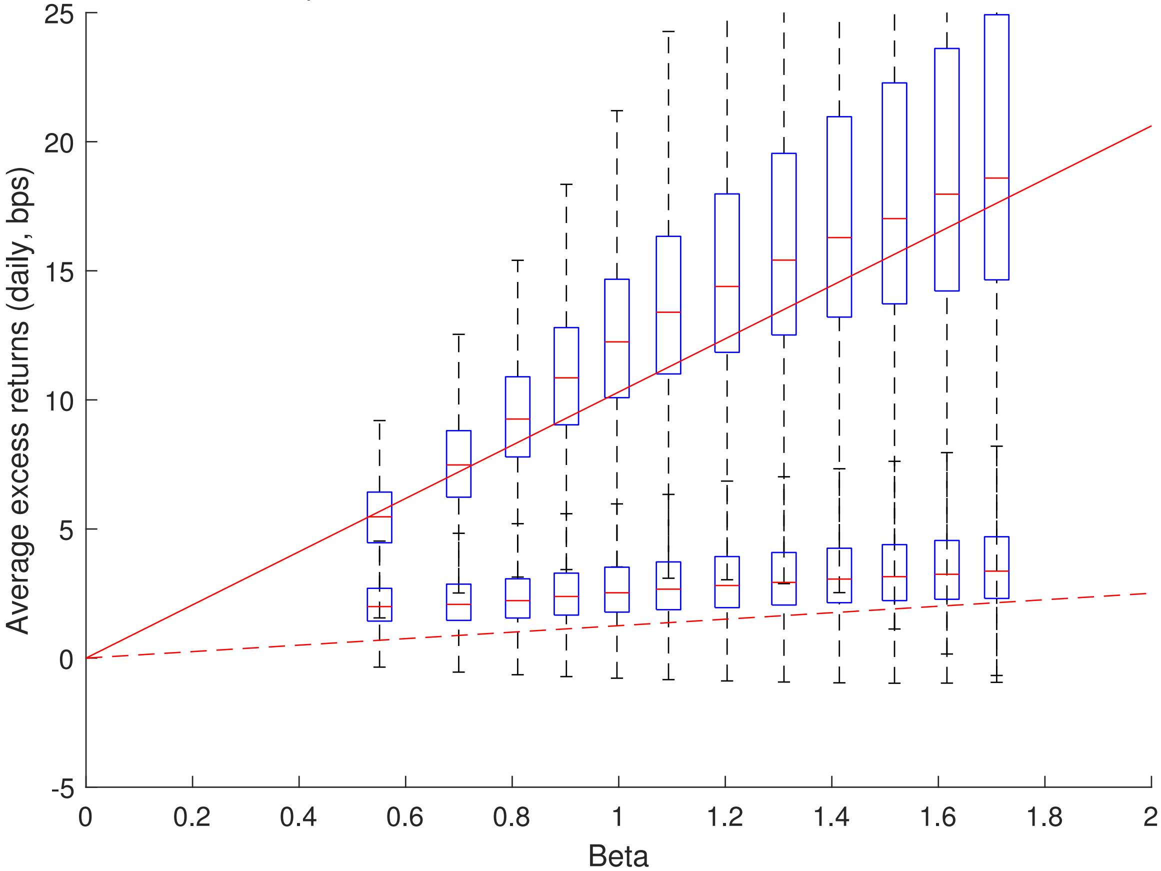
Figure 4: Boxplots of simulated portfolio average excess returns on announcement and non-announcement days



Notes: We compute average excess returns on announcement and non-announcement days for a cross-section of assets in data simulated from the model. The red line shows the median for each portfolio across samples; the box corresponds to the interquartile range (IQR), and the whiskers correspond to the highest and lowest data value within $1.5 \times$ IQR of the highest and lowest quartile. We plot returns against the median CAPM beta across samples for each portfolio. The red solid and dashed lines are the empirical regression lines of portfolio mean excess returns against market beta on announcement and non-announcement days, respectively.

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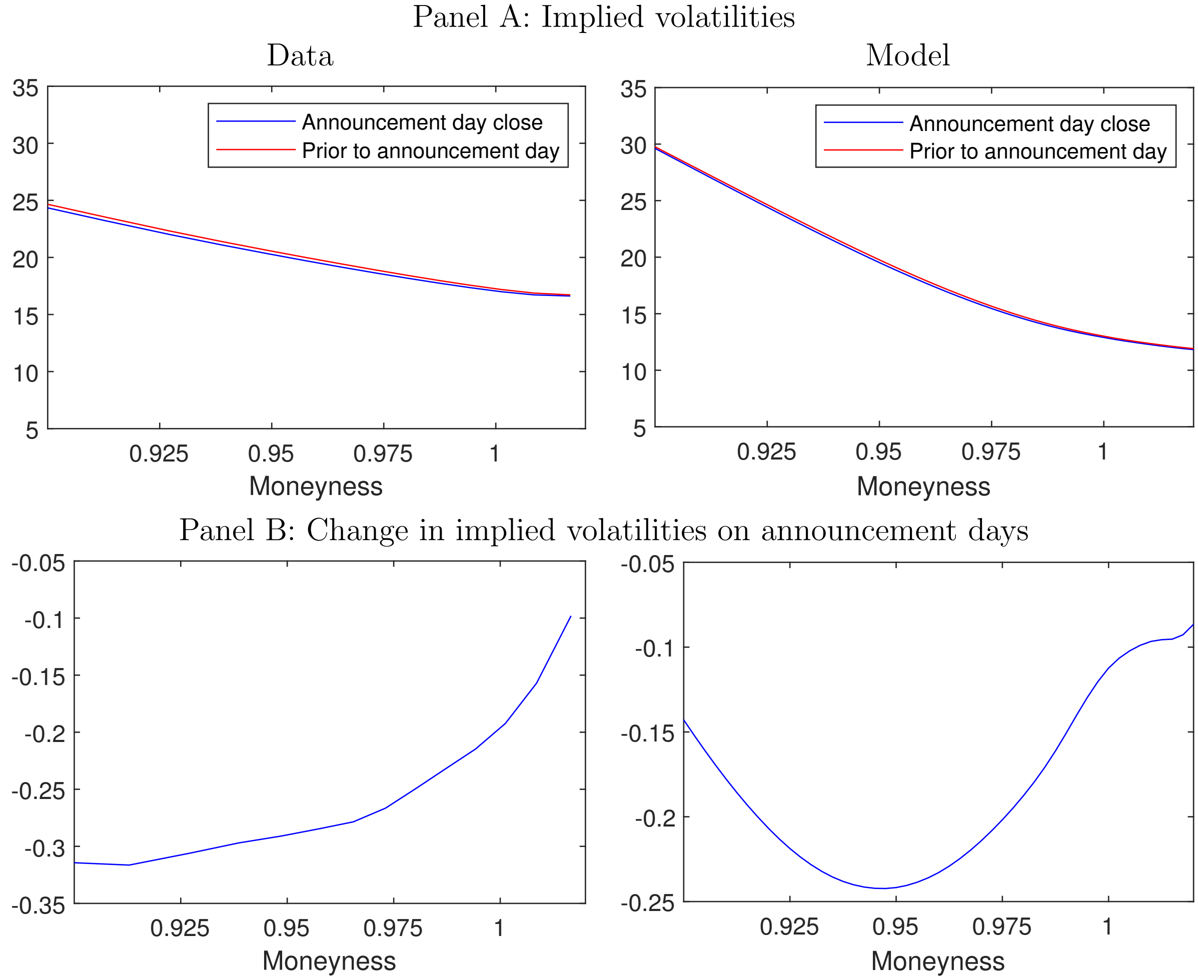
Figure 5: Annualized implied volatilities at announcement day closes and prior to announcements



Notes: Panel A shows the average implied volatility surfaces computed from put options on the S&P 500 index against the moneyness of the options. The option's moneyness is defined as the ratio of the strike price and the underlying asset's forward price. The blue line stands for the average implied volatilities at close on the announcement days, while the red line is the average implied volatilities at the close prior to announcements. The left panel is the empirical results, and the right panel shows the model implied moments generated from simulation. Panel B shows the difference between the implied volatilities at the announcement day close and the day prior. Implied volatilities fall for all levels of moneyness following the announcement, but the decline is most pronounced for out-of-the-money options. The sample period is 1996.01 to 2016.12.

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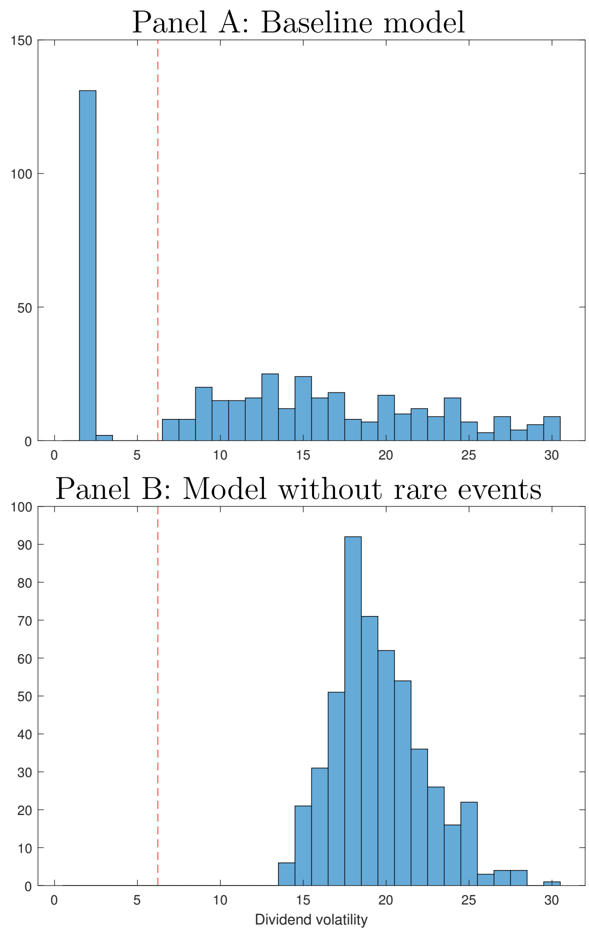
Figure 6: Simulated volatility of dividend growth



Notes: In Panel A we show a histogram of dividend volatility in repeated samples from the baseline model. Panel B shows dividend volatility in a model in which normal-times volatility arises from realized cash flows (Section 5). The red line denotes the data.

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Table 1: Statistics on excess returns of 10 beta-sorted portfolios

	Unconditional			Announcement day			Non-announcement day		
k	$E[RX^k]$	σ^k	β^k	$E[RX^k]$	σ^k	β^k	$E[RX^k]$	σ^k	β^k
1	1.53	53.1	0.20	3.32	52.8	0.18	1.30	53.2	0.20
2	1.91	59.2	0.44	6.64	58.8	0.42	1.30	59.2	0.44
3	2.64	69.2	0.57	7.31	70.8	0.57	2.04	69.0	0.58
4	2.63	77.4	0.69	8.00	77.1	0.67	1.94	77.4	0.69
5	2.53	87.9	0.81	7.56	87.6	0.78	1.88	87.9	0.81
6	2.52	96.2	0.90	8.54	96.7	0.88	1.75	96.1	0.91
7	2.56	105.4	1.00	8.58	107.5	0.99	1.79	105.1	1.00
8	2.34	118.9	1.14	10.31	121.8	1.13	1.32	118.5	1.14
9	2.36	136.5	1.31	12.88	139.1	1.30	1.01	136.2	1.31
10	2.25	176.2	1.67	17.86	176.9	1.63	0.25	176.0	1.67

Notes: Sample statistics for excess returns of ten beta-sorted portfolios in daily data from 1961.01–2016.09. We show the sample mean excess returns ($E[RX^k]$), and CAPM beta (β^k), where k indexes the beta sorted portfolio. Column 1-3 report estimates from the full sample. Column 4-6 and column 7-9 use returns on announcement and non-announcement days, respectively. Excess returns and volatilities are in units of basis points per day.

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Table 2: Statistics on excess bond returns

Maturity	Unconditional		Announcement day		Non-announcement day	
k	$E[RX^k]$	β^k	$E[RX^k]$	β^k	$E[RX^k]$	β^k
1	0.363	0.000	−0.043	0.007	0.415	−0.001
5	0.855	−0.007	3.211	0.029	0.549	−0.013
10	0.779	−0.010	3.882	0.051	0.376	−0.019
20	1.122	−0.021	4.988	0.060	0.620	−0.033
30	0.986	−0.045	5.219	0.046	0.437	−0.058

Notes: Sample statistics for excess returns on Treasury bonds in daily data from 1961.01–2016.09. We show the sample mean excess returns ($E[RX^k]$) and CAPM beta (β^k). The excess returns are computed using as the difference between CRSP nominal bond returns and the CRSP riskfree rates. Returns and betas are computed using the full sample (first two columns), announcement days (second two columns), and non-announcement days (last two columns). Maturity is in units of years; returns are in units of basis points per day.

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Table 3: Parameter values for the baseline model

Panel A: Basic parameters	
Expected normal-times growth in consumption μ, (%)	2.52
Expected normal-times growth in dividend μ_D, (%)	6.02
Volatility of consumption growth σ(%)	2.00
Rate of time preference β	0.012
Relative risk aversion γ	3.00
Average leverage ϕ	3.00
Panel B: The process for λ_{1t}	
Probability of disaster in the low-risk state λ^L	0
Probability of disaster in the high-risk state λ^H	0.293
Probability of switching to high-risk state $\phi_{L\to H}$	0.02
Probability of switching to low-risk state $\phi_{H\to L}$	0.40
Panel C: The process for λ_{2t}	
Average probability of disaster $\bar{\lambda}_2$	0.021
Mean reversion in disaster probability κ	0.08
Volatility for disaster probability σ_λ	0.067
Panel D: Inflation	
Expected inflation in the low-risk state $\bar{q}^L$	0.023
Expected inflation in the high-risk state $\bar{q}^L$	0.113
Mean reversion in expected inflation κ_q	0.09
Volatility for expected inflation σ_q	0.013
Volatility for realized inflation σ_P	0.008

Notes: Parameter values used in the simulation of the benchmark model. Parameters are expressed in annual terms.

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Table 4: Annual moments for aggregate market and riskfree rate

Panel A: Summary statistics

	Data	Simulation quantiles 0.05	0.5	0.95
$\mathbb{E}[R_{ft}]$	0.94	−4.37	0.47	2.64
$\sigma[R_{ft}]$	2.26	0.94	4.57	9.91
$\mathbb{E}[R^{\text{mkt}}_{t+1} - R_{ft}]$	6.73	4.39	8.32	14.21
$\sigma[R^{\text{mkt}}_{t+1} - R_{ft}]$	17.50	8.72	18.79	29.31
Sharpe Ratio	0.38	0.27	0.46	0.82
Skewness	−0.67	−2.46	0.81	3.95
$\exp(\mathbb{E}[pd])$	36.38	29.34	38.52	62.95
$\sigma(pd)$	0.40	0.11	0.25	0.51
AR1(pd)	0.91	0.52	0.82	0.96

Panel B: predictive regressions: 1-year ahead excess returns

	Data	Simulation quantiles 0.05	0.5	0.95
β_{pd}	0.07	−0.18	0.20	0.65
R^2	0.03	0.00	0.10	0.47

Panel C: predictive regressions: 5-year ahead excess returns

	Data	Simulation quantiles 0.05	0.5	0.95
β_{pd}	0.19	−0.80	0.69	1.57
R^2	0.06	0.01	0.29	0.76

Notes: The table reports statistics for the excess market return, the riskfree rate, and the price-dividend ratio in simulated and historical data from 1961–2009. Historical data are annual. Model-simulated data are daily, aggregated to an annual frequency. Panel A reports the mean ($\mathbb{E}[R^{\text{mkt}}_{t+1} - R_{ft}]$), the volatility, ($\sigma(R^{\text{mkt}}_{t+1} - R_{ft})$), the Sharpe ratio (mean divided by volatility), and the skewness, where $R^{\text{mkt}}_{t+1} - R_{ft}$ is the market return in excess of the riskfree rate. Similarly, $\mathbb{E}[R_{ft}]$ is the mean riskfree rate and $\sigma(R_{ft})$ is its volatility. We also report the exponentiated mean of the log annual price-dividend ratio pd, and its volatility and first-order autocorrelation. In the data, the market is the CRSP index. The moments of riskfree rate are computed using the realized real 30-day Treasury bill return, (i.e. the return on a 30-day Treasury bill minus realized inflation). Market excess returns are computed using the difference between the market return and the Treasury bill return. Panel B reports moments from predictive regressions. Specifically, we run the regression $\log R^{\text{mkt}}_{t:t+k} - r_{ft} = a + \beta_{pd} \times pd_t + \varepsilon_{t+1}$, where $R^{\text{mkt}}_{t:t+k}$ is the market return from time t to $t+k$, $r_{ft} = \log R_{ft}$ and pd_t is defined as the log price-dividend at time t. We run this regression for horizons of 1 and 5 years. For each simulated statistic, we report the median, the 5th, and the 95th percentile value. Units are in percentage per annum.

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Table 5: The equity premium and volatility, riskfree rate and VIX on announcement and non-announcement days

Statistic	Data	Simulation Median	90 % CI
$\mathbb{E}_a[RX_t^{\text{mkt}}]$	10.79	11.45	$[3.38, 17.87]$
$\sigma_a[RX_t^{\text{mkt}}]$	101.2	247.9	$[49.7, 449.1]$
$\mathbb{E}_n[RX_t^{\text{mkt}}]$	1.16	2.55	$[0.97, 5.09]$
$\sigma_n[RX_t^{\text{mkt}}]$	97.8	81.6	$[47.4, 124.6]$
$\mathbb{E}_a[RX_t^{\text{mkt}}] - \mathbb{E}_n[RX_t^{\text{mkt}}]$	9.63	9.06	$[-0.17, 15.37]$
$\sigma_a[RX_t^{\text{mkt}}] - \sigma_n[RX_t^{\text{mkt}}]$	3.4	154.7	$[-31.1, 377.1]$
$\mathbb{E}[R_{ft}]$	0.42	0.13	$[-2.00, 1.08]$
$\sigma[R_{ft}]$	1.14	2.4	$[0.4, 4.8]$
Pre-announcement VIX	20.1	26.1	$[22.4, 33.9]$
Post-announcement VIX	19.82	25.45	$[21.70, 33.39]$
VIX change on announcement days	-0.29	-0.61	$[-0.69, -0.48]$

Notes: $\mathbb{E}_a[RX_t^{\text{mkt}}]$ and $\mathbb{E}_n[RX_t^{\text{mkt}}]$ denote the average excess return on the market portfolio on announcement days and non-announcement days respectively. $\sigma_a[RX_t^{\text{mkt}}]$ and $\sigma_n[RX_t^{\text{mkt}}]$ denote analogous statistics for the standard deviation. $\mathbb{E}[R_{ft}]$ and $\sigma[R_{ft}]$ denote the unconditional average and standard deviation of the real riskfree rate. We use the the difference between the Federal Funds Rate and average realized inflation of the calendar month as the empirical proxy of the real daily riskfree rate. Pre-announcement VIX is defined as VIX at close one day before a scheduled announcement, while post-announcement VIX is the VIX at close of an announcement day. Their difference is defined as the change of VIX on announcement days. The first column reports the empirical estimate. The second column reports the median across samples simulated from the model. The third column reports the two-sided 90% confidence intervals from simulated samples. The units are in basis points per day.

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Table 6: Cross-sectional regressions on announcement and non-announcement days

Panel A: Equity Portfolios			
Coefficient	Data	Simulation Median	90 % CI
δ_a	10.30	11.95	$[1.33, 18.64]$
δ_n	1.23	1.75	$[0.14, 4.57]$
$\delta_a - \delta_n$	9.07	9.72	$[-2.21, 17.17]$
Panel B: Nominal Bonds			
Coefficient	Data	Simulation Median	90 % CI
δ_a	93.33	8.93	$[-341.35, 270.31]$
δ_n	-0.51	6.42	$[-505.30, 686.74]$
$\delta_a - \delta_n$	93.84	-6.19	$[-783.37, 736.38]$

Notes: For each sample, the regression $\mathbb{E}[RX_t^k \mid t \in i] = \delta_i \beta_i^k + \eta_i^k$ is estimated, where $i = a, n$ stands for sets of announcement and non-announcement days, respectively. These regressions are estimated for beta-sorted equity portfolios (Panel A) and for Treasury bonds (Panel B). The first column reports regression slopes in daily data from 1961.01-2016.09. The second column reports medians in simulated samples. The third column reports 90% confidence intervals computed using simulations.

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Table 7: Summary statistics for simulated equity assets

Panel A: Mean excess returns: announcement days						
Portfolio	1	2	3	4	5	6
Median	6.40	9.99	12.76	14.87	16.59	18.17
90% CI	[2.75, 9.76]	[3.78, 14.53]	[4.57, 19.39]	[5.32, 23.97]	[5.62, 28.62]	[5.44, 32.78]
Panel B: Mean excess returns: non-announcement days						
Portfolio	1	2	3	4	5	6
Median	2.03	2.31	2.60	2.87	3.09	3.28
90% CI	[0.90, 4.09]	[0.93, 4.67]	[1.06, 5.33]	[1.10, 5.93]	[1.15, 6.52]	[1.20, 7.05]
Panel C: Volatility: announcement days						
Portfolio	1	2	3	4	5	6
Median	120.69	223.80	314.73	398.68	477.68	550.08
90% CI	[33.85, 200.77]	[43.06, 378.24]	[49.24, 530.93]	[54.62, 668.70]	[59.72, 798.74]	[64.44, 916.98]
Panel D: Volatility: non-announcement days						
Portfolio	1	2	3	4	5	6
Median	54.91	70.07	81.42	93.51	106.19	120.37
90% CI	[31.49, 98.55]	[40.22, 121.06]	[46.25, 137.29]	[51.54, 155.52]	[56.36, 177.36]	[60.66, 199.95]

Notes: In this table, we report the summary statistics of the equity assets from simulated data. We report the distribution of mean excess returns and volatility of the assets on announcement and non-announcement days across simulated samples. The units are in basis points per day.

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Table 8: Difference in announcement and non-announcement day betas in simulated data

Panel A: Equity Portfolios						
Portfolio	1	2	3	4	5	6
Median	-0.15	0.01	0.07	0.20	0.33	0.42
90% CI	$[-0.31, 0.07]$	$[-0.16, 0.24]$	$[-0.00, 0.52]$	$[-0.01, 0.78]$	$[-0.07, 0.99]$	$[-0.17, 1.20]$
Panel B: Bonds						
Maturity	1	3	5	7	10	
Median	0.00	0.08	0.19	0.35	0.42	
90% CI	$[-0.00, 0.01]$	$[-0.01, 0.12]$	$[-0.02, 0.30]$	$[-0.03, 0.54]$	$[-0.04, 0.65]$	

Notes: In data simulated from the model, we compute betas on announcement days and non-announcement days. We do this for beta-sorted equity portfolios (Panel A) and for zero-coupon bonds (Panel B). The table reports the median difference and 90% confidence intervals for the difference.

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Table 9: Statistics on the implied volatility surface

Moneyness	0.87	0.94	0.99	1.02	Slope
Announ. days	26.80	21.11	17.75	16.62	10.18
Pre-announ. days	27.09	21.41	17.98	16.72	10.37
Change	−0.29	−0.30	−0.23	−0.10	−0.19
t-stat	[−3.73]	[−4.34]	[−3.30]	[−0.80]	[−2.03]

Notes: We report the summary statistics of the average 30-day implied volatility surface computed using put options on the index. The surfaces are computed using the closing prices of each trading day. The pre-announcement days are the trading days right before the pre-scheduled macro-economic announcements. The option's delta is defined as the sensitivity of the option price relative to the underlying asset, or the change in option price per unit change of underlying asset price. The implied volatility slope is defined as the difference between the implied volatilities of options with delta -0.8 and -0.1. The volatilities are in units of percentage per annum. The sample period is 1996.01 to 2016.12.

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Table 10: Parameter values for the model with frequent and minor Poisson events

Panel A: Basic parameters	
Expected normal-times growth in consumption μ, (%)	3.06
Expected normal-times growth in dividend μ_D, (%)	6.83
Volatility of consumption growth σ(%)	2.53
Rate of time preference β	0.012
Relative risk aversion γ	8.70
Average leverage ϕ	5.10
Panel B: The process for λ_{1t}	
Probability of disaster in the low-risk state λ^L	0
Probability of disaster in the high-risk state λ^H	8.73
Probability of switching to high-risk state $\phi_{L\to H}$	0.06
Probability of switching to low-risk state $\phi_{H\to L}$	1.10
Panel C: The process for λ_{2t}	
Probability of disaster $\bar{\lambda}_2$	0.979

Notes: In this table, we report an alternative calibration in which announcements pertain to frequent, minor Poisson events, and normal-times volatility is due to cash flow volatility.

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Table 11: The equity premium and volatility on announcement and non-announcement days when Poisson events are frequent and minor

Statistic	Data	Simulation Median	90 % CI
$\mathbb{E}_a[RX_t^{\text{mkt}}]$	10.79	9.92	$[1.71, 16.87]$
$\sigma_a[RX_t^{\text{mkt}}]$	101.2	220.1	$[117.8, 305.5]$
$\mathbb{E}_n[RX_t^{\text{mkt}}]$	1.16	1.16	$[-0.29, 2.81]$
$\sigma_n[RX_t^{\text{mkt}}]$	97.8	102.6	$[96.7, 110.5]$
$\mathbb{E}_a[RX_t^{\text{mkt}}] - \mathbb{E}_n[RX_t^{\text{mkt}}]$	9.63	8.92	$[-0.27, 15.76]$
$\sigma_a[RX_t^{\text{mkt}}] - \sigma_n[RX_t^{\text{mkt}}]$	3.4	116.6	$[18.9, 200.9]$
$\mathbb{E}[R_{ft}]$	0.42	0.91	$[0.58, 1.08]$
$\sigma[R_{ft}]$	1.14	0.8	$[0.0, 1.3]$
Pre-announcement VIX	20.1	18.4	$[18.1, 19.2]$
Post-announcement VIX	19.82	18.15	$[17.96, 18.52]$
Change on announcement days	-0.29	-0.39	$[-0.89, -0.13]$

Notes: In this table report the simulation result of our model based on a calibration in which announcements pertain to frequent, minor Poisson events, and normal-times volatility is due to cash flow volatility. $\mathbb{E}_a[RX_t^{\text{mkt}}]$ and $\mathbb{E}_n[RX_t^{\text{mkt}}]$ denote the average excess return on the market portfolio on announcement days and non-announcement days respectively. $\sigma_a[RX_t^{\text{mkt}}]$ and $\sigma_n[RX_t^{\text{mkt}}]$ denote analogous statistics for the standard deviation. We use the the difference between the Federal Funds Rate and average realized inflation of the calendar month as the empirical proxy of the real daily riskfree rate. The VIX is the risk-neutral volatility of the market portfolio. The first column reports the empirical estimate. The second column reports the median across samples simulated from the model. The third column reports the two-sided 90% confidence intervals from simulated samples. For riskfree rate, we use realized riskfree rate to compute the mean. The units for market portfolio and risk-free rate moments are in basis points per day, while VIX is reported in percentage per annum.

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Table 12: Parameter values for a model with normally distributed news on announcements.

Expected normal-times log growth in consumption $\bar{\mu}(\%)$	2.5
Consumption volatility on non-announcement days $\sigma_{c,n}(\%)$	15.15
Consumption volatility on announcement days $\sigma_{c,a}(\%)$	15.31
Consumption growth volatility on non-announcement days $\sigma_{\mu,n}(\%)$	0.186
Consumption growth volatility on non-announcement days $\sigma_{\mu,a}(\%)$	3.21
Persistence of consumption growth ρ	0.836
Rate of time preference β	0.97
Relative risk aversion γ	1.2
EIS ψ	1.001
Log-linearizing constant κ_1	0.965

Notes: In this table, we report the parameter values used for a model with normally distributed news on announcements. All parameters are in annual terms, except $\sigma_{\mu,n}$ and $\sigma_{\mu,a}$, which pertain to daily consumption growth.

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Table 13: The equity premium and volatility on announcement and non-announcement days in a model with normally-distributed announcement news.

Statistic	Data	Simulation Median	90 % CI
$\mathbb{E}_a[RX_t^{\text{mkt}}]$	10.79	11.98	$[7.20, 16.58]$
$\sigma_a[RX_t^{\text{mkt}}]$	101.2	101.41	$[97.78, 105.25]$
$\mathbb{E}_n[RX_t^{\text{mkt}}]$	1.16	1.19	$[-0.26, 2.65]$
$\sigma_n[RX_t^{\text{mkt}}]$	97.8	97.87	$[96.22, 99.58]$
$\mathbb{E}_a[RX_t^{\text{mkt}}] - \mathbb{E}_n[RX_t^{\text{mkt}}]$	9.63	10.71	$[5.57, 15.49]$
$\sigma_a[RX_t^{\text{mkt}}] - \sigma_n[RX_t^{\text{mkt}}]$	3.4	3.91	$[0.20, 7.51]$
$\mathbb{E}[R_{ft}]$	0.42	2.10	$[-116.52, 136.80]$
$\sigma[R_{ft}]$	1.14	147.20	$[103.96, 209.51]$
Pre-announcement VIX	20.1	15.20	
Post-announcement VIX	19.82	15.18	
VIX change on announcement days	−0.28	−0.02	

Notes: In this table, we report the simulated moments for the model of Savor and Wilson (2013). $\mathbb{E}_a[RX_t^{\text{mkt}}]$ and $\mathbb{E}_n[RX_t^{\text{mkt}}]$ denote the average excess return on the market portfolio on announcement days and non-announcement days respectively. $\sigma_a[RX_t^{\text{mkt}}]$ and $\sigma_n[RX_t^{\text{mkt}}]$ denote analogous statistics for the standard deviation. We use the the difference between the Federal Funds Rate and average realized inflation of the calendar month as the empirical proxy of the real daily riskfree rate. The VIX is the risk-neutral volatility of the market portfolio. The first column reports the empirical estimate. The second column reports the median across samples simulated from the model. The third column reports the two-sided 90% confidence intervals from simulated samples. For riskfree rate, we use realized riskfree rate to compute the mean. The units for market portfolio and risk-free rate moments are in basis points per day, while VIX is reported in percentage per annum.

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