Fluctuating Attention and Financial Contagion☆

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Abstract

Financial contagion occurs when return and volatility transmit between fundamentally unrelated sectors. We develop an equilibrium model showing that contagion arises because investors pay fluctuating attention to news. As a negative shock hits one sector, investors pay more attention to it. This raises the volatility of equilibrium discount rates resulting in simultaneous spikes in cross-sector correlations and volatilities. We test the economic mechanism of our model on fundamentally unrelated U.S. industries, which we identity using their customer-supplier relationships. Consistent with the model's predictions, empirical evidence shows that fluctuating attention generates return and volatility spillovers between fundamentally unrelated industries.

Keywords: Learning, Attention to News, Contagion, Return and Volatility Spillovers

JEL classification: D51, G12

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1. Introduction

Contagion in financial markets has been extensively documented in the empirical literature (e.g., Hamao et al., 1990; Lin et al., 1994).[1] Indeed, there is ample evidence of return and volatility spillovers between two fundamentally unrelated securities. Such phenomena have become increasingly important in light of the subprime and sovereign debt crises. This is because simultaneous spikes in return volatilities and cross-return correlations significantly alter risk management strategies, optimal portfolio choices, and the trading of derivatives.

In this paper, we provide theoretical and empirical evidence that investors' fluctuating attention to news is an important channel through which contagion arises in financial markets. We show that when investors' attention to a particular sector increases, risk-adjusted discount rates become more volatile. As a result, return volatilities and cross-return correlations increase simultaneously in the entire market, despite the fact that cash-flows and news associated to each sector are independent from one another.

We consider a pure-exchange economy *à la* Lucas (1978) with two risky assets—*sectors*—that are claims to two exogenous and independent dividend streams. The economy is populated by a representative investor who needs to estimate both unobservable expected dividend growth rates (henceforth *fundamentals*). The investor has two different types of relevant information at hand: information provided by the observation of dividends, and information provided by the observation of news. The key innovation here is that the investor pays fluctuating attention to news, which is supported by recent empirical evidence in Fisher et al. (2017) and Rossi and Gargano (2017).[2] In other words, there are periods when she is well focused and capable of processing many news sources, and periods when she is not. Motivated by the findings of Andrei and Hasler (2015), we let investor's attention to a given sector depend on the past performance of that sector's dividend growth. We emphasize that attention to one sector is independent from attention to the other sector because their dividend dynamics are independent.

[1] See also King and Wadhwani (1990), King et al. (1994), Karolyi and Stulz (1996), Fleming et al. (1998), Kaminsky and Reinhart (2000), Bae et al. (2003), Bekaert et al. (2005), Kallberg and Pasquariello (2005, 2008), Barberis et al. (2005), Boyer et al. (2006), and Diebold and Yilmaz (2009).

[2] See also Da et al. (2011), Vlastakis and Markellos (2012), and Sicherman et al. (2015).

We fit the model to the realized and expected real dividend growth rates of U.S. industry sectors. We define industries following the Fama-French 48 (FF48) industry classification and fit the model using maximum likelihood. This estimation allows us to examine how investor attention changes following dividend growth shocks. We find that attention increases following negative dividend growth shocks, and decreases following positive shocks. This finding is consistent with recent empirical findings. For instance, the media attention measures of Fisher et al. (2017) increase following adverse fundamental shocks. The attention to financial and economic news index of Andrei and Hasler (2015) spikes during the recent financial crisis. Vlastakis and Markellos (2012) and Goddard et al. (2015) find a positive relation between attention and volatility in the cross-section of U.S. stocks and exchanges rates, respectively.

The model estimation also allows us to extract the monthly time series of investor attention to each industry, which we later use to empirically test the model's predictions. We illustrate that these model-implied attention measures are indeed capturing time-varying investor attention in a number of ways. For instance, Fisher et al. (2017) and Gargano and Rossi (2017) show that stock trading volume and investor attention are positively and strongly related. We find strong evidence in support of their findings using our model-implied attention measures. Dellavigna and Pollet (2009) find that post-earnings-announcement drifts (PEAD) are much stronger for Friday earnings announcements when investor attention is likely lower. We reach a similar conclusion by finding that PEAD is significantly stronger when our model-implied attention measures are relatively lower. Consistent with the model's prediction, we also find that future uncertainty, proxied by the absolute analysts' forecast error on real GDP growth (van Nieuwerburgh and Veldkamp, 2006), is inversely related to the current model-implied attention.

The model predicts that fluctuating attention implies return and volatility spillover effects among fundamentally unrelated sectors. The intuition is as follows. As a negative shock hits one sector, more attention is paid to news on that sector. Since the content of news is used to estimate the economic fundamental, a rise in attention implies a faster transmission of news, thereby increasing the volatility of that sector's estimated fundamental. In equilibrium, a more volatile estimated fundamental endogenously generates more volatile equilibrium discount rates. This in turn implies increases in the volatility of the sector hit by the shock, the volatility of the sector that is unrelated to it, and the cross-sector return correlation. The key mechanism of how shocks propagate from one sector to another is therefore through attention and discount rates.

We put our model to the test by examining financial contagion among unrelated sectors in the U.S. equity market from 1972 through 2015. Our goal is to examine contagion between FF48 industries that are likely to be fundamentally unrelated to one another. We use firms' customer-supplier relationships information constructed from the COMPUSTAT Segment Customer File to identify a network of their suppliers and customers. For any two firms to be considered fundamentally unrelated, they must belong to different industries and must have at least six degrees of separation between them in the customer-supplier relationships database. To obtain a fundamentally unrelated industry pair, we require that less than 5% of firms in the first industry are fundamentally related to firms in the second industry, and vice versa. Using this method, we are able to identify 18 unique pairs of fundamentally unrelated industries.

We empirically test the model's predictions on these 18 pairs of unrelated industries. We use a panel-regression framework that examines how monthly changes in investor attention affect industry return volatilities and cross-industry return correlations. Industry return volatilities and correlations are calculated using the exponentially-weighted moving-average (EWMA) model, and investor attention measures to each industry are obtained from the model-implied estimates through maximum likelihood.

The model predicts that fluctuating attention generates volatility spillovers and return spillovers between two fundamentally unrelated sectors. We confirm these empirical predictions. We find that an increase in attention to one industry leads to an increase in its return volatility as well as in the return volatility of its unrelated industry. Moreover, we find that the returns of two unrelated industries are more positively correlated when attention to one of the two industries increases.

This paper contributes to two strands of literature. The first is that examining how contagion arises in financial markets. It is generally difficult to explain both return and volatility spillover effects in a unified general equilibrium framework. For instance, in Cochrane et al.

(2008) return volatilities and the cross-return correlation are driven by dividend shares. An increase in the dividend share of one sector mechanically decreases that of the other causing volatilities to move in opposite directions. Therefore, although the model implies a positive correlation, it cannot generate simultaneous increases in volatilities and correlation. Yuan (2005) shows that asymmetric information and financial constraints lead to contagion. In Pasquariello (2007), contagion is implied by asymmetric information and systemic risk. In these two studies, contagion is defined as the correlation in excess of a benchmark model. Such definition differs from ours in that we require return volatilities and cross-return correlations of fundamentally unrelated sectors to increase simultaneously. Using the same definition of contagion as ours, Kyle and Xiong (2001) show that contagion is implied by wealth effects. In contrast, our paper shows both theoretically and empirically that investors' fluctuating attention to news leads to financial contagion.

Our paper also contributes to the literature examining how investor attention affects asset prices. Huberman and Regev (2001) provide evidence that new information can only influence prices if investors pay attention to it. Dellavigna and Pollet (2009) find the post-earnings announcement drift is particularly strong subsequent to Friday announcements, suggesting that inattention delays the incorporation of information into prices. Da et al. (2011) provide evidence that attention predicts short-term stock returns. Garcia (2013) shows that news explain market returns better in recessions than in expansions, suggesting that investors' attention to news concentrates in down markets. Andrei and Hasler (2015) find that stock market volatility and risk premia increase with both investors' attention and uncertainty. Peng and Xiong (2006) show that investors optimally gather market and industry-specific information as opposed to firm-specific information when their information processing capacity is constrained. van Nieuwerburgh and Veldkamp (2010) show that investors with limited information processing capacity optimally learn about a subset of assets only, leading to under-diversification.[3] Veldkamp (2006a) and Veldkamp (2006b) show that optimal information acquisition helps explain the positive co-movement among assets and stock market frenzies, respectively. Andrei and Hasler (2017) show that optimal attention

[3] In a similar framework, Mondria and Quintana-Domeque (2013) show that high cash-flow volatility in one market attracts attention to that market, and therefore implies a low asset price in the other market.

to news is highest when the stock return predictor is far away from its mean. It is important to note that information acquisition is endogenous and optimal in the last five studies, whereas it is modeled in reduced form (exogenous) in our framework. By showing the effect of fluctuating attention on the cross-section of returns and volatilities, our paper adds a new and complementary contribution to this literature.

The remainder of the paper is organized as follows. Section 2 describes the model and derives the equilibrium variables. Section 3 exposes the model's predictions. Section 4 discusses our empirical tests and results. Section 5 concludes. Derivations and computational considerations are provided in the appendix.

2. The Economy

In this section, we describe the economic environment as well as the learning and optimization problems faced by a representative investor who pays fluctuating attention to news. We then solve the learning and optimization problems and characterize the corresponding equilibrium asset prices.

We consider an infinite horizon economy populated by a representative investor who consumes the sum of two output streams (henceforth the *dividends*) with unobservable expected growth rates (henceforth the *fundamentals*). All quantities are expressed in units of a single perishable good with price equal to unity. The set of securities available for investment consists in one riskless asset in zero net supply and two risky assets (stocks) in positive supply of one unit. The riskless asset is locally deterministic and pays a riskless rate r to be determined in equilibrium. The two stocks are claims to the exogenous dividends δ_1 and δ_2 and have prices P_1 and P_2, respectively. Dividends dynamics are written as

$$\frac{d\delta_{it}}{\delta_{it}} = f_{it}dt + \sigma_\delta dW^\delta_{it}, \quad i \in \{1, 2\} \tag{1}$$

where $\left(W^\delta_1, W^\delta_2\right)^\top$ is a standard Brownian motion.

Although the investor does not observe fundamentals f_1 and f_2, she knows that these processes follow

$$df_{it} = \lambda(\bar{f} - f_{it})dt + \sigma_f dW^f_{it}, \;\; i \in \{1, 2\} \tag{2}$$

where $\left(W^f_1, W^f_2\right)^\top$ is a standard Brownian motion. Hence fundamentals mean-revert to their long-term means $\bar{f}$ at speed λ.

The investor has four pieces of information available to estimate the value of the fundamentals. The first two pieces consist in the dividend growth rates $\frac{d\delta_1}{\delta_1}$ and $\frac{d\delta_2}{\delta_2}$. Because fundamentals drive dividends, observing dividend growth rates provides valuable information about the level of fundamentals.

The remaining two pieces of information are signals denoted by s_1 and s_2. Their dynamics are

$$ds_{it} = \Phi_{it} dW^f_{it} + \sqrt{1 - \Phi^2_{it}} dW^s_{it}, \;\; i \in \{1, 2\} \tag{3}$$

where $\Phi_1, \; \Phi_2 \in (0, 1)$ represent fluctuating accuracies of the signals. We assume that Brownian shocks in Equations (1)-(3) are independent. This assumption implies that markets are perfectly symmetric and fundamentally unrelated, which allows us to precisely determine the mechanism leading to contagion.

The dynamics of the information signals in Equation (3) are motivated as follows. Assume the investor collects $m_{it}, \; i \in \{1, 2\}$ signals $s^j_{it}, \; j = 1, \ldots, m_{it}$ at time t. s^j_i is the j-th noisy signal providing information on fundamental i. For simplicity, let assume that accuracies of these individual signals are given by a similar process as follows $ds^j_{it} = a dW^f_{it} + \sqrt{1 - a^2} dW^j_{it}$, where $0 < a < 1$ is the accuracy of the individual signals and all Brownian motions are uncorrelated. By aggregating, the investor can summarize these m_i sources of information into two signals s_i whose dynamics are

$$ds_{it} = \Phi_{it} dW^f_{it} + \sqrt{1 - \Phi^2_{1t}} dW^s_{it}, \tag{4}$$

where $\Phi_{it} = \frac{a}{\sqrt{\frac{1}{m_{it}}(1 + (m_{it} - 1)a^2)}}$. Comparing (3) and (4) shows that both specifications are equivalent. That is, the investor can change the accuracy of information Φ_i by choosing the number of signals m_i she acquires. When the investor is very attentive to news, the number of individual signals collected is large and leads to high accuracy. When the investor is inattentive to news, the number of signals acquired is small and leads to low accuracy. For this reason, we call Φ_i the *attention* to news associated to stock i.

Our specification for the information signal in (3) follows that in Scheinkman and Xiong (2003), Dumas et al. (2009), and Xiong and Yan (2010). It shows that signals, s_1 and s_2, provide information on the unexpected shocks driving fundamentals and not on their levels, as in Detemple and Kihlstrom (1987) and Veronesi (2000) among others. Although we adopt the former specification, our results also hold under the alternative.

2.1. Definition of Fluctuating Attention

Attention to stock i is defined as follows:

$$\Phi_{it} = \frac{\Psi}{\Psi + (1-\Psi)e^{\Lambda \pi_{it}}}, \quad i \in \{1, 2\} \tag{5}$$

$$\pi_{it} = \int_0^t e^{-\omega(t-u)} \left(\frac{d\delta_{iu}}{\delta_{iu}} - \widehat{f}_{iu} du \right), \tag{6}$$

where $\Psi > 0$, $\omega > 0$, $\Psi > 0$, and $\Lambda \in \mathbb{R}$.

The parameter Ψ is the long-run level of attention paid to each stock. Attention paid to stock i depends on the process π_i, which measures the performance of dividend i's past growth rate relative to the investor's estimate of the fundamental, $\widehat{f}_i$.[4,5] For this reason, we refer to π_i as dividend i's *performance index*. In order to map the level of the performance index, $\pi_i \in \mathbb{R}$, to the level of attention, $\Phi_i \in (0, 1)$, we use the logistic transformation as described in Equation (5).

The coefficient Λ indicates how the level of attention Φ_i changes in relation to the dividend performance index π_i. If Λ is positive, a positive shock to π_i, i.e., a positive dividend growth surprise, decreases the level of attention. That is, attention decreases when the investor underestimates the dividend growth rate (when $\widehat{f}_i < d\delta_i/\delta_i$). If Λ is negative, a positive

[4]The dividend performance index is inspired by Koijen et al. (2009) who assume that expected stock returns depend on the past performance of realized returns.

[5]The investor's estimate of the fundamental, $\widehat{f}_i$, is described in details in Section 2.2.

shock to π_i increases Φ_i, implying that attention increases when the investor underestimates the growth rate. The magnitude of Λ determines the range of attention. If Λ is large, attention effectively belongs to the entire interval $(0, 1)$. If instead Λ is relatively small, the range of attention is narrow. If Λ is zero, attention is constant and equal to the long-run level Ψ.

The parameter ω in (6) controls the importance of past dividend growth surprises relative to the current dividend growth surprise. If ω is small, past dividend surprises matter in the determination of the current performance index. If instead ω is large, past realizations of dividend surprises do not significantly alter the value of the performance index. Applying Itô's lemma to Equation (6) yields the following dynamics for the performance indices

$$d\pi_{it} = -\omega\pi_{it}dt + \sigma_\delta dW_{it}, \quad i \in \{1, 2\}, \tag{7}$$

where $dW_{it} = \frac{1}{\sigma_\delta}\left(\frac{d\delta_{it}}{\delta_{it}} - \widehat{f}_i dt\right)$ is dividend i's scaled surprise at time t. The dynamics of the performance indices in (7) show that π_i reverts to 0 at speed ω.

Equations (5) and (6) show a one-to-one mapping between attention and dividend performance indices. Thus, attention is observable and the vector of state variables is conditionally Gaussian. This implies that standard Bayesian filtering techniques can be applied to our model, a task that we undertake in the next section.

2.2. Filtered State Variables

The investor learns about the fundamental f_i, $i \in \{1, 2\}$ by observing two different sources of information: the dividend δ_i and the signal s_i.[6] Proposition 1 describes the dynamics of the state variables inferred using these two sources of information.

Proposition 1. *Following Liptser and Shiryaev (2001), the dynamics of the state variables inferred by the investor satisfy*

[6] Note that the dividend performance index π_i, or equivalently the attention process Φ_i, does not provide more information than the dividend δ_i and is therefore not part of the filtering problem.

$$\frac{d\delta_{it}}{\delta_{it}} = \widehat{f}_{it}dt + \sigma_\delta dW_{it}, \tag{8}$$

$$d\widehat{f}_{it} = \lambda(\bar{f} - \widehat{f}_{it})dt + \frac{\gamma_{it}}{\sigma_\delta}dW_{it} + \sigma_f \Phi_{it} dW_{i+2,t}, \tag{9}$$

$$d\pi_{it} = -\omega\pi_{it}dt + \sigma_\delta dW_{it}, \tag{10}$$

$$d\gamma_{it} = \left(-\frac{\gamma_{it}^2}{\sigma_\delta^2} - 2\lambda\gamma_{it} + \sigma_f^2\left(1 - \Phi_{it}^2\right)\right)dt, \qquad i \in \{1, 2\}. \tag{11}$$

The 4-dimensional innovation process W is a standard Brownian motion defined by

$$dW_t \equiv \begin{pmatrix} dW_{1t} & dW_{2t} & dW_{3t} & dW_{4t} \end{pmatrix}^\top = \begin{pmatrix} \frac{1}{\sigma_\delta}\left(\frac{d\delta_{1t}}{\delta_{1t}} - \widehat{f}_{1t}dt\right) & \frac{1}{\sigma_\delta}\left(\frac{d\delta_{2t}}{\delta_{2t}} - \widehat{f}_{2t}dt\right) & ds_{1t} & ds_{2t} \end{pmatrix}^\top. \tag{12}$$

Proof. See Theorem 12.7 in Liptser and Shiryaev (2001).

The dynamics of the dividend process in (8) follow closely those in (1), but with the filtered fundamental $\widehat{f}_i$ replacing the true fundamental f_i. The dynamics of the filtered fundamentals, however, differ from those in Equation (2). When the investor learns about the fundamental by observing the dividend and the signal, the dynamics in Equation (9) show that the volatility of the filtered fundamental is stochastic and driven by two components. The first, $\gamma_{it} \equiv \mathbb{E}\left((f_{it} - \widehat{f}_{it})^2 | \mathcal{O}_t\right)$, is the *uncertainty* about the current value of the fundamental given the investor's current observation filtration. The second is *attention* Φ_i.

Looking at Equations (9) and (12), we see that uncertainty loads on the dividend innovation while attention loads on the news signal innovation. As attention increases, the investor perceives the news source as more important relative to the dividend source. Conversely, reduced attention pushes the investor to weigh the information content of the dividend more than that of the news signal. This naturally implies that an increase (decrease) in attention weakens (strengthens) the correlation between dividends and fundamentals.

The dynamics in Equation (11) show that attention also impacts the level of uncertainty. As attention increases, the investor gathers more accurate information. Therefore, the learning procedure becomes more efficient and uncertainty decreases. Conversely, as attention drops investors acquire less accurate information and uncertainty rises. For sufficiently high (low) attention level, the third component in Equation (11) decreases (increase) enough to generate lower (higher) uncertainty. Interestingly, there is a lag between a change in attention and a change in uncertainty because uncertainty is locally deterministic. That is, high attention implies low future uncertainty, whereas low attention is followed by high uncertainty.

2.3. Equilibrium

The representative investor has CRRA utility over consumption. Since the investment horizon is assumed to be infinite, the investor maximizes her expected lifetime utility of consumption subject to a budget constraint

$$\begin{aligned}&\sup_{C,h} \mathbb{E}_t \left(\int_t^{\infty} e^{-\Delta(s-t)} \frac{C_s^{1-\alpha}}{1-\alpha} ds \right) \\ &\text{s.t } dV_t = \left(r_t V_t + h_t \text{diag}\left(P_t\right)\left(\mu_t - r_t \mathbb{1}_{2\times 1}\right) - C_t\right) dt + h_t \text{diag}\left(P_t\right) D_t dW_t,\end{aligned}$$

where C is consumption, V is wealth, μ is the 2×1 vector of expected stock returns, h is the 1×2 vector of risky asset holdings, D is the 2×4 matrix of stock return diffusion, Δ is the subjective discount rate, and α is the coefficient of relative risk aversion. The risk-free rate r and the 2×1 vector of stock prices P are determined in equilibrium.

Solving the optimization problem and clearing markets yields the following state-price density

$$\xi_t = e^{-\Delta t} \left(\frac{C_t}{C_0} \right)^{-\alpha} = e^{-\Delta t} \left(\frac{\delta_{1t} + \delta_{2t}}{\delta_{1,0} + \delta_{2,0}} \right)^{-\alpha}. \tag{13}$$

Equation (13) shows that the state-price density depends on dividend 1 and dividend 2. As either fundamental 1 or fundamental 2 increases, the expected value of discount factors decreases or, in other words, the expected discount rates increase. As will be explained further, the interactions between fundamentals and discount rates implied by fluctuating attention to news are key determinants of the contagion phenomenon.

Since the state-price density ξ prices future cash-flows, the price P_i^T of a security paying a single-dividend δ_{iT} at time T is defined by

$$P_{it}^T = e^{-\Delta(T-t)}\mathbb{E}_t\left(\left(\frac{\delta_{1T}+\delta_{2T}}{\delta_{1t}+\delta_{2t}}\right)^{-\alpha}\delta_{iT}\right).$$

Proposition 2 characterizes the price of the single-dividend paying securities.

Proposition 2. *At time t, the prices P_{1t}^T and P_{2t}^T of the securities paying the single-dividends δ_{1T} and δ_{2T} at time T satisfy*

$$P_{1t}^T = e^{-\Delta(T-t)}e^{\alpha(\zeta_{1t}-Q_t)}\mathbb{E}_t\left(e^{(1-\alpha)\zeta_{1T}+\alpha Q_T}\right) \tag{14}$$

$$P_{2t}^T = e^{-\Delta(T-t)}e^{\alpha(\zeta_{1t}-Q_t)}\mathbb{E}_t\left(e^{(1-\alpha)\zeta_{1T}+(\alpha-1)Q_T}\right) - P_{1t}^T, \tag{15}$$

where $\zeta_i \equiv \log\delta_i$ is the log-dividend, and $Q = \log\frac{\delta_1}{\delta_1+\delta_2}$ the log-dividend share.

Proof. See Appendix D.

The stock price $P_{it},\ i \in \{1,2\}$ at current time t is defined as the sum of the single-dividend paying securities P_{it}^T over maturities T

$$P_{it} = \int_t^\infty P_{it}^T dT. \tag{16}$$

Equations (14) and (15) show that the single-dividend paying securities are determined by moment-generating functions (henceforth *transforms*) of the vector $(\zeta_1, Q)^\top$. Computing these transforms is challenging, as the vector of state variables is not affine-quadratic. Appendix E exposes a simple methodology that allows us to accurately approximate them.

2.4. Model Calibration

We fit the model to the realized and expected real dividend growth rates of U.S. industry sectors using maximum likelihood. We define industries following the Fama-French 48 (FF48) industry classification. The data is available at the monthly frequency from 08/1972 to 08/2015. Details on the data and the estimation are provided in Appendix C.

Table 1 reports the parameter estimates obtained from the model calibration. Consistent with the estimation performed by Andrei and Hasler (2015) on real GDP growth rates, the parameter Λ is positive and significant, suggesting that the investor is more attentive to news when the dividend performance index is low than when it is high. We find that the estimate for ω is 0.122. This estimate implies that the dividend performance index in Equation (6) assigns an 85% weight to the past 15 years of dividend surprise observations.[7] Our estimate of ω, therefore, indicates that dividend surprises observed more than 15 years ago have little impact on current attention.

The maximum likelihood estimation allows us to extract the monthly time series of model-implied attention to each of the Fama-French 48 industries. Their time series are depicted in Appendix F. We later use these calibrated attention measures as our proxies for investor attention when testing the model's predictions in Section 4.

[Insert Table 1 about here.]

3. Model Implications

In this section, we investigate the implications of fluctuating attention on the dynamics of return volatilities and cross-return correlation between two fundamentally unrelated stocks. We show that increased attention to one stock raises return volatilities on both stocks, as well as their cross-return correlation. That is, fluctuating attention implies return and volatility spillover effects among fundamentally unrelated stocks.

3.1. Volatility Spillovers

In order to understand the mechanism leading to contagion, let us first characterize the components of the stock return diffusion. Since the innovation process (12) driving the filtered state variables consists of four components, applying Itô's lemma to stock prices in (16) yields the following stock return diffusion matrix D

$$D \equiv \begin{pmatrix} D_{11} & D_{12} & D_{13} & D_{14} \\ D_{21} & D_{22} & D_{23} & D_{24}, \end{pmatrix},$$

[7] Note that the weights assigned to the past 7, 10, 15, and 20 years of dividend surprise observations are about 60%, 70%, 85%, and 90%, respectively.

where D_{ij} is the j-th component of the return diffusion of stock i. The components of the diffusion matrix D are provided in Proposition 3 below.

Proposition 3. *The diffusion components of stock i satisfy*

$$D_{i1} = \frac{P_{i\widehat{f}_1}}{P_i}\frac{\gamma_1}{\sigma_\delta} + \sigma_\delta\left(1 + \frac{P_{i\pi_1}}{P_i} + \frac{P_{iQ}}{P_i}\left(1 - e^Q\right)\right), \quad D_{i2} = \frac{P_{i\widehat{f}_2}}{P_i}\frac{\gamma_2}{\sigma_\delta} + \sigma_\delta\left(\frac{P_{i\pi_2}}{P_i} + \frac{P_{iQ}}{P_i}\left(e^Q - 1\right)\right),$$

$$D_{i3} = \frac{P_{i\widehat{f}_1}}{P_i}\sigma_f\Phi_1, \qquad D_{i4} = \frac{P_{i\widehat{f}_2}}{P_i}\sigma_f\Phi_2,$$

where P_{iy} stands for the derivative of stock i with respect to the state variable y.

For brevity, we drop the time t notation when writing the stock price P_i and its partial derivative P_{iy} with respect to state y. Nevertheless, we note that all notations regarding the stock price should be referenced against the current time t.

Definition 1. *The return variance of stock i, σ_i^2, satisfies*

$$\sigma_i^2 = \sum_{j=1}^{4} D_{ij}^2,$$

where the component of the stock return diffusion D_{ij} is provided in Proposition 3.

Proposition 3 and Definition 1 show that a change in attention to stock 1 impacts the return volatility of both stock 1 and stock 2 through the stock return diffusion component D_{i3}. The significance of the impact is determined by the sensitivity of stock prices P_1 and P_2 to a shock in the filtered fundamental $\widehat{f}_1$. The properties of the sensitivity, $P_{i\widehat{f}_1}$, are discussed below.

A positive shock in the filtered fundamental $\widehat{f}_1$ has two opposite effects on stock 1. First, dividend δ_1 is expected to increase. This is the *direct channel*. Second, discount rates rise (see Equation (13)), which represent the *indirect channel*. The direct channel pushes stock price P_1 up, while the indirect channel pushes stock price P_1 down. As explained in Veronesi (2000), the indirect discounting channel is stronger than the direct dividend channel as long as risk aversion is sufficiently large. Indeed, an increase in expected future consumption increases current consumption because the investor smoothes consumption over time. This implies that savings/investments decrease as do the demands for risky assets and the riskless asset. As a result, the prices of stock 1 and stock 2 decline while the risk-free rate rises. The decline in stock price P_2 is more pronounced than the decline in stock price P_1 because stock 2 is only impacted by the discounting effect. Note that if the representative agent had either a risk aversion smaller than one or recursive utility (Epstein and Zin, 1989) with an elasticity of intertemporal substitution larger than one, then stock 1 would be more sensitive to a change in fundamental 1 than stock 2.

[Insert Figure 1 about here.]

Figure 1 illustrates the relationship between the return volatilities of both stocks and attention to stock 1. As attention to stock 1 increases, both return volatilities increase. That is, fluctuating attention implies volatility spillover effects. The volatility of stock 2 increases more than that of stock 1 because stock 2 is influenced by the indirect discounting channel only. Regarding stock 1, the direct channel of dividend δ_1 dampens the indirect discounting channel and therefore implies a weaker increase in its volatility. Symmetrically, the volatility of stock 1 increases more than that of stock 2 as attention to stock 2 increases.

Overall, an increase in attention to any stock leads to contagion in the form of increased return volatility of each stock. A consequence of this result is that an increase in aggregate attention $\Phi_1 + \Phi_2$ also implies an increase in each stock return volatility.

[Insert Table 2 about here.]

While Figure 1 describes the static relationship between attention and volatilities, we next examine how stock return volatilities react to a change in attention in a dynamic setting. Such analysis is useful for understanding the economic relevance of fluctuating attention on volatilities under the presence of noises generated by the other state variables. We simulate the model at the monthly frequency for 50 years, using the parameters and initial variables reported in Table 1. Table 2 shows the dependence of stock return volatilities on attention paid to stocks 1 and 2 as well as on aggregate attention. Consistent with the results of Figure 1, stock return volatilities increase with attention to stock 1 and attention to stock 2. All coefficients are positive and significant at the 1% level, which shows that volatility spillovers are statistically detectable and strong. Furthermore, there is a positive and statistically significant relationship between the volatilities of both stocks and aggregate attention. Overall, these results show that, although volatilities are also influenced by the other state variables of the model, the impact of these other state variables is not strong enough to make attention-driven volatility spillovers statistically insignificant.

3.2. Return Spillovers

We now turn to the relationship between attention and the co-movement of stock returns. The covariance and correlation between returns of stock 1 and stock 2 are described in Definition 2 below.

Definition 2. *The cross-return covariance, σ_{12}, and the cross-return correlation, ρ_{12}, satisfy*

$$\sigma_{12} = \sum_{j=1}^{4} D_{1j} D_{2j}, \qquad \rho_{12} = \frac{\sigma_{12}}{\sigma_1 \sigma_2} = \frac{\sum_{j=1}^{4} D_{1j} D_{2j}}{\sqrt{\sum_{j=1}^{4} D_{1j}^2}\sqrt{\sum_{j=1}^{4} D_{2j}^2}},$$

where the component of the stock return diffusion D_{ij} is provided in Proposition 3.

[Insert Figure 2 about here.]

We plot the static relationship between attention paid to stock 1 and the cross-return correlation in Figure 2. The cross-return correlation between stock 1 and stock 2 is positive and increases with attention to stock 1 even though dividends, fundamentals, and signals are uncorrelated. We note that by symmetry, the relationship between attention paid to stock 2 and the cross-return correlation looks identical. Similar to our results for volatilities, we find that an increase in attention to stock 1 and stock 2, together, further strengthens the return spillover effects. Thus, contagion arises most prominently when aggregate attention increases.

We now discuss the economic mechanism leading to a positive cross-return correlation in our model. We first explain how a non-zero cross-return correlation can arise in a standard equilibrium model with learning and unrelated fundamentals, and then discuss how the fluctuating attention feature produces the positive cross-return correlation observed in our model. Following the exposition in Cochrane et al. (2008), the cross-return correlation between stock 1 and stock 2 can arise due to co-movements in one of the following four relationship pairs. The first is the co-movement between price-dividend ratio $\frac{P_1}{\delta_1}$ and dividend δ_2. The second is the co-movement between price-dividend ratio $\frac{P_2}{\delta_2}$ and dividend δ_1. The third is the co-movement between price-dividend ratios $\frac{P_1}{\delta_1}$ and $\frac{P_2}{\delta_2}$. Finally, the fourth, is the co-movement between dividends δ_1 and δ_2. Because our model assumes that dividend δ_1 and dividend δ_2 are uncorrelated, the fourth relationship source can be eliminated.

In our model, the positive correlation between returns of stock 1 and stock 2 arises through discount rates. To understand the economic mechanism, let us consider a negative shock in the dividend of stock 1, i.e., the shock dW_{1t} in (8) is negative. This shock decreases the performance of dividend 1, thereby raising the attention paid to stock 1 (see Equations (10) and (5)). In the meantime, the negative shock also pushes the investor to decrease her estimation of the fundamental $\widehat{f_1}$ (see Equation (9)). This decrease in the expectation of future dividend growth causes discount rates to fall and triggers an increase in price-dividend ratio $\frac{P_2}{\delta_2}$. As for stock 1, because risk aversion is sufficiently large, the discounting channel outweighs the dividend channel and implies an increase in price-dividend ratio $\frac{P_1}{\delta_1}$. The end result is a positive co-movement between price-dividend ratios $\frac{P_1}{\delta_1}$ and $\frac{P_2}{\delta_2}$, while the co-movement between δ_1 and $\frac{P_2}{\delta_2}$ is negative. The former effect dominates the latter and implies a positive cross-return correlation because the discounting channel is the strongest.

In the previous paragraph we explain how, given a sufficiently large risk aversion, returns of two fundamentally unrelated stocks co-move positively due to the the discount rate channel. However, an important result from our model is that the magnitude of cross-return correlation depends on the level of investor attention (see Figure 2). This result can also be directly seen from Proposition 3, which shows that when attention paid to stock 1 increases, the cross-return correlation rises because the diffusion components D_{13} and D_{23} increase (in absolute value). The intuition to why attention impacts the magnitude of return spillover effects is discussed below.

Recall that the diffusion of the filtered fundamentals reflects two pieces of information: dividend innovations (dW_{1t}, dW_{2t}) and signal innovations (dW_{3t}, dW_{4t}). It follows from (9) that the uncertainty γ_i loads on dividend innovations, while attention Φ_i loads on signal innovations. As a negative shock hits dividend 1, attention to stock 1 increases but uncertainty γ_1

remains currently unchanged because it is locally deterministic. In other words, the weight assigned to signal innovations rises while the weight assigned to dividend innovations remains unchanged. Consequently, the variance of the filtered fundamental increases while the covariance between the dividend growth and the filtered fundamental, i.e., $\mathrm{cov}_t \left[\frac{d\delta_{1t}}{\delta_{1t}}, d\widehat{f}_{1t}\right]$, remains constant. This means that an increase in attention disconnects the dividend from the filtered fundamental. Since the filtered fundamental drives discount rates, the correlation between discount rates and dividend 1 is reduced in absolute terms. This implies that the negative co-movement between price-dividend ratio 2 and dividend 1 is less pronounced when attention to stock 1 is high, and therefore that the cross-return correlation is larger.

This mechanism explains why the cross-return correlation increases with attention to stock 1, and by symmetry, with attention to stock 2. As a result, the cross-return correlation rises, exactly like stock return volatilities, with aggregate attention. Table 3 reports the relationship between attention to stock 1, attention to stock 2, aggregate attention, and the cross-return correlation. The regressions are performed using 50 years of model-simulated data at the monthly frequency. Consistent with the results of Figure 2, the cross-return correlation increases with attention to stock 1 and attention to stock 2. Coefficients are positive and significant at the 1% level, which shows that attention-driven return spillovers are statistically detectable and strong. That is, the impact of the other state variables of the model on the cross-return correlation are not strong enough to make the relationship between attention and correlation insignificant. Furthermore, the relationship between the correlation and aggregate attention is positive and statistically significant at the 1% level, confirming that aggregate attention is an important driver of the cross-return correlation.

[Insert Table 3 about here.]

4. Empirical Evidence

In this section, we first show that the model-implied attention measures for the FF48 industries (see Section 2.4) are indeed representative of investors' attention to their respective industries. Then, we empirically test the model's predictions described in Section 3 that time-varying investor attention generates return and volatility spillovers between fundamentally unrelated industries.

4.1. Properties of Model-Implied Attention Measures

We illustrate that our model-implied attention measures indeed capture time-varying investor attention. To do so, we run three different tests. First, we focus on the relation between our attention measures and stock trading volume. As argued by Gervais et al. (2001) and recently shown in Fisher et al. (2017) and Gargano and Rossi (2017), trading volume and attention are positively and strongly related. To test this relation, we perform the following simple regression

$$\Delta \text{Volume}_{it} = \alpha_i + \gamma_t + \beta \Delta \Phi_{it} + \epsilon_{it},$$

where $\Delta \mathit{Volume}_{it}$ is the monthly change in log shares turnover (trading volume divided by the number of common shares) of industry i at time t. We include industry-fixed effects represented by α_i, and year-month-fixed effects represented by γ_t. $\Delta \Phi_{it}$ is the change in model-implied attention to industry i in month t, which we obtain in Section 2.4. Time series are at the monthly frequency from 08/1972 to 08/2015. We find that the slope coefficient is positive ($\beta = 0.106$) and statistically significant at the 5% level (t-stat is 2.20), confirming a positive relation between our model-implied attention measure and the trading volume.

Second, as discussed near the end of Section 2.2, a high-attention period should be followed by lower uncertainty. To test this relation, we follow van Nieuwerburgh and Veldkamp (2006) and proxy for uncertainty using the absolute deviation of the median analysts' real GDP growth forecast from the realized real GDP growth. This proxy provides an aggregate measure of economic uncertainty at the quarterly frequency. We relate the aggregate uncertainty measure to the model-implied attention to each industry by aggregating the attention measures across the FF48 industries. We then compute the average aggregate attention over three (non-overlapping) consecutive months. This procedures yields a quarterly measure of aggregate model-implied attention from 1972 to 2015. Figure 3 plots the t-statistic of the slope coefficient obtained by regressing the future aggregate uncertainty on the current level of aggregate attention. The time-period lag is shown on the x-axis. As expected, we find that high model-implied attention is followed by lower uncertainty.

[Insert Figure 3 about here.]

Third, we show that our model-implied attention measure proxies for investor attention by examining its relation to the post-earnings-announcement drift (PEAD). Dellavigna and Pollet (2009) find that the PEAD is significantly stronger for earnings released on Friday relative to other weekdays because investor attention is likely to be lower. In particular, their study shows that this effect concentrates among earnings announcements with strong negative earnings surprises. In line with Dellavigna and Pollet (2009), we provide in Table 4 evidence of stronger PEAD during periods of lower model-implied attention.

Table 4 reports the average cumulative adjusted return following firms' earnings announcements, CAR$(1, t)$, which is from day 1 to day t relative to the event date. We sort earnings announcements into 5×5 portfolios based on each firm's standardized unadjusted earnings (SUE) and the level of attention to the industry each firm belongs to. We calculate SUE using two methods (Livnat and Mendenhall, 2006): the random walk model in Panel A and the analysts' forecast errors in Panel B. *Negative (Positive) Earnings Surprise* refers to the first (fifth) quintile of the SUE measure. For the level of attention, we sort earnings announcements based on the demeaned model-implied attention to the industry each firm belongs to. We demean the monthly attention measures using their respective five-year moving average. This method helps us identify periods of increasing and decreasing attention to each industry. *Low (High) Attention* refers to the first (fifth) quintile of the demeaned attention measure.

The results in Table 4 show that the average cumulative adjusted returns following negative (positive) earnings surprises exhibit a negative (positive) drift. However, the effect is weaker when investor attention to the industry is high. The difference in 1-month CARs (21 trading days) following negative earnings surprises between low- and high-investor attention periods is statistically significant in both Panels A and B. This finding is largely consistent with Dellavigna and Pollet (2009), who find that the effect of PEAD following negative earnings surprises are stronger for Friday earnings announcements—when investor attention is likely lower.

Overall, the evidence obtained from running these three different tests indicate that our model-implied attention measures are likely to capture investor attention to each industry.

[Insert Table 4 about here.]

4.2. Data and Method for Testing the Model's Predictions

We empirically test the model's predictions shown in Section 3 on fundamentally unrelated U.S. industry sectors. The objective is to show that the transmission of return and volatility from one sector to other fundamentally unrelated sectors is associated with changes in investor attention. We group U.S. incorporated firms that are traded on the NYSE/AMEX/NASDAQ into 48 industries following the Fama-French's 48 (FF48) definitions. Industry classifications are obtained from Kenneth French's website.[8]

We define fundamentally unrelated industries as those that are unlikely to have substantial cash flow relationships. We identify cash flow relationships at the firm level using customer-supplier data constructed from the COMPUSTAT Segment Customer File. Statement of Financial and Account Standards (SFAS) No. 14 requires that each firm discloses the existence and sales to individual customers (public or private entities) accounting for more than 10% of its revenue.[9] In practice, customers representing less than 10% of a supplier firms' total revenue are often voluntarily reported. We retain all relationships reported as identifications of relevant cash flow relationships. The names of corporate customer are manually matched with their COMPUSTAT identifiers, i.e., GVKEYS, following the approach used in Banerjee et al. (2008) and Cohen and Frazzini (2008).The customer-supplier relationships database that we obtain is updated annually from 1979 to 2009.

For each calendar year, we identify firms in the CRSP universe that are either a customer of or a supplier to one another. We consider that firms are currently related if their relationships appear in the customer-supplier database in the current year, the past year, as well as the next year. We use the three-year identification window in order to account for relationships that are emerging, and those may have been delayed in the reporting. A direct customer-supplier relationship between two firms is referred to as the first-level relationship. When two firms are connected indirectly via their connections with a common firm, we refer to the link as the second-level relationship. We consider that firms are fundamentally related if they have direct or indirect customer-supplier relationships up to the sixth level.

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

[9]This requirement is relaxed after 1998 (See SFAS No. 131). However, most firms continue to report the names of their customers in COMPUSTAT as well as in their 10-K filing.

Using relationships information identified at the firm level, we calculate the level of relatedness between all possible pairs of industries defined following the FF48 definitions. We measure the relatedness between two industries i and j as the percentage of firms in industry i that is fundamentally related to firms in industry j, and vice versa, whichever value is higher. We refer to this measure of industry-pair relationship importance as *Pct Related*, which is updated annually. We assume that any two industries are fundamentally unrelated if the times-series median of their *Pct Related* is below 5%. We do not consider the four financial industries classified following the FF48 definitions (i.e., *Banking, Insurance, Real estate*, and *Trading*) as firms in these sectors may have lending and underwriting relationships that cannot be identified using the customer-supplier relationships. We also remove the industry labeled as *Others*. Out of the 43 remaining industries, we find 94 unique industry pairs that have *Pct Related* below 5%.

The general equilibrium model that we introduced in Section 2 provides predictions of financial contagion between two sectors with comparable dividend shares. We therefore require industry pairs that we consider to have a similar size in their dividend payouts. We calculate the total dividend payout by each industry annually and use its inflation-adjusted time-series median for the comparison. We require that the median aggregate dividend payouts between two fundamentally unrelated industries are not larger (or smaller) than one another by more than twice (or less than half). This filter leaves us with 18 industry pairings that are made up of 21 unique industries.[10] Table 5 reports the FF48 industries that are in our sample. Panel A describes these industry names and their characteristics. Panel B reports the unique matched pairs of fundamentally unrelated industries and their time-series median for *Pct Related*.

[Insert Table 5 about here.]

We obtain monthly value-weighted industry returns for each industry in Panel A of Table 5 from 1972 to 2015 from Kenneth French's website. We also verify that our results are virtually identical when obtained using our own calculated monthly industry returns. Monthly

[10] Our main results are qualitatively similar when filtering industry pairs based on the size of their book equity or their market equity.

time-varying volatilities for each industry is estimated using the exponentially weighted moving average (EWMA) model. We prefer the EWMA model for volatility estimation because it is simple and requires no further estimation. An alternative approach is a GARCH model for volatility modeling, but this is less practical for our short monthly time-series data with 516 observations. The EWMA variance $\sigma^2_{i,t}$ for industry i in month t is updated using a recursive relation: $\sigma^2_{i,t} = \lambda r^2_{i,t} + (1-\lambda)\,\sigma^2_{i,t-1}$, where $r_{i,t}$ is the monthly return of industry i, and λ is the EWMA weight. We set λ to 0.50. This implies that past volatility estimates are as equally important as the most recent return observation in determining the current volatility level.[11]

We also estimate time-varying monthly return correlations between two industries using the EWMA model. We first calculate time-varying covariances $\sigma_{ij,t}$ between monthly returns of industries i and j in month t using a recursive relation: $\sigma_{ij,t} = \lambda\,(r_{i,t} r_{j,t}) + (1-\lambda)\,\sigma_{ij,t-1}$. The return correlation between industries i and j is then calculated as $\rho_{ij,t} = \sigma_{ij,t}/\,(\sigma_{i,t}\sigma_{j,t})$, where $\sigma_{i,t}$ and $\sigma_{j,t}$ are EWMA volatilities calculated previously. Similar to the EWMA model for return volatilities, we set λ equal to 0.50 for the EWMA covariance model. This ensures that monthly correlations that we obtain are bounded between -1 and $+1$.

4.3. Hypotheses and Empirical Findings

We empirically test our model's predictions using the 18 fundamentally unrelated industry pairs shown in Table 5. Specifically, we test whether monthly volatilities and return correlations between two fundamentally unrelated industries can be explained by the fluctuation in these industries' attention measures. Our sample period is at the monthly frequency from 08/1972 to 08/2015. Below, we describe and test four hypotheses.

The *first hypothesis*, illustrated in Figure 1, is that an increase in attention to one industry leads to an increase in the return volatility of that industry, as well as an increase in the return volatility of its fundamentally unrelated industry. To test this, we estimate the following panel regression:

$$\Delta\sigma_{i,t+1} = \alpha_{ij} + \gamma_t + \beta_1 \Delta\Phi_{i,t} + \beta_2 \Delta\Phi_{j,t} + \Sigma^p_{s=0}\Gamma'_s X_{t-s} + \varepsilon_{i,t+1},$$

[11] We verify that our main conclusions are robust to a relatively large range of λ between 0.3 and 0.7.

where i and j refer to the fundamentally unrelated industry pairs shown in Panel B of Table 5. The dependent variable $\Delta\sigma_{i,t+1}$ is the change in return volatility of industry i at time $t+1$, and $\varepsilon_{i,t+1}$ is the regression residual. Industry-pair fixed effects are denoted by α_{ij}, and year-month fixed effects are denoted by γ_t. Other control variables are represented by X_{t-s}. The independent variables of interest are $\Delta\Phi_{i,t}$ and $\Delta\Phi_{j,t}$, which represent monthly changes in attention to industries i and j at time t, respectively. Descriptive statistics of monthly investor attention and return volatility are reported in Appendix Table G3.

Column (1) of Table 6 reports the baseline regression results. Consistent with the model's prediction, we find evidence for the volatility spillover effects between fundamentally unrelated industries. That is, an increase in attention to industry i, as well as an increase in attention to its fundamentally unrelated industry j, both lead to an increase in the return volatility of industry i. In Column (2), we add year-month fixed effects to control for aggregate shocks that may commonly affect return volatilities of all industries. In Column (3), we include standard macro variables that may affect the return volatility of each industry. We find that coefficient estimates on $\Delta\Phi_{i,t}$ and $\Delta\Phi_{j,t}$ slightly increase both in magnitude and statistical significance when more controls are added to the baseline specification. Focusing on Column (2), a one-standard deviation increase in $\Phi_{i,t}$ ($\Phi_{j,t}$) implies a 0.36 (0.21) percentage point increase in volatility, which represents about 6.4% (4.9%) of the average return volatility.[12] Thus, the impact of attention on volatility is economically important.

It is worth noting that σ_i is more sensitive to Φ_j in the model (see Table 2), whereas it is more sensitive to Φ_i in Columns (1)–(3) of Table 6. In Appendix G, we discuss the model-implied sensitivity of volatility in more detail. We show that σ_i is more sensitive to Φ_j when risk aversion is high, whereas σ_i is more sensitive to Φ_i when risk aversion is low. We provide empirical support for the latter prediction in Appendix G as well.

[Insert Table 6 about here.]

The *second hypothesis* is that an increase in total attention to two fundamentally unrelated industries implies an increase in each industry's return volatility. This hypothesis is a

[12]These estimates are calculated based on descriptive statistics shown in Table G3. The average standard deviation of monthly attention measures across industries is 10.6%, while the average mean of monthly return volatility across industries is 5.63%.

consequence of the results shown in Figure 1. We test this by running the following panel regression:

$$\Delta\sigma_{i,t+1} = \alpha_{ij} + \gamma_t + \beta\Delta(\Phi_{i,t} + \Phi_{j,t}) + \Sigma_{s=0}^{p}\Gamma_s' X_{t-s} + \varepsilon_{i,t+1},$$

where all variables are as defined previously. The independent variable of interest here is the total change in attention $\Delta(\Phi_{i,t} + \Phi_{j,t})$ to industries i and j.

Column (4) reports the baseline regression results. Columns (5) and (6) report the results with the inclusion of year-month fixed effects and macro controls, respectively. We find that the coefficient estimates on $\Delta(\Phi_{i,t} + \Phi_{j,t})$ are positive with strong statistical significance in all columns, and their magnitude reflects the average effect of the change in two attention measures separately on the return volatility of industry i. For instance, we can compare coefficients estimates in Column (4) to those in Column (1). Here, the estimate on $\Delta(\Phi_{i,t} + \Phi_{j,t})$ is 2.4%, which is roughly the average value of the coefficient estimates 1.9% and 3.2% found on $\Phi_{i,t}$ and $\Phi_{j,t}$, respectively.

The *third hypothesis*, illustrated in Figure 2, is that an increase in attention to one industry implies an increase in the correlation between that industry's return and the return of its fundamentally unrelated industry. We test this using the following panel regression:

$$\Delta\rho_{ij,t+1} = \alpha_{ij} + \gamma_t + \beta_1\Delta\Phi_{i,t} + \beta_2\Delta\Phi_{j,t} + \Sigma_{s=0}^{p}\Gamma_s' X_{t-s} + \varepsilon_{i,t+1},$$

where $\Delta\rho_{ij,t+1}$ is the change in return correlation at time $t+1$.

Column (1) of Table 7 reports the baseline regression results without macro controls and year-month fixed effects. We find that the coefficient estimates on $\Delta\Phi_{i,t}$ and $\Delta\Phi_{j,t}$ are positive, however, only the estimate on $\Delta\Phi_{j,t}$ is statistically significant at the conventional level. Nevertheless, as we add more controls to the regression model, our results become stronger in magnitude and statistical significance. Column (3) shows that when macro variables are added to the regression model, the estimates increase by about 50%. When we apply the most conservative regression specification (Column (2)) with year-month fixed effects to control for potentially omitted time-varying aggregate shocks that could imply co-movements in industry returns, the estimates almost double. These coefficient estimates imply that a one-standard deviation increase in $\Phi_{i,t}$ ($\Phi_{j,t}$) yields a 6.85 (7.29) percentage point increase in correlation, which represents about 23.3% (24.8%) of the average return correlation. This shows that the economic impact of attention on return correlation is sizable.

[Insert Table 7 about here.]

Finally, the *fourth hypothesis* is that an increase in total attention to two fundamentally unrelated industries leads to an increase in the correlation between these industries' returns. To test this, we estimate the following panel regression:

$$\Delta\rho_{ij,t+1} = \alpha_{ij} + \gamma_t + \beta\Delta(\Phi_{i,t} + \Phi_{j,t}) + \Sigma_{s=0}^{p}\Gamma'_s X_{t-s} + \varepsilon_{i,t+1},$$

where all variables are as defined previously. Consistent with the model's prediction, we find a positive and statistically significant coefficient estimate on $\Delta(\Phi_{i,t} + \Phi_{j,t})$ for all three specifications (see Columns (4)–(6) of Table 7).

Overall, our results are supportive of the model's predictions that increasing attention to one industry leads to a higher return volatility in that industry, a higher return volatility in its fundamentally unrelated industry, and a higher return correlation between these two industries. We emphasize that these findings are unlikely driven by aggregate macro shocks. In fact, Tables 6 and 7 show that our main results are generally stronger when we control for macro variables or year-month fixed effects in the regression. This suggests that the exclusion of aggregate and macro variables is more likely to bias us against finding the volatility and return spillover results. Further, the addition of market and macro control variables to the regression model can help us rule out alternative theories based on borrowing constraints (Yuan, 2005), downside risk (Ang et al., 2006; Lettau et al., 2014), systematic risk (Pasquariello, 2007), and disappointment aversion (Routledge and Zin, 2010; Delikouras, 2017). The reason is that borrowing constraints bind in bad times, downside risk is particularly high during market declines, systematic risk measures market risk, and disappointment events occur in bad times when aggregate consumption drops significantly. Each of these features are closely related to the business cycle and market risk, which our control variables capture.

5. Conclusion

Recent empirical studies document that investor attention to news fluctuates. In this paper, we show both theoretically and empirically that fluctuating attention implies return and volatility spillover effects among fundamentally unrelated sectors. Indeed, a negative shock affecting one sector propagates to other sectors through an increase in investor attention, which simultaneously raises each sector's volatility and cross-sector correlation. The model predicts that the shock propagates from one sector to another through discount rates.

We empirically test the key mechanism of our model on the Fama-French 48 industries. We use customer-supplier relationship data to identify fundamentally unrelated industries. Using a panel regression, we show that time-varying attention yields return and volatility spillovers among fundamentally unrelated industries, lending support to the predictions of the model.

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Table 1: Calibration.
This table reports the parameter estimates of the model. Parameters determining the dynamics of dividends are estimated by maximum likelihood using realized and expected real dividend growth rates of the Fama-French 48 industries. The data is available at monthly from August 1972 to August 2015. Newey-West t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The relative risk aversion $\alpha = 3$ and subjective discount rate $\Delta = 0.01$ are chosen and not estimated. Initial values of the state variables are $\zeta_{1,0} \equiv \log(\delta_{1,0}) = \zeta_{2,0} \equiv \log(\delta_{2,0}) = 0$, $Q_0 \equiv \log(\delta_{1,0}/(\delta_{1,0} + \delta_{2,0})) = \log(0.5)$, $\widehat{f}_{1,0} = \widehat{f}_{2,0} = \bar{f}$, $\pi_{1,0} = \pi_{2,0} = 0$, and $\gamma_{1,0} = \gamma_{2,0} = \gamma_{ss}$. Note that initial fundamentals, performance indices, and uncertainties are set to their long-term levels derived in Appendix A and Appendix B.

Parameter	σ_δ	$\bar{f}$	λ	σ_f	ω	Ψ	Λ
Estimate	0.010***	0.040***	0.861***	0.086***	0.122***	0.645***	17.070***
t-stat	(27.19)	(3.26)	(7.38)	(22.23)	(4.30)	(28.05)	(20.27)

Table 2: Model-Implied Regressions of Return Volatility on Attention.
This table reports regression results based on the model-simulated data. We report outputs obtained from regressing: (1) stock 1's return volatility change, $\Delta\sigma_1$, on stock 1's attention change, $\Delta\Phi_1$, and stock 2's attention change, $\Delta\Phi_2$; (2) stock 2's return volatility change, $\Delta\sigma_2$, on both attention changes; (3) stock 1's return volatility change on aggregate attention change, $\Delta(\Phi_1+\Phi_2)$, and (4) stock 2's return volatility change on aggregate attention change. The model-implied regression outputs are obtained by simulating the model at a monthly frequency over a 50-year horizon. Newey-West t-statistics are reported in parentheses below each estimate. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Although not reported, each regression features an intercept.

	Dependent variable:			
	$\Delta\sigma_1$	$\Delta\sigma_2$	$\Delta\sigma_1$	$\Delta\sigma_2$
	(1)	(2)	(3)	(4)
$\Delta\Phi_1$	0.036***	0.074***		
	(9.66)	(19.75)		
$\Delta\Phi_2$	0.070***	0.031***		
	(18.58)	(8.22)		
$\Delta(\Phi_1 + \Phi_2)$			0.053***	0.053***
			(19.36)	(18.91)
Adj. R^2	0.423	0.433	0.384	0.373
Nobs.	600	600	600	600

Table 3: Model-implied Regressions of Cross-Return Correlation on Attention. This table reports regression results based on the model-simulated data. We report outputs obtained from regressing: (1) the cross-return correlation change, $\Delta\rho_{12}$, on stock 1's attention change, $\Delta\Phi_1$, and stock 2's attention change, $\Delta\Phi_2$, and (2) the cross-return correlation change on aggregate attention change, $\Delta(\Phi_1 + \Phi_2)$. The model-implied regression outputs are obtained by simulating the model at a monthly frequency over a 50-year horizon. Newey-West t-statistics are reported in parentheses below each estimate. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Although not reported, each regression features an intercept.

	Dependent variable:	
	$\Delta\rho_{12}$	$\Delta\rho_{12}$
	(1)	(2)
$\Delta\Phi_1$	0.063***	
	(8.91)	
$\Delta\Phi_2$	0.060***	
	(8.30)	
$\Delta(\Phi_1 + \Phi_2)$		0.061***
		(12.22)
Adj. R^2	0.197	0.198
Nobs.	600	600

Table 4: Investor Attention and Post-earnings-announcements Drifts

We report the average cumulative adjusted return (CAR) calculated from day 1 to day t after the earnings announcement date. Adjusted return is calculated as the stock return minus the CRSP value-weighted index return. We calculate CARS for double-sorted portfolios (5×5) based on the level of the firm's quarterly standardized unadjusted earnings (SUE) and the level of investor attention (demeaned) to the industry the firm belongs to. We calculate SUE based on two approaches (Livnat and Mendenhall, 2006): the random walk model (Panel A) and the analyst forecast errors (Panel B). The monthly investor attention to each FF48 industry is obtained by calibrating our model to monthly dividend growth rates from 08/1972 to 08/2015. We refer to Section 1 and Appendix F for descriptions of the resulting attention measures. The monthly investor attention to each industry is demeaned by subtracting its monthly value with its five-year moving average. *Negative (Positive) Earnings Surprise* corresponds earnings announcements that are in the lowest (highest) quintile of the SUE measure. *Low (High) Attention* corresponds to periods when investor attention to an industry is in the lowest (highest) quintile. The columns under *Low–High* report the difference between CARs observed for the low versus the high investor attention portfolios. T-statistics are reported in parentheses next to each estimate.

Panel A: SUE based on Seasonal Random Walk Model

	Days since	Low Attention		High Attention		Low−High	
	Earnings (t)	CAR(1, t) (%)	t-stat	CAR(1, t)(%)	t-stat	Diff (%)	t-stat
	1	−0.73	(−5.62)	−0.48	(−3.48)	−0.26	(−1.42)
Negative	5	−1.05	(−4.47)	−0.55	(−1.78)	−0.50	(−1.36)
Earnings	10	−1.23	(−4.46)	−0.08	(−0.27)	−1.16	(−3.10)
Surprise	15	−1.10	(−3.36)	0.10	(0.26)	−1.20	(−2.54)
	21	−1.09	(−3.30)	0.31	(0.80)	−1.40	(−2.90)
	1	0.36	(1.70)	0.15	(1.29)	0.20	(0.88)
Positive	5	0.64	(2.01)	0.14	(0.63)	0.49	(1.32)
Earnings	10	0.75	(1.63)	0.49	(1.60)	0.26	(0.50)
Surprise	15	0.58	(1.19)	0.24	(0.66)	0.34	(0.59)
	21	0.55	(0.89)	0.23	(0.46)	0.27	(0.33)

Panel B: SUE based on Analyst Earnings Forecasts Errors

	Days Since	Low Attention		High Attention		Low−High	
	Earnings Ann. (t)	CAR(1, t) (%)	t-stat	CAR(1, t) (%)	t-stat	Diff (%)	t-stat
	1	−1.48	(−6.45)	−1.25	(−4.78)	−0.23	(−0.71)
Negative	5	−1.89	(−7.38)	−1.35	(−3.70)	−0.54	(−1.30)
Earnings	10	−1.84	(−5.83)	−1.35	(−3.26)	−0.49	(−1.01)
Surprise	15	−1.88	(−5.15)	−1.07	(−2.47)	−0.81	(−1.61)
	21	−2.05	(−4.42)	−0.96	(−1.95)	−1.09	(−1.72)
	1	1.24	(5.40)	0.90	(5.55)	0.34	(1.29)
Positive	5	1.56	(5.65)	1.13	(6.81)	0.43	(0.92)
Earnings	10	1.91	(6.38)	1.34	(6.02)	0.57	(0.68)
Surprise	15	1.98	(5.42)	1.60	(6.67)	0.38	(0.89)
	21	2.39	(5.74)	1.66	(7.08)	0.73	(1.39)

Table 5: Descriptions of the Fundamentally Unrelated Industry Pairings

This table describes the industry sectors and the matched pairs that we use to test the empirical predictions of our model. We define industries following the FF48 industry classifications. Panel A reports the 21 industries that are present in our sample. Panel B reports the 18 matched pairs of fundamentally unrelated industries. For each industry in Panel A, we report its FF48 industry code and number. The time-series median values for the number of firms, the total market book equity value (*Size*), and the total annual dividend payout (*Dividend*). *Size* and *Dividend* are inflation-adjusted to year 2015 (in millions $). The matched industry pairs are reported in increasing order of their relatedness identified using the Customer-Supplier relationships data obtained from COMPUSTAT. For each matched pair, *Pct. Related* measures the fraction of firms in industry i that are related (as either customers or suppliers) to firms in industry j, and vice versa, with the higher value of the two being reported. The matched pairs in Panel B consists of similar sized industries with *Pct. Related* below 5%. See Section 4.2 for more details.

Panel A: Descriptions of the Fama-French 48 Industries in our Sample

FF48 Industry Name	Ind Code	Ind No.	Industry Characteristics (Median)		
			No. of firms	Size (mils)	Dividend (mils)
Food Products	FOOD	2	100	67,566	2,629
Tobacco Products	SMOKE	5	9	29,350	1,741
Recreaction	TOYS	6	57	7,287	101
Entertainment	FUN	7	108	25,372	33
Healthcare	HLTH	11	131	24,506	76
Medical Equipment	MEDEQ	12	196	42,750	1,493
Textiles	TXTLS	16	45	85,269	2,627
Construction Materials	BLDMT	17	137	5,576	40
Construction	CNSTR	18	88	13,165	72
Steel Works Etc	STEEL	19	83	2,240	62
Fabricated Products	FABPR	20	25	1,698	28
Shipbuilding & Railroad Equip.	SHIPS	25	8	8,347	133
Defense	GUNS	26	11	6,079	105
Precious Metals	GOLD	27	98	11,655	128
Non-Metallic & Industrial Metal	MINES	28	46	3,821	76
Coal	COAL	29	13	10,110	134
Personal Services	PERSV	33	74	151,414	2,761
Electronic Equipment	CHIPS	36	370	83,717	1,075
Business Supplies	PAPER	38	71	57,658	1,548
Transportation	TRANS	40	161	104,440	1,415
Wholesale	WHLSL	41	273	42,122	895

Panel B: Matched Pairs of Unrelated Industries

Pair No.	Industry	Industry	Pct. Related	Pair No.	Industry	Industry	Pct. Related
1	SMOKE	MEDEQ	0.49%	10	GOLD	PERSV	2.0%
2	SMOKE	BUSSV	0.62%	11	SMOKE	PAPER	2.1%
3	GOLD	COAL	0.80%	12	TOYS	GOLD	2.2%
4	SMOKE	CHEM	0.82%	13	SMOKE	TRANS	2.3%
5	SMOKE	CHIPS	1.73%	14	FOOD	SMOKE	3.8%
6	FUN	SHIPS	1.79%	15	TXTLS	SHIPS	3.8%
7	GUNS	GOLD	1.86%	16	CNSTR	GOLD	4.3%
8	FABPR	GOLD	1.96%	17	GOLD	MINES	4.3%
9	HLTH	GOLD	2.00%	18	SMOKE	WHLSL	4.5%

Table 6: Time-varying Attention and Cross-Industry Volatility Spillover
We report panel regression results examining the impact of time-varying industry attentions on the cross-industry volatility spillover. We estimate the monthly panel regression on 18 fundamentally unrelated pairs of Fama-French 48 industries from 1972 to 2015. See Table 5 for details of the industry pairings. The dependent variable is $\Delta\sigma_{i,t+1}$, the monthly change in return volatility of industry i at time $t+1$. Panel A reports results where the independent variables of interest are the monthly changes in attention to the i industry, $\Delta\Phi_{i,t}$, and to its fundamentally unrelated j industry, $\Delta\Phi_{j,t}$, at time t. Panel B reports results where the independent variable of interest is the monthly change in total attention to industries i and j at time t. Industry-pair fixed effects are included in all specifications. Year-month fixed effects are added to the regression in Columns (3) and (5). Macro control variables are added to regressions in Columns (3) and (6). $\Delta\sigma_{sp500,t}$ and $Return_{sp500,t}$ are the change in volatility and the return of the S&P500 index at time t. $GDP\ growth_{i,t}$ and $Inflation\ growth_{i,t}$ are monthly GDP and inflation growth rates (log) obtained from the Federal Reserve. All specifications include 3 lags (one quarter) of dependent variables and of the monthly change in attention variables. Newey-West t-statistics adjusted for heteroskedasticity and autocorrelations are reported in parentheses below each estimate. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent var: $\Delta\sigma_{i,t+1}$					
	Panel A			Panel B		
	(1)	(2)	(3)	(4)	(5)	(6)
Change in Attentions						
$\Delta\Phi_{i,t}$	0.032*	0.034*	0.039**			
	(1.76)	(1.89)	(2.10)			
$\Delta\Phi_{j,t}$	0.019*	0.020*	0.025**			
	(1.72)	(1.90)	(2.37)			
Change in Total Attentions						
$\Delta\left(\Phi_{i,t}+\Phi_{j,t}\right)$				0.024***	0.025***	0.031***
				(2.73)	(2.51)	(3.42)
Macro Controls						
$\Delta\sigma_{sp500,t}$			0.040**			0.0341*
			(2.04)			(1.70)
$\text{Return}_{sp500,t}$			−0.061***			−0.061***
			(−7.86)			(−7.90)***
$\text{GDP growth}_{i,t}$			0.014			0.015
			(1.16)			(1.18)
$\text{Inflation growth}_{i,t}$			0.309***			0.299***
			(4.12)			(3.93)
Lagged dependent var	✓	✓	✓	✓	✓	✓
Lagged attention var(s)	✓	✓	✓	✓	✓	✓
Industry-pair FE	✓	✓	✓	✓	✓	✓
Year-month FE		✓			✓	
No. cross sections	18	18	18	18	18	18
Time-series length	516	516	516	516	516	516
Adjusted R^2	9.4%	39.4%	10.2%	9.4%	39.3%	10.2%

Table 7: Time-varying Attention and Cross-Industry Return Correlation
We report panel regression results examining the impact of time-varying industry attentions on their cross-industry return correlations. We estimate the monthly panel regression on 18 fundamentally unrelated pairs of Fama-French 48 industries from 1972 to 2015. See Table 5 for details of the industry pairings. The dependent variable is $\Delta\rho_{ij,t+1}$, the monthly change in return correlation between industries i and j at time $t+1$. Panel A reports results where the independent variable of interests are monthly changes in attention to the i industry, $\Delta\Phi_{i,t}$, and to its fundamentally unrelated j industry, $\Delta\Phi_{j,t}$, at time t. Panel B reports results where the independent variable of interest is the monthly change in total attention to industries i and j at time t. Industry-pair fixed effects are included in all specifications. Year-month fixed effects are added in Columns (3) and (5). Macro control variables are added to regressions in Columns (3) and (6). $\Delta\sigma_{sp500,t}$ and $Return_{sp500,t}$ are the change in volatility and the return of the S&P500 index at time t. $GDP\ growth_{i,t}$ and $Inflation\ growth_{i,t}$ are monthly GDP and inflation growth rates (log) obtained from the Federal Reserve. All specifications include 3 lags (one quarter) of dependent variables and of the monthly change in attention variables. Newey-West t-statistics adjusted for heteroskedasticity and autocorrelations are reported in parentheses below each estimate. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent var: $\Delta\rho_{ij,t+1}$					
	Panel A			Panel B		
	(1)	(2)	(3)	(4)	(5)	(6)
Change in Attentions						
$\Delta\Phi_{i,t}$	0.272	0.645***	0.366*			
	(1.49)	(3.14)	(1.88)			
$\Delta\Phi_{j,t}$	0.285*	0.686***	0.370***			
	(1.89)	(3.47)	(2.45)			
Change in Total Attentions						
$\Delta\left(\Phi_{i,t}+\Phi_{j,t}\right)$				0.281***	0.670***	0.370***
				(2.56)	(4.17)	(3.38)
Macro Controls						
$\Delta\sigma_{sp500,t}$			−0.522**			−0.549**
			(−2.03)			(−2.13)
$\text{Return}_{sp500,t}$			−0.328***			−0.329***
			(−3.19)			(−3.21)
$\text{GDP growth}_{i,t}$			0.875*			0.852*
			(1.71)			(1.67)
$\text{Inflation growth}_{i,t}$			−0.074			0.177
			(−0.05)			(0.11)
Lagged dependent var	✓	✓	✓	✓	✓	✓
Lagged attention var(s)	✓	✓	✓	✓	✓	✓
Industry-pair FE	✓	✓	✓	✓	✓	✓
Year-month FE		✓			✓	
No. cross sections	18	18	18	18	18	18
Time-series length	516	516	516	516	516	516
Adjusted R^2	11.3%	30.0%	11.3%	11.2%	29.9%	11.3%

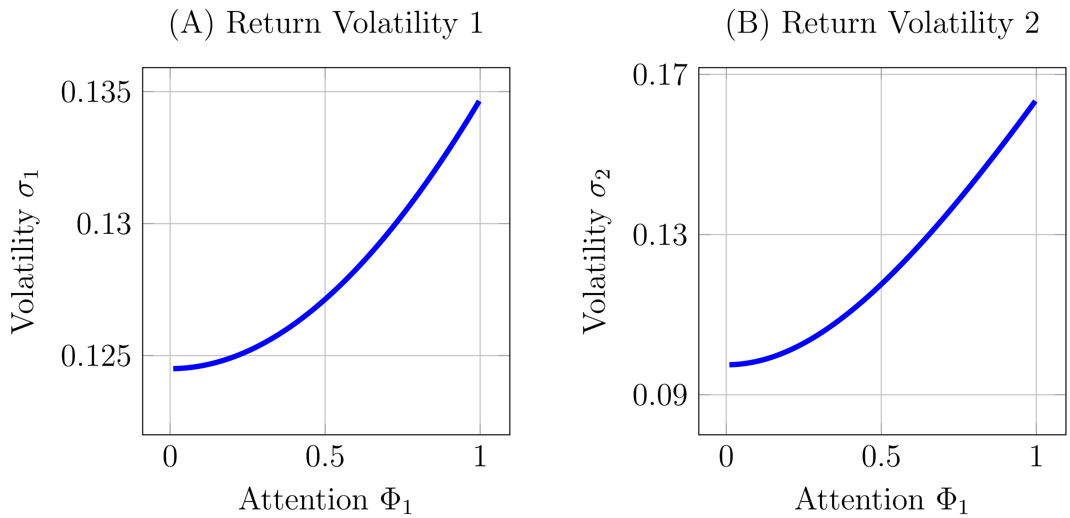

Figure 1: Model-Implied Relationship between Stock Return Volatility and Attention.
This figure provides a static illustration of the attention-driven volatility spillover effect. Panels A and B plot the relationship between attention paid to stock 1 and the return volatilities of stock 1 and 2, respectively.

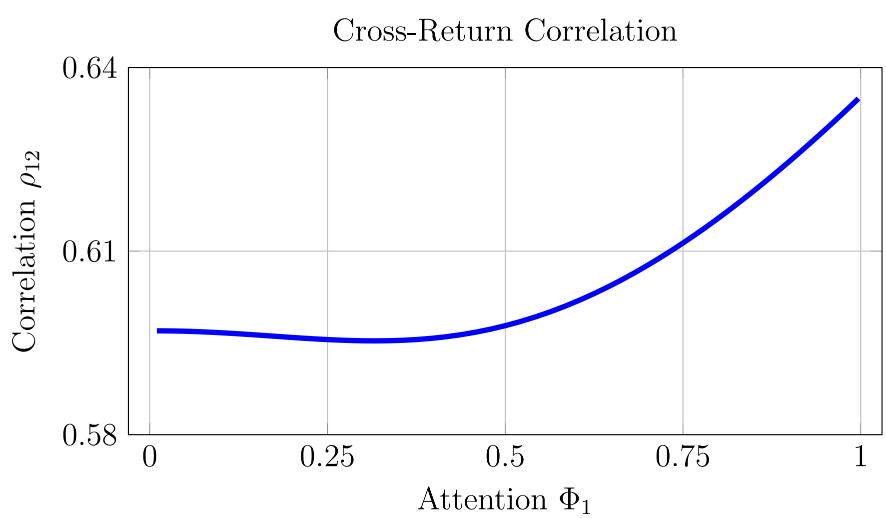

Figure 2: Model-Implied Relationship between Cross-Return Correlation and Attention.
This figure provides a static illustration of the attention-driven return spillover effect. The correlation between the return of stock 1 and the return of stock 2 is plotted against attention paid to stock 1.

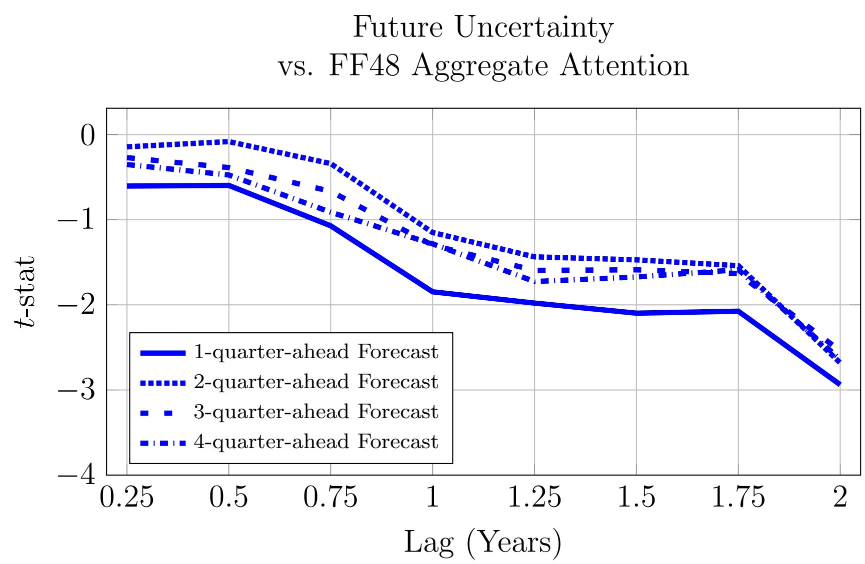

Figure 3: Relationship between Future Uncertainty and Current Attention. This figure plots the Newey-West t-statistic of the slope coefficient obtained by regressing future uncertainty on current FF48 aggregate attention. Uncertainty is proxied by the absolute deviation of the median analysts forecast from the realized real GDP growth rate. Each curve is obtained by considering a different forecast horizon: 1- to 4-quarter-ahead. The lag used in the regressions is represented on the x-axis. FF48 stands for the Fama-French 48 industries.

Appendix A. Long-Term Means and Variances

Let us consider the 4-dimensional vector $Y = \begin{pmatrix} \widehat{f}_1 & \widehat{f}_2 & \pi_1 & \pi_2 \end{pmatrix}^\top$. The dynamics of Y in vector notation is

$$dY_t = (A - BY_t)\, dt + C dW_t$$

where

$$A = \begin{pmatrix} \lambda\bar{f} & \lambda\bar{f} & 0 & 0 \end{pmatrix}^\top$$
$$B = \begin{pmatrix} \lambda & 0 & 0 & 0 \\ 0 & \lambda & 0 & 0 \\ 0 & 0 & \omega & 0 \\ 0 & 0 & 0 & \omega \end{pmatrix}$$
$$C = \begin{pmatrix} \frac{\gamma_{1t}}{\sigma_\delta} & 0 & \sigma_f \Phi_{1t} & 0 \\ 0 & \frac{\gamma_{2t}}{\sigma_\delta} & 0 & \sigma_f \Phi_{2t} \\ \sigma_\delta & 0 & 0 & 0 \\ 0 & \sigma_\delta & 0 & 0 \end{pmatrix}.$$

Applying Itô's lemma on $F \equiv e^{Bt} Y$ yields

$$dF = \begin{pmatrix} \frac{e^{\lambda t}\left(\lambda \bar{f} \sigma_\delta dt + \gamma_{1t} dW_{1t} + \sigma_f \sigma_\delta \Phi_{1t} dW_{3t}\right)}{\sigma_\delta} \\ \frac{e^{t\lambda}\left(\lambda \bar{f} \sigma_\delta dt + \gamma_{2t} dW_{2t} + \sigma_f \sigma_\delta \Phi_{2t} dW_{4t}\right)}{\sigma_\delta} \\ e^{\omega t} \sigma_\delta dW_{1t} \\ e^{\omega t} \sigma_\delta dW_{2t} \end{pmatrix}.$$

Integrating from 0 to t and taking expectation yields

$$\begin{pmatrix} e^{\lambda t} \mathbb{E}\left(\widehat{f}_{1t}\right) - \widehat{f}_{10} \\ e^{\lambda t} \mathbb{E}\left(\widehat{f}_{2t}\right) - \widehat{f}_{20} \\ e^{\omega t} \mathbb{E}\left(\pi_{1t}\right) - \pi_{10} \\ e^{\omega t} \mathbb{E}\left(\pi_{2t}\right) - \pi_{20} \end{pmatrix} = \begin{pmatrix} \left(e^{\lambda t} - 1\right) \bar{f} \\ \left(e^{\lambda t} - 1\right) \bar{f} \\ 0 \\ 0 \end{pmatrix}.$$

Therefore, the long-term means satisfy

$$\lim_{t\to+\infty}\begin{pmatrix}\mathbb{E}\left(\widehat{f}_{1t}\right)\\ \mathbb{E}\left(\widehat{f}_{2t}\right)\\ \mathbb{E}\left(\pi_{1t}\right)\\ \mathbb{E}\left(\pi_{2t}\right)\end{pmatrix}=\begin{pmatrix}\bar{f}\\ \bar{f}\\ 0\\ 0\end{pmatrix}.$$

Similar computations yield the long-term variances

$$\lim_{t\to+\infty}\begin{pmatrix}\mathrm{Var}\left(\widehat{f}_{1t}\right)\\ \mathrm{Var}\left(\widehat{f}_{2t}\right)\\ \mathrm{Var}\left(\pi_{1t}\right)\\ \mathrm{Var}\left(\pi_{2t}\right)\end{pmatrix}=\begin{pmatrix}\frac{\sigma_f^2}{2\lambda}\\ \frac{\sigma_f^2}{2\lambda}\\ \frac{\sigma_\delta^2}{2\omega}\\ \frac{\sigma_\delta^2}{2\omega}\end{pmatrix}.$$

Appendix B. Long-Term Uncertainty

The dynamics of the uncertainty γ_i conditional on $\pi_i = 0$ is

$$d\gamma_{it}=\left(-\frac{\gamma_{it}^2}{\sigma_\delta^2}-2\lambda\gamma_{it}+\sigma_f^2\left(1-\Psi^2\right)\right)dt.$$

The dynamics of the uncertainty at the "steady-state" is

$$\frac{d\gamma_{ss}}{dt}=0.$$

Solving yields

$$\gamma_{ss}=\sigma_\delta\sqrt{\sigma_f^2\left(1-\Psi^2\right)+\lambda^2\sigma_\delta^2}-\lambda\sigma_\delta^2.$$

Appendix C. Maximum Likelihood Estimation

The state variables are discretized as follows:

$$
\begin{aligned}
\log\left(\delta_{i,t+\bar{\Delta}}/\delta_{it}\right) &= \left(\widehat{f}_{it} - \frac{1}{2}\sigma_\delta^2\right)\bar{\Delta} + u_{i,t+\bar{\Delta}}, \\
\widehat{f}_{i,t+\bar{\Delta}} &= e^{-\lambda\bar{\Delta}}\widehat{f}_{it} + \left(1 - e^{-\lambda\bar{\Delta}}\right)\bar{f} + u_{i+2,t+\bar{\Delta}}, \\
\pi_{i,t+\bar{\Delta}} &= e^{-\omega\bar{\Delta}}\pi_{it} + \sigma_\delta\sqrt{\frac{1-e^{-2\omega\bar{\Delta}}}{2\omega}}\frac{u_{i,t+\bar{\Delta}}}{\sigma_\delta\sqrt{\bar{\Delta}}},
\end{aligned}
$$

$$
\begin{aligned}
\gamma_{i,t+\bar{\Delta}} &= \gamma_{it} + \left(-\frac{\gamma_{it}^2}{\sigma_\delta^2} - 2\lambda\gamma_{it} + \sigma_f^2(1-\Phi^2)\right)\bar{\Delta}, \\
\Phi_{i,t+\bar{\Delta}} &= \frac{\Psi}{\Psi + (1-\Psi)e^{\Lambda\pi_{i,t+\bar{\Delta}}}},
\end{aligned}
$$

where $\bar{\Delta}$ is the time interval between two observations and i stands for the industry index.

We consider the Fama-French 48 industries for our model calibration. We use the realized real log-dividend growth and expected real log-dividend growth of industry i as a proxy for $\log(\delta_{i,t+\bar{\Delta}}/\delta_{it})$ and $(\widehat{f}_{it} - \frac{1}{2}\sigma_\delta^2)\bar{\Delta}$, respectively. Monthly dividend growth rates for each firm are calculated using the merged CRSP/COMPUSTAT dataset. Outliers at the 1st and 99th percentiles are replaced with their 12-month moving average. Realized dividend growth rate for each industry is then calculated as the value-weighted dividend growth rate of all the firms in that industry. We use the firms' market value observed from the most recent June as their weights. The expected log-dividend growth is the fitted value of an ARMA(1,1) model to the realized log-dividend growth. Realized log-dividend growth rates and expected log-dividend growth rates are observed monthly ($\bar{\Delta} = 1/12$) from 08/1972 to 08/2015. To obtain real log dividend growth rates, we subtract the log-realized and log-expected dividend growth rates with the log-inflation growth rate obtained from the Federal Reserve.

The system above shows that, conditional on knowing the parameters of the model and the initial values $(\pi_{i,0}, \gamma_{i,0})$, the time series of the dividend growth and expected dividend growth allow us to sequentially back out the time series $(\pi_{i,t}, \gamma_{i,t}, \Phi_{i,t})$ as well as the noises $(u_{i,t}, u_{i+2,t})$ for $t = \bar{\Delta},\ 2\bar{\Delta},\ 3\bar{\Delta}, \ldots$. The initial performance index $\pi_{i,0}$ is set to its long-term mean, which is zero. The initial uncertainty $\gamma_{i,0}$ is set to the long-term uncertainty γ_{ss} defined in Appendix B.

The log-likelihood function L_i satisfies

$$L_i(\Theta; u_{\bar{\Delta}}, \ldots, u_{N\bar{\Delta}}) = \sum_{j=1}^{N} \log\left(\frac{1}{(2\pi)^2\sqrt{|\Sigma_{(j-1)\bar{\Delta}}|}}\right) - \frac{1}{2} u_{j\bar{\Delta}}^{\top} \Sigma_{(j-1)\bar{\Delta}}^{-1} u_{j\bar{\Delta}}, \tag{C.1}$$

where $\Theta \equiv (\sigma_\delta, \bar{f}, \lambda, \sigma_f, \omega, \Psi, \Lambda)^{\top}$, N is the number of observations, $\top$ is the transpose operator, and $|.|$ is the determinant operator. The 2-dimensional vector u satisfies

$$u_{t+\bar{\Delta}} \equiv \begin{pmatrix} u_{i,t+\bar{\Delta}} \\ u_{i+2,t+\bar{\Delta}} \end{pmatrix} = \begin{pmatrix} \log\left(\delta_{i,t+\bar{\Delta}}/\delta_{it}\right) - \left(\widehat{f}_{it} - \frac{1}{2}\sigma_\delta^2\right)\bar{\Delta} \\ \widehat{f}_{i,t+\bar{\Delta}} - e^{-\lambda\bar{\Delta}}\widehat{f}_{it} - \left(1 - e^{-\lambda\bar{\Delta}}\right)\bar{f} \end{pmatrix}.$$

The conditional expectation and conditional variance-covariance matrix of $u_{t+\bar{\Delta}}$ are

$$\mathbb{E}_t(u_{t+\bar{\Delta}}) = \begin{pmatrix} 0 \\ 0 \end{pmatrix},$$

$$\Sigma_t \equiv \mathrm{Var}_t(u_{t+\bar{\Delta}}) = \begin{pmatrix} \sigma_\delta^2\bar{\Delta} & \sqrt{\bar{\Delta}}\gamma_{it}\sqrt{\frac{1-e^{-2\lambda\bar{\Delta}}}{2\lambda}} \\ \sqrt{\bar{\Delta}}\gamma_{it}\sqrt{\frac{1-e^{-2\lambda\bar{\Delta}}}{2\lambda}} & \left[\frac{\gamma_{it}^2}{\sigma_\delta^2} + \sigma_f^2\Phi_{it}^2\right]\frac{1-e^{-2\lambda\bar{\Delta}}}{2\lambda} \end{pmatrix}.$$

Given that our dataset consists of 48 industries, we can construct 48 log-likelihood functions as defined in Equation (C.1). To obtain the vector of parameters Θ, we maximize the sum of these 48 log-likelihood functions.

Appendix D. Proof of Proposition 2

The price of the single-dividend paying securities S_1^T is defined by

$$P_{1t}^T = \mathbb{E}_t\left(\frac{\xi_T}{\xi_t}\delta_{1T}\right). \tag{D.1}$$

Substituting Equation (13) in Equation (D.1) yields

$$
\begin{aligned}
P_{1t}^T &= e^{-\Delta(T-t)}(\delta_{1t}+\delta_{2t})^\alpha \mathbb{E}_t\left(\delta_{1T}\left(\frac{1}{\delta_{1T}+\delta_{2T}}\right)^\alpha\right)\\
&= e^{-\Delta(T-t)}(\delta_{1t}+\delta_{2t})^\alpha \mathbb{E}_t\left(\delta_{1T}^{1-\alpha}\left(\frac{\delta_{1T}}{\delta_{1T}+\delta_{2T}}\right)^\alpha\right)\\
&= e^{-\Delta(T-t)}e^{\alpha(\zeta_{1t}-Q_t)}\mathbb{E}_t\left(e^{(1-\alpha)\zeta_{1T}+\alpha Q_T}\right)
\end{aligned}
$$

where $\zeta_i \equiv \log \delta_i$ is the log-dividend and $Q = \log \frac{\delta_1}{\delta_1+\delta_2}$ the log-dividend share. Similarly, the price of the single-dividend paying security P_2^T satisfies

$$
\begin{aligned}
P_{2t}^T &= \mathbb{E}_t\left(\frac{\xi_T}{\xi_t}\delta_{2T}\right)\\
&= e^{-\Delta(T-t)}(\delta_{1t}+\delta_{2t})^\alpha \mathbb{E}_t\left(\delta_{2T}\left(\frac{1}{\delta_{1T}+\delta_{2T}}\right)^\alpha\right)\\
&= e^{-\Delta(T-t)}(\delta_{1t}+\delta_{2t})^\alpha \mathbb{E}_t\left(\delta_{1T}^{-\alpha}\delta_{2T}\left(\frac{\delta_{1T}}{\delta_{1T}+\delta_{2T}}\right)^\alpha\right)\\
&= e^{-\Delta(T-t)}e^{\alpha(\zeta_{1t}-Q_t)}\mathbb{E}_t\left(e^{-\alpha\zeta_{1T}}\left(e^{-Q_T}-1\right)e^{\zeta_{1T}}e^{\alpha Q_T}\right)\\
&= e^{-\Delta(T-t)}e^{\alpha(\zeta_{1t}-Q_t)}\mathbb{E}_t\left(e^{(1-\alpha)\zeta_{1T}+(\alpha-1)Q_T}-e^{(1-\alpha)\zeta_{1T}+\alpha Q_T}\right)\\
&= e^{-\Delta(T-t)}e^{\alpha(\zeta_{1t}-Q_t)}\mathbb{E}_t\left(e^{(1-\alpha)\zeta_{1T}+(\alpha-1)Q_T}\right)-P_{1t}^T
\end{aligned}
$$

□

Appendix E. Approximation of the Transforms

The idea consists in approximating the dynamics of the state-vector, and then computing the transforms appearing in Equations (14) and (15) by applying the theory on affine processes (e.g., Duffie et al., 2000). An accurate approximation of the dynamics includes second-order terms. Consequently, before approximating we augment the state-vector by these second order terms (Cheng and Scaillet, 2007). Then, we compute the drift and variance-covariance matrix of the augmented state-vector. Finally, we approximate the augmented drift and variance-covariance matrix by performing a Taylor expansion.

Because the dividend share belongs to the interval $(0,1)$, the log-dividend share Q belongs to $(-\infty,0)$. Therefore, the dynamics of Q cannot be accurately approximated by performing

Taylor expansions. To overcome this problem we perform the following change of variable[13]

$$\tilde{Q} \equiv \log\left(1+\frac{\delta_1}{\delta_1+\delta_2}\right) = \log\left(1+e^{Q}\right)$$

where $\tilde{Q} \in]0, \log(2)[$. The dynamics of $\tilde{Q}$ are

$$\begin{aligned} d\tilde{Q}_t &= e^{-2\tilde{Q}_t}\left(e^{\tilde{Q}_t}-2\right)\left(e^{\tilde{Q}_t}-1\right)\left(\left(e^{2\tilde{Q}_t}-2\right)\sigma_\delta^2 + e^{\tilde{Q}_t}\left(\widehat{f}_{2t}-\widehat{f}_{1t}\right)\right)dt \\ &+ \begin{pmatrix}\sigma_\delta\left(3-2e^{-\tilde{Q}_t}-e^{\tilde{Q}_t}\right) & \sigma_\delta\left(-3+2e^{-\tilde{Q}_t}+e^{\tilde{Q}_t}\right) & 0 & 0\end{pmatrix} dW_t. \end{aligned}$$

Proposition 4. *Under the change of variable stated above and the assumption that the coefficient of relative risk aversion α is an integer, the single-dividend paying securities appearing in Equations* (14) *and* (15) *satisfy*

$$P_{1t}^T = e^{-\Delta(T-t)}\left(\frac{e^{\zeta_{1t}}}{e^{\tilde{Q}_t}-1}\right)^\alpha \sum_{j=0}^{\alpha}\binom{\alpha}{j}(-1)^{\alpha-j}\mathbb{E}_t\left(e^{(1-\alpha)\zeta_{1T}+j\tilde{Q}_T}\right) \tag{E.1}$$

$$P_{2t}^T = e^{-\Delta(T-t)}\left(\frac{e^{\zeta_{1t}}}{e^{\tilde{Q}_t}-1}\right)^\alpha \sum_{j=0}^{\alpha-1}\binom{\alpha-1}{j}(-1)^{\alpha-1-j}\mathbb{E}_t\left(e^{(1-\alpha)\zeta_{1T}+j\tilde{Q}_T}\right) - S_{1t}^T. \tag{E.2}$$

Proof. The single-dividend paying securities price P_1^T satisfies

$$\begin{aligned} P_{1t}^T &= e^{-\Delta(T-t)}e^{\alpha(\zeta_{1t}-Q_t)}\mathbb{E}_t\left(e^{(1-\alpha)\zeta_{1T}+\alpha Q_T}\right) \\ &= e^{-\Delta(T-t)}\left(\frac{e^{\zeta_{1t}}}{e^{\tilde{Q}_t}-1}\right)^\alpha \mathbb{E}_t\left(e^{(1-\alpha)\zeta_{1T}}\left(e^{\tilde{Q}_T}-1\right)^\alpha\right) \\ &= e^{-\Delta(T-t)}\left(\frac{e^{\zeta_{1t}}}{e^{\tilde{Q}_t}-1}\right)^\alpha \mathbb{E}_t\left(e^{(1-\alpha)\zeta_{1T}}\sum_{j=0}^{\alpha}\binom{\alpha}{j}(-1)^{\alpha-j}e^{j\tilde{Q}_T}\right) \\ &= e^{-\Delta(T-t)}\left(\frac{e^{\zeta_{1t}}}{e^{\tilde{Q}_t}-1}\right)^\alpha \sum_{j=0}^{\alpha}\binom{\alpha}{j}(-1)^{\alpha-j}\mathbb{E}_t\left(e^{(1-\alpha)\zeta_{1T}+j\tilde{Q}_T}\right). \end{aligned} \tag{E.3}$$

Similarly, P_2^T satisfies

[13]Note that this change of variable could be omitted. If it was, then the approximation of the transforms would be slightly less accurate.

$$
\begin{aligned}
P_{2t}^T &= e^{-\Delta(T-t)} e^{\alpha(\zeta_{1t}-Q_t)} \mathbb{E}_t \left(e^{(1-\alpha)\zeta_{1T}+(\alpha-1)Q_T} \right) - P_{1t}^T \\
&= e^{-\Delta(T-t)} \left(\frac{e^{\zeta_{1t}}}{e^{\tilde{Q}_t}-1} \right)^{\alpha} \mathbb{E}_t \left(e^{(1-\alpha)\zeta_{1T}} \left(e^{\tilde{Q}_T}-1 \right)^{\alpha-1} \right) - P_{1t}^T \\
&= e^{-\Delta(T-t)} \left(\frac{e^{\zeta_{1t}}}{e^{\tilde{Q}_t}-1} \right)^{\alpha} \sum_{j=0}^{\alpha-1} \binom{\alpha-1}{j} (-1)^{\alpha-1-j} \mathbb{E}_t \left(e^{(1-\alpha)\zeta_{1T}+j\tilde{Q}_T} \right) - P_{1t}^T. \qquad \text{(E.4)}
\end{aligned}
$$

$\square$

We now proceed with the approximation method that allows us to compute the transforms appearing in Equations (E.3) and (E.4). Let the state-vector x be defined by

$$
\begin{aligned}
x &\equiv (x_i)_{i=1}^8 \\
&= \begin{pmatrix} \zeta_1 & \tilde{Q} & \widehat{f}_1 & \widehat{f}_2 & \pi_1 & \pi_2 & \gamma_1 & \gamma_2 \end{pmatrix}^\top,
\end{aligned}
$$

with the dynamic

$$
dx_t \equiv \mu(x_t) + \sigma(x_t) dW_t. \qquad \text{(E.5)}
$$

In Equation (E.5), the state-vector x has a non-affine dynamic with a non-affine drift $\mu(x)$ and a non-affine variance-covariance matrix $\sigma(x)\sigma(x)^\top$. Given the structure of $\mu(x)$ and $\sigma(x)\sigma(x)^\top$, the augmented state-vector X is chosen to be

$$
\begin{aligned}
X &\equiv (X_i)_{i=1}^{17} \\
&= \Big(\zeta_1 \quad \tilde{Q} \quad \widehat{f}_1 \quad \widehat{f}_2 \quad \pi_1 \quad \pi_2 \quad \gamma_1 \quad \gamma_2 \quad \ldots \\
&\qquad \ldots \quad \tilde{Q}^2 \quad \tilde{Q}\widehat{f}_1 \quad \tilde{Q}\widehat{f}_2 \quad \tilde{Q}\gamma_1 \quad \tilde{Q}\gamma_2 \quad \pi_1^2 \quad \pi_2^2 \quad \gamma_1^2 \quad \gamma_2^2 \Big)^\top \\
dX_t &\equiv \mu(X_t) + \sigma(X_t) dW_t.
\end{aligned}
$$

Approximated expressions for the augmented drift $\mu(X)$ and the variance-covariance matrix $\Sigma(X) \equiv \sigma(X)\sigma(X)^\top$ are derived using a Taylor expansion around the reference vector x_0. We discuss the procedure below in Definition 3.

Definition 3. *The reference vector x_0 satisfies*

$$x_{02} = \log(1.5) \qquad x_{03} = x_{04} = \bar{f}$$
$$x_{05} = x_{06} = 0 \qquad x_{07} = x_{08} \equiv \gamma_{ss}.$$

Note that x_{01} is not defined because ζ_1 neither shows up in the drift $\mu(X)$ nor in the variance-covariance matrix $\Sigma(X)$. $\bar{f}$ is the long-term mean of $\widehat{f}_1$ and $\widehat{f}_2$, 0 is the long-term mean of π_1 and π_2, and $\gamma_{ss} = \sigma_\delta\sqrt{\sigma_f^2(1-\Psi^2)+\lambda^2\sigma_\delta^2} - \lambda\sigma_\delta^2$ is the uncertainty conditional on $\pi_i = 0$. The derivations of the long-term means are provided in Appendix A. The long-term uncertainty γ_{ss} is computed in Appendix B.

The drift $\mu(X)$ and the variance-covariance matrix $\Sigma(X)$ are expanded around the reference vector x_0 defined in 3. More precisely, $\mu(X)$ and $\Sigma(X)$ are written

$$\mu(X) \approx K_0 + K_1 X$$
$$\Sigma(X) \approx H_0 + \sum_{i=1}^{17} H_i X_i,$$

where K_1 and $H_i,\ i = 0,\dots,17$ are 17-dimensional squared matrices and K_0 a 17-dimensional vector. K_0, K_1, and $H_i,\ i = 0,\dots,17$ are available upon request.

Using the approximation, the theory on affine processes applies. Following Duffie et al. (2000), the transforms defined in Equations (E.1) and (E.2) are approximated by

$$\mathbb{E}_t\left(e^{\epsilon\zeta_{1T}+\chi\tilde{Q}_T}\right) \approx e^{\bar{\alpha}(T-t)+\sum_{i=1}^{17}\bar{\beta}_i(T-t)X_i}, \tag{E.6}$$

where the functions $\bar{\alpha}(.)$ and $\bar{\beta}_i(.),\ i = 1,\dots,17$, solve a set of 18 Riccati equations subject to $\bar{\alpha}(0) = 0$, $\bar{\beta}_1(0) = \epsilon$, $\bar{\beta}_2(0) = \chi$, and $\bar{\beta}_i(0) = 0,\ i = 3,\dots,17$.

The system of Riccati equations is

$$\bar{\beta}'(\tau) = K_1^\top \bar{\beta}(\tau) + \frac{1}{2}\bar{\beta}(\tau)^\top H_+ \bar{\beta}(\tau)$$
$$\bar{\alpha}'(\tau) = K_0^\top \bar{\beta}(\tau) + \frac{1}{2}\bar{\beta}(\tau)^\top H_0 \bar{\beta}(\tau),$$

where $\tau = T - t$.[14] The set of Riccati equations is solved numerically. Then, substituting Equation (E.6) in Equations (E.1) and (E.2) determines the single-dividend paying securities prices P_1^T and P_2^T. As described in Equation (16), stock prices are obtained by numerically integrating over the single-dividend paying securities.

Appendix F. Illustration of FF48 Attention Measures

Figure G.1 depicts the time series of model-implied attention to each of the Fama-French 48 industries. Time series are at the monthly frequency from 08/1972 to 08/2015, and are extracted from the maximum likelihood estimation described in Section 2.4 and Appendix C. It is worth noting that attention measures feature important swings and are weakly correlated among each other. The mean and median cross-industry attention correlations are 0.11 and 0.12, respectively.

[Insert Figure G.1 about here.]

Appendix G. Risk Aversion, the Volatility-Attention Relationship, and the Business Cycle

Table G1 shows the model-implied relationship between volatility and attention when the coefficient of relative risk aversion is $\alpha = 0.8 < 1$. While the volatility to stock i is more sensitive to attention to stock $j \neq i$ when risk aversion is larger than one (see Table 2), the volatility of stock i becomes more sensitive to attention to stock i when risk aversion is smaller than one (see Table G1). That is, the model implies that the relative impact of individual attentions on volatility depends on the value of risk aversion.

[14] Note that the matrix H_+ is 3-dimensional. It consists in the concatenation of the matrices H_i, $i = 1, \dots, 17$. This notation is used to avoid writing an equation for each $\bar{\beta}$.

To test this prediction, we regress industry i's return volatility change on industry i's attention change, industry j's attention change, industry i's attention change interacted with the dummy variable $\mathbb{1}_t(\text{Boom})$, and industry j's attention change interacted with $\mathbb{1}_t(\text{Boom})$. The dummy variable $\mathbb{1}_t(\text{Boom})$ is equal to 1 when the GDP growth rate in month t is greater than its 5-year moving average (i.e., economic boom), and 0 otherwise. As in Section 4, industries i and j are fundamentally unrelated.

Column (2) of Table G2 shows that, in bad times (when $\mathbb{1}_t(\text{Boom}) = 0$), industry i's volatility reacts more to industry j's attention. Indeed, the coefficient on industry j's attention is equal to 0.032 and is statistically significant at the 5% level, whereas that on industry i's attention is insignificant. In contrast, industry i's volatility reacts more to industry i's attention in good times (when $\mathbb{1}_t(\text{Boom}) = 1$). Indeed, the coefficient on industry i's attention is equal to $-0.008 + 0.087 = 0.079$, whereas that on industry j's attention is equal to $0.032 - 0.008 = 0.024$.

These empirical results are consistent with our model's prediction that industry i's volatility is more sensitive to industry j's (resp., industry i's) attention when risk aversion is high (resp., low). The reason is that risk aversion is counter-cyclical (Brandt and Wang, 2003; Bollerslev et al., 2011), being larger in bad times than in good times. In particular, Bollerslev et al. (2011) show that risk aversion tends to drop below one during high growth periods.

[Insert Tables G1 and G2 about here.]

Table G1: Model-Implied Regressions of Return Volatility on Attention when Risk Aversion is $\alpha = 0.8$.

This table reports the outputs obtained by regressing: (1) stock 1's return volatility change, $\Delta\sigma_1$, on stock 1's attention change, $\Delta\Phi_1$, and stock 2's attention change, $\Delta\Phi_2$; and (2) stock 2's return volatility change, $\Delta\sigma_2$, on both attention changes. The model-implied regression outputs are obtained by simulating the model at a monthly frequency over a 50-year horizon. t-statistics are in brackets and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Although not reported, each regression features an intercept.

	$\Delta\sigma_1$	$\Delta\sigma_2$
	(1)	(2)
$\Delta\Phi_1$	0.037^{***}	0.007^{***}
	(24.42)	(4.41)
$\Delta\Phi_2$	0.004^{**}	0.036^{***}
	(2.37)	(23.90)
Adj. R^2	0.501	0.496
Nobs.	600	600

Table G2: Time-varying Attention and Cross-Industry Volatility Spillover: Effect of the Business Cycle

This table reports results examining the impact of the business cycle on the relationship between time-varying attentions and cross-industry volatility spillovers. We estimate the monthly panel regression on 18 fundamentally unrelated pairs of Fama-French 48 industries from 1972 to 2015. See Table 5 for details of the industry pairings. The dependent variable is $\Delta\sigma_{i,t+1}$, the monthly change in return volatility of industry i at time $t+1$. The independent variables of interests are the monthly changes in attention to the i industry, $\Delta\Phi_{i,t}$, and to its fundamentally unrelated j industry, $\Delta\Phi_{j,t}$. The regression specification that we examine is similar to that in Column (3) of Table 6, and for convenience, this result is replicated here in Column (1). $\mathbb{1}_t$(Boom) is an indicator variable equal to 1 when the GDP growth rate at time t is greater than its 5-year moving average (i.e., economic boom), and 0 otherwise. Industry-pair fixed effects and Macro control variables are included in all specifications. All specifications include 3 lags (one quarter) of the dependent variable and of the monthly change in attention variables. Newey-West t-statistics adjusted for heteroskedasticity and autocorrelations are reported in parentheses below each estimate. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent var: $\Delta\sigma_{i,t+1}$	
	(1)	(2)
$\Delta\Phi_{i,t}$	0.039**	−0.008
	(2.10)	(−0.35)
$\Delta\Phi_{j,t}$	0.025**	0.032**
	(2.37)	(1.99)
$\Delta\Phi_{i,t} \times \mathbb{1}_t$(Boom)		0.087***
		(2.52)
$\Delta\Phi_{j,t} \times \mathbb{1}_t$(Boom)		−0.008
		(−0.46)
$\mathbb{1}_t$(Expansion)		0.001
		(1.52)
Lagged dependent var	✓	✓
Lagged attentions var	✓	✓
Macro controls	✓	✓
Industry-pair FE	✓	✓
No. cross sections	18	18
Time-series length	516	516
Adjusted R^2	10.2%	10.6%

Table G3: Monthly Attention, Volatilities, and Correlations

We report summary statistics of the variables used to test the model's empirical predictions. Table 5 describes the industry sectors and the matched industry pairs that are in our sample. Panel A reports summary statistics of monthly investor attention, and return volatilities. Panel B reports summary statistics of monthly cross-industry return correlations for the 18 matched pairs of fundamentally unrelated industries. See Section 4.2 for details of these variable constructions. The sample period is from 08/1972 to 08/2015.

Panel A: Summary Statistics of Monthly Attention and Volatilities

Ind Code	Φ_t				σ_t			
	Mean	Stdev	Min	Max	Mean	Stdev	Min	Max
FOOD	0.615	0.091	0.422	0.762	0.037	0.028	0.002	0.190
SMOKE	0.613	0.121	0.362	0.863	0.051	0.039	0.005	0.275
TOYS	0.638	0.112	0.411	0.942	0.058	0.043	0.004	0.403
FUN	0.635	0.147	0.256	0.895	0.061	0.051	0.002	0.366
HLTH	0.605	0.134	0.308	0.764	0.062	0.047	0.003	0.361
MEDEQ	0.640	0.090	0.359	0.809	0.044	0.032	0.003	0.221
CHEM	0.653	0.066	0.414	0.770	0.046	0.036	0.004	0.314
TXTLS	0.655	0.063	0.458	0.823	0.056	0.051	0.003	0.446
CNSTR	0.628	0.091	0.409	0.747	0.059	0.043	0.005	0.356
FABPR	0.597	0.064	0.375	0.731	0.058	0.042	0.006	0.297
SHIPS	0.678	0.121	0.249	0.916	0.060	0.046	0.004	0.372
GUNS	0.646	0.102	0.397	0.929	0.052	0.040	0.004	0.343
GOLD	0.575	0.150	0.235	0.983	0.087	0.064	0.006	0.557
MINES	0.562	0.220	0.080	0.971	0.062	0.048	0.004	0.408
COAL	0.603	0.098	0.251	0.836	0.085	0.066	0.005	0.452
PERSV	0.626	0.115	0.411	0.804	0.053	0.039	0.005	0.318
BUSSV	0.641	0.075	0.503	0.800	0.054	0.040	0.004	0.308
CHIPS	0.649	0.123	0.336	0.809	0.062	0.048	0.005	0.376
PAPER	0.644	0.057	0.459	0.775	0.045	0.034	0.003	0.293
TRANS	0.666	0.088	0.381	0.801	0.047	0.034	0.004	0.313
WHLSL	0.652	0.100	0.426	0.832	0.043	0.033	0.001	0.323

Panel B: Summary Statistics of Monthly Return Correlations

Pair No.	Industry	Industry	ρ_t			
			Mean	Stdev	Min	Max
1	SMOKE	MEDEQ	0.345	0.709	-1.0	1.0
2	SMOKE	BUSSV	0.345	0.709	-1.0	1.0
3	GOLD	COAL	0.249	0.747	-1.0	1.0
4	SMOKE	CHEM	0.345	0.709	-1.0	1.0
5	SMOKE	CHIPS	0.345	0.709	-1.0	1.0
6	FUN	SHIPS	0.420	0.681	-1.0	1.0
7	GUNS	GOLD	0.086	0.756	-1.0	1.0
8	FABPR	GOLD	0.123	0.759	-1.0	1.0
9	HLTH	GOLD	0.099	0.76	-1.0	1.0
10	GOLD	PERSV	0.249	0.747	-1.0	1.0
11	SMOKE	PAPER	0.345	0.709	-1.0	1.0
12	TOYS	GOLD	0.159	0.763	-1.0	1.0
13	SMOKE	TRANS	0.345	0.709	-1.0	1.0
14	FOOD	SMOKE	0.568	0.612	-1.0	1.0
15	TXTLS	SHIPS	0.472	0.655	-1.0	1.0
16	CNSTR	GOLD	0.198	0.753	-1.0	1.0
17	GOLD	MINES	0.249	0.747	-1.0	1.0
18	SMOKE	WHLSL	0.345	0.709	-1.0	1.0

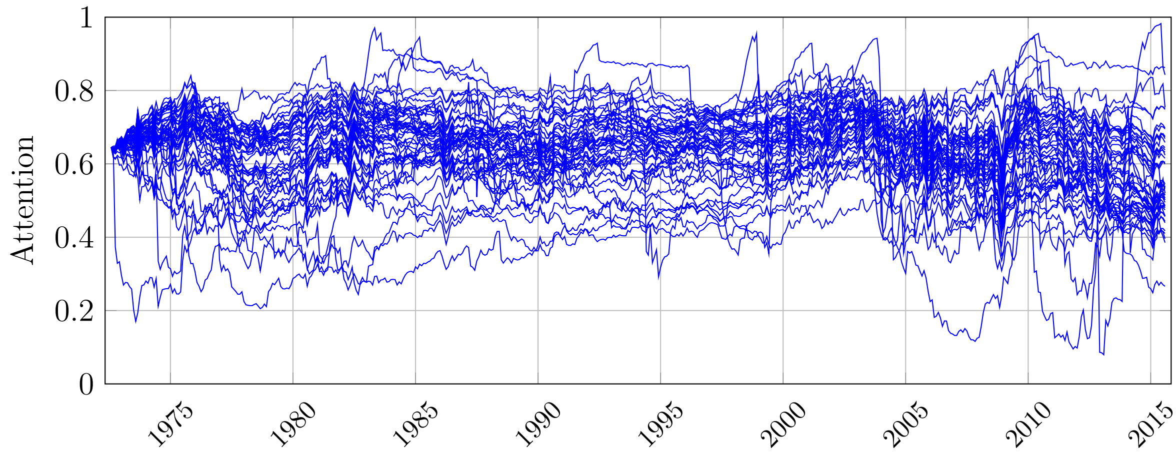

Figure G.1: Time Series of FF48 Attention Measures.
FF48 stands for the Fama-French 48 industries. Each curve represents attention to one particular industry.

Manuscript 17-028 – Fluctuating Attention and Financial Contagion

Letter to the Editor

Dear Professor Jermann,

We are resubmitting herewith the paper entitled "*Fluctuating Attention and Financial Contagion*." We are grateful for the feedback that we received from you and the two anonymous referees on our previous version of the paper. We made sincere effort to address all the concerns that were raised.

Our reading of the comments from the previous submission indicated that there are four main areas that we need to improve in this revision. We list these areas and summarize how we address the associated comments below:

- *Measuring attention.* The second referee (R2) was not convinced by our attention measures and suggested that we more closely tie the model to the data by fitting it to dividend growth rates, and therefore extract attention measures from the estimation. We have closely followed this suggestion and fit the model to the Fama-French 48 (FF48) industries' realized and expected dividend growth rates using maximum likelihood. This allows us to directly extract the model-implied attention paid to each industry. Our model-implied attention measures are highly related to changes in trading volume in their respective industries. This is consistent with the argument in Gervais et al. (2001) and the recent empirical evidence in Fisher et al. (2017) and Gargano and Rossi (2017) that trading volume and attention are positively and strongly related. Overall, the main empirical results in the paper are qualitatively unaffected when we use these new model-implied attention measure.

  Relatedly, the first referee (R1) suggested that we test whether our attention measures are more likely to depend on the direction of dividend surprise shocks or on the magnitude of dividend surprise shocks. The estimation shows that attention depends strongly and inversely on the direction of dividend surprise shocks, whereas the dependence on the magnitude of these shocks is much weaker.

- *Identifying fundamentally unrelated industries.* R2 questioned the way we identified fundamentally unrelated industry returns by decomposing them into the cash-flow news component and the discount-rate news component. The referee (R2), instead, suggested that we identify fundamentally unrelated industries based on their trading relationship with one another. We follow this suggestion and use customer-supplier relationship data at the individual firm level to identify fundamentally unrelated industry pairs, and show that attention-driven return and volatility spillovers exist among these pairs.

- *Other implications of the attention measure.* The referees requested that we provide additional evidence in support of our attention measures. R1 suggested that we test an additional prediction of our model which implies that there is a negative relation between current attention and future uncertainty. Consistent with the model's prediction, we provide evidence that attention is inversely related to future uncertainty, defined as the absolute deviation of the median real GDP growth forecast from the realized GDP growth (van Nieuwerburgh and Veldkamp, 2006). Further, as suggested to us by R2, we show that the post-earnings-announcement drift (PEAD) to each security is weaker when our attention measure to the industry is high. This finding is largely consistent with Dellavigna and Pollet (2009), who find that the effect of PEAD following earnings announcement surprises are stronger for Friday earnings announcements—when investor attention is likely lower. Results from these additional tests provide further support for the models predictions and suggest that our attention measures are indeed measuring investors attention.

- *Asymmetry in the volatility response to attention.* The second referee (R2) suggests that we provide a discussion on why the return volatility of industry 1 is more sensitive to industry 1's attention in the data, whereas it is more sensitive to industry 2's attention (i.e., its unrelated industry's attention) in the model. We now show that the model's prediction on the sensitivity of industry 1's volatility to the respective industries 1's and 2's attentions depends on the value of the risk aversion coefficient. When risk aversion is high (resp., low), the volatility of industry 1 reacts more to industry 2's (resp., industry 1's) attention. We empirically verify this prediction by measuring the response of industry 1's volatility to its respective industry attentions in good and bad times. We show that industry 1's volatility reacts more to industry 2's attention in bad times, whereas it reacts more to industry 1's attention in good times. Since risk aversion is high in bad times and low in good times (Brandt and Wang, 2003; Bollerslev et al., 2011), these empirical findings lend support to the prediction of the model.

All the comments raised by the referees are addressed in detail in their response letters, as well as discussed in the paper. In addition to the points raised by the referees, we have addressed your two specific comments as follows.

First, we now discuss in the introduction the difference between our exogenously-driven attention model and the endogenously-driven attention models of Veldkamp (2006a,b) and van Nieuwerburgh and Veldkamp (2010).

Second, we now show in Table 3 that, although the change in correlation that is due to a change in attention might appear relatively small in Figure 2, such a change is easily detectable using standard statistical methods. Using model-simulated data, we regress changes in return correlation on changes in attention to stock 1 and stock 2 and find positive and statistically significant (at the 1% level) slope coefficients. Also note that, although the variation in correlation depicted in Figure 2 might appear relatively small (the correlation varies from 0.59 to 0.64, which is an 8.5% increase), this variation is quite sensitive to the values of state variables and preference parameters. For instance, we find that: (1) The correlation varies between 0.54 and 0.73 (i.e., a 35% increase) when the dividend share is 0.6 instead of 0.5; (2) The correlation varies between 0.53 and 0.67 (i.e., a 26% increase) when attention to stock 2 is 0 instead of 0.64; and (3) The correlation varies between 0.2 and 0.3 (i.e., a 50% increase) when the representative agent has Epstein-Zin utility with risk aversion equal to 6 and elasticity of intertemporal substitution equal to 0.5 instead of CRRA utility with risk aversion equal to 3.

This paper has neither been published elsewhere, nor accepted for publication elsewhere, or under editorial review for publication elsewhere.

Thank you very much for considering our work and for giving us the opportunity to revise and resubmit our paper. We believe that the paper has improved significantly in response to the feedback that we received from the previous round. We hope that you will agree.

Sincerely,

Michael Hasler and Chayawat Ornthanalai

Manuscript 17-028 – Fluctuating Attention and Financial Contagion

Response to Referee # 1's Report

Thank you very much for your constructive and insightful comments on our paper. We are grateful for your feedback and have made sincere efforts to address all the comments that you raised. We believe that the paper has improved significantly as a result. We first highlight the main changes that we made in response to the overall comments that we received. After, we provide a detailed response to each of your comments.

We summarize below the three areas where we made substantial changes in response to the comments that we received from the review team.

- *Measuring attention.* To more closely tie the model to the data, we now fit it to the Fama-French 48 (FF48) industries' realized and expected dividend growth rates using maximum likelihood. This approach allows us to directly extract the model-implied attention paid to each industry. Our model-implied attention measures are highly related to changes in trading volume in their respective industries. This is consistent with the argument in Gervais et al. (2001) and the recent empirical evidence in Fisher et al. (2017) and Gargano and Rossi (2017) that trading volume and attention are positively and strongly related. Overall, the main empirical results in the paper are qualitatively unaffected when we use these model-implied attention measure.

  Relatedly, your report suggested that we test whether our attention measures are more likely to depend on the direction of dividend surprise shocks or on the magnitude of dividend surprise shocks. The model estimation shows that attention depends strongly and inversely on the direction of dividend surprise shocks, whereas the dependence on the magnitude of these shocks is much weaker.

- *Identifying fundamentally unrelated industries.* The review team suggested that a more natural way to identify fundamentally unrelated industries is to look at their trading relationship with one another. We follow this suggestion and use customer-supplier relationship data at the individual firm level to identify fundamentally unrelated industry pairs, and show that attention-driven return and volatility spillovers exist among these pairs.

- *Other implications of the attention measure.* It has been requested that we provide additional evidence in support of our attention measures. In particular, your report suggested that we test an additional prediction of our model which implies that there is a negative relation between current attention and future uncertainty. Consistent with this model's prediction, we provide evidence that attention is indeed inversely related to future uncertainty, defined as the absolute deviation of the median real GDP growth forecast from the realized GDP growth (van Nieuwerburgh and Veldkamp, 2006). Further, we also show that the post-earnings-announcement drift (PEAD) to each security is weaker when our attention measure to the industry is relatively high. This finding is largely consistent with Dellavigna and Pollet (2009), who find that the effect of PEAD following earnings announcement surprises are stronger for Friday earnings announcements—when investor attention is likely lower. Overall, results from these additional tests which we discuss in Section 4.1 provide further support for the model's predictions and suggest that our attention measures are indeed measuring investors' attention.

The remainder of this response letter addresses each of your specific comments in detail. Your comments are in italics and our responses are in normal font.

Comments

1. *I would like to see more support to one of the key assumptions of the model. That is, why investors pay more attention to bad news, rather than good news? It would be nice to cite more explicit and direct empirical evidence to support this key assumption of the model [...] To me, investors can easily pay more attention after good news [...] Also it is plausible that investors pay more attention to extreme news, either good or bad (see Barber and Odean (2008)). Thus, the attention is increasing in the absolute level of past news.*

More important, the cited evidence is based on attention to the aggregate variable. The attention in the current paper is mostly about industry level. It would be nice to point out a few more papers documenting this key asymmetric attention assumption. Also since the authors have a proxy for attention, ***one can formally test whether attention level is indeed higher after adverse shocks, or the attention increases with the magnitude of the shock, regardless of the direction of the shock.***

Response. In the introduction, we now cite more papers supporting that investor attention tends to be higher in bad times, or after adverse shocks. Vlastakis and Markellos (2012) and Goddard, Kita, and Wang (2015) show that there is a strong positive relation between attention and return volatility in the cross-section of stocks and exchange rates, respectively. Since volatility is countercyclical, attention to individual stocks and exchanges rates is higher in bad times than in good times. Andrei and Hasler (2015) show that attention to financial and economic news, measured using Google search volumes, spikes during the recent financial crisis. Fisher, Martineau, and Sheng (2017) construct attention indices paid to 9 different types of fundamental news, and provide evidence that attention increases following adverse shocks. For example, they show that attention increases following a rise in unemployment or a decline in house prices.

In order to more closely link our model to the data, we now fit the model to the Fama-French 48 industries realized and expected real dividend growth rates by maximum likelihood (see Section 2.4). This allows us to directly test whether attention to each industry is positively (if $\Lambda < 0$) or negatively (if $\Lambda > 0$) related to the industry shock (see Equations (5) and (6) for the relation between attention and the industry shock). As shown in Table 1, the parameter Λ is positive and statistically significant at the 1% level, which confirms that industry attention rises following a negative/adverse industry shock. Note that if, instead, the estimation had provided a negative and significant parameter Λ, then attention would rise following a positive shock.

Although not reported in the paper, we have estimated an alternative model in which attention to industry i is specified as follows:

$$\Phi_{it} = \frac{\Psi}{\Psi + (1-\Psi)e^{\Lambda \pi_{it}^2}},$$

where the performance index, π_{it}, is defined as in the paper (see Equation (6)). In this case, attention to each industry would depend on the magnitude of the shock, regardless of its direction. While the estimation of the model described in the paper (where Φ_{it} depends directly on π_{it} and not π_{it}^2) yields a t-stat of 20 for the estimate of Λ, estimation of the above model yields a t-stat of -1.42 for Λ (the negative t-stat shows that attention increases with the magnitude of the shock). We therefore find a sizable drop in the t-stat for the estimate of Λ when we let attention depends on the magnitude of π_{it} regardless of its direction. This suggests that attention is much more strongly related to the direction of the shock than to the magnitude of the shock.[15] For robustness, we verify that this result also holds when we estimate the model using S&P500 index instead of using the FF48 industries. In this case, we fit the attention model described in the paper (Equation (5)) and the model described above using S&P500 realized and expected real dividend growth rates. Consistent with the previous discussion, the t-stat of Λ is equal to 4.80 in the former model and drops to about -0.73 in the latter model.

2. *In the key regression analysis in Tables 5 and 6, it seems to me that one should use changes in volatility and changes in correlations as dependent variables, since the independent variables are the innovations to attention. The theory implies that the dependent variables should be changes, rather than levels. If one uses innovations in volatility and correlations as dependent variables, it would be nice to show that attention can account for a significant portion of their variation, and thus, to highlight the quantitative importance of the channel proposed by this paper.*

Response. We now use changes in volatility, correlation, and attention consistently throughout our regression analyses. This practice applies to the regression conducted on the model-simulated data (see Tables 2 and 3), and to the regression conducted on the

[15]Note that the conclusion is the same if π_{it}^2 is substituted by $\text{abs}(\pi_{it})$ in the model above.

FF48 industry data (see Tables 6 and 7).

Following your comment, we now provide a discussion on the quantitative importance of our attention measures in driving the volatility and return spillover effects in Section 4.3. To help facilitate the economic interpretation, we also include descriptive statistics of relevant variables (i.e., attention measure, return volatility, and return correlation) for the industries in our sample in Appendix Table G3. We provide a brief summary of our findings on the economic importance of the attention-driven financial contagion below.

Table 6 tests the model's prediction on the effect of fluctuating investor attention on volatility spillovers between two fundamentally unrelated industries i and j. The coefficient estimates from this table indicates that a one-standard deviation increase in monthly attention to industry i (resp., industry j) yields a 0.36% (resp., 0.21%) increase in monthly return volatility of industry i. Given that the average monthly return volatility across industries is 5.6%, this implies that a one-standard deviation increase in attention raises an industry return volatility by about 6.4% (resp., 4.9%) of its average, which is economically sizable.

Table 6 tests the model's prediction on the effect of fluctuating investor attention on return correlations between two fundamentally unrelated industries i and j. The coefficient estimates from this table indicates that a one-standard deviation increase in monthly attention to either industry i or j could lead to an increase in their monthly return correlations of up 7.3%. Given that the average return correlation across our fundamentally unrelated industry pairs is 29%, this implies that a one-standard deviation shock in attention to either industry i or j raises the return correlation by about 25% of its average, which is economically large.

Overall, our regression estimates in Table 6 and 6 show that fluctuating investor attention can explain a substantial variation in the volatility and return correlations of fundamentally unrelated industries. This suggests that the attention channel has an economically important impact on the return and volatility spillover effects.

3. *The model also has clear implications on the relation between attention and uncertainty as defined in the paper. In particular, the model implies that high attention predicts low future uncertainty, whereas low attention is followed by high uncertainty. It would be nice to test this prediction using forecast/survey data such as those from SPF or Livingston.*

Response. We precisely follow your suggestion and show that our model-implied attention measure is inversely related to future uncertainty. This finding is shown in Section 4.1. Here, we measure uncertainty as the absolute deviation of the median real GDP growth forecast from the realized real GDP growth rate (see also van Nieuwerburgh and Veldkamp (2006)). Data are obtained from the Survey of Professional Forecasters. To obtain an aggregate attention measure, we sum up the 48 industry attention measures. Figure 3 shows that regressing future uncertainty on current FF48 aggregate attention yields a negative and significant slope coefficient. This indicates that high attention today yields lower uncertainty in the future, lending support to an important model's implication for which you highlighted.

For robustness, we also verify that our results hold when we use the model-implied attention measure that are fitted to the S&P500 index rather than to the FF48 industries. Here, we regress future uncertainty as defined above on current S&P 500 attention, where S&P 500 attention is obtained by fitting our time-varying attention model to S&P 500 realized and expected real dividend growth rates. Although not reported in the paper, the t-stat of the slope coefficient is again negative and significant (t-stats range between -2.5 and -4 depending on the time lag under consideration), confirming the model's prediction that current attention and future uncertainty are inversely related.

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Response to Referee # 2's Report

Thank you very much for your constructive and insightful comments on our paper. We are grateful for your feedback and have made sincere efforts to address all the comments that you raised. We believe that the paper has improved significantly as a result.

We group your comments by topic and summarize them below in italics. Each comment is followed by our response in normal font, which explains how we address the comment and how we incorporate the changes that we have made in response to it in the new version of the paper.

Comments on Attention Proxies

1.
   - *The authors argue high trading volume proxies for high attention [...] In addition, why should institutional ownership be associated with attention? [...] The same applies to the number of analysts following a stock. Also, the paper argues trading requires attention. In time of increasing importance of automated trading, how relevant is this argument?*
   - *[...] To create the measure of attention the authors log transform each variable, regress it on a time trend, normalize it by full sample moments, then take the average across the measures and apply a first-order autoregressive model and use the residual from this regression as predictor. This raises a couple of concerns. First, the authors should adjust standard errors in the forecasting regressions for the multiple generated regressor problem. Second, the predictor uses forward-looking data.*
   - ***The model, instead, implies the authors could calculate their attention measure at the industry level using actual dividend payments and a statistical model for dividend-growth expectations. This would tie the empirical analysis more tightly to the model and would circumvent several of the concerns I raise above.***

Response. In order to closely tie our model to the data, we now follow your suggestion by fitting the model to the Fama-French 48 industries' realized and expected real dividend growth rates using maximum likelihood (see Section 2.4). This implies that the current attention paid to an industry is determined by the industry's history of dividend surprises (see Equations (5) and (6)) and no longer by trading volume, institutional ownership, and analyst coverage.

2. *How highly correlated are the attention measures across industries in the data? If they are highly correlated, then it might suggest they just capture overall attention to aggregate shocks and it might be difficult to argue that we see contagion due to spillovers.*

   Response. The mean and median of cross-industry attention correlations are 0.11 and 0.12, respectively (see Appendix F for their time-series plots). This finding suggests that our attention measures are less likely to capture the overall attention to aggregate shocks. Also, please refer to Comment 8 below for details on how our regression analysis controls for the potential impact of aggregate shocks.

3. *To get a better feeling for the data, I would love to see time-series plots of the raw attention measures.*

   Response. Time-series plots of the attention measures are provided in Appendix F.

Comments on Unrelated Fundamentals

4. *One of the key stylized facts of business cycles around the world are substantial comovements across aggregate series such as real GDP, investment, and consumption but also across sectors. This would somewhat question the arguments in the paper. In fact, a growing literature in macroeconomics argues sectoral linkages through intermediate inputs might be a central driver for aggregate fluctuations (see Acemoglu et al. (2012) and Ozdagli and Weber (2016)).*

   The model predict fundamentals are orthogonal [...] So far, the authors do not provide evidence that sectors are fundamentally unrelated as they write in the abstract. One way to test that would be to use the input-output tables from the Bureau of Economic Analysis *and show spillovers exists for industries which do not have direct or indirect trade linkages through intermediate input production.*

Response. We have followed your suggestion in the current version of the paper and identify Fama-French 48 (FF48) industries that are unrelated to each other using their trading relationships. We use the firm-level customer-supplier relationship data constructed from the COMPUSTAT Segment Customer File to identify a network of suppliers and customers for each firm (see also Cohen and Frazzini (2008)). We consider any direct and indirect customer-supplier relationships that can be linked up to the sixth-degree of separation. This method allows us to calculate the degree of relatedness between all possible pairs of industries. We consider only industry pairs for which less than 5% of firms in the first industry are related to firms in the second industry, and vice versa. Financial industries are excluded. Using this method, we are able to identify 18 pairs of similarly-sized industries that are unlikely to be fundamentally related. Our main empirical tests in the current version are conducted using these 18 pairs of industries. We find that our main conclusions drawn in the previous version are unaffected by showing that attention-driven return and volatility spillovers exist among these industry pairs.

Comments on Cash-flow and Discount-rate News

5.
- *[...] Cash-flow news are measured as residual and there is evidence return predictability decreased in the 1990s, possibly due to structural changes in the economy, see, e.g., Lettau and Van Nieuwerburgh (2007). Is the reduced return predictability responsible for the importance of cash-flow news?*
- *Relatedly, from Cochrane (1992) and others, we know discount-rate news are the main driver of the aggregate market. Vuolteenaho (2002) rationalizes the two findings by showing cash-flow news are mainly idiosyncratic, consistent with the paper, but discount rate news are highly correlated across firms. The main question, then, is whether the authors of the current paper just pick up this high correlation in discount-rate news across sectors rather than a spillover effect.*
- *Weber (2015) is a recent application of the Campbell (1991) return decomposition.*

- *The authors follow Vuolteenaho (2002) and use, for example, the log return on equity or log excess return. How do they handle zero or negative observations?*
- *I find the language sometimes confusing and would prefer the authors to refer to $Ndr^2_{i,t}$ as discount-rate news rather than discount-rate return.*
- *The authors should provide some falsification tests and show their predictions are not borne out by cash-flow news.*
- *I'm not exactly sure why the authors use discount- and cash-flow news rather than raw returns, given they do not show the results do not hold for cash-flow news.*

Response. In the previous version of the paper, we decomposed raw returns into discount-rate news and cash-flow news components. Since discount-rate news are defined as returns which have been stripped out of their cash-flow news component, we interpreted discount-rate news of two fundamentally related industries as returns of two fundamentally unrelated industries. Since the model predicts that "contagion" arises between fundamentally unrelated industries/sectors (i.e., industries that have unrelated cash flows), we used industry discount-rate returns to empirically test that contagion exists in the U.S. equity market.

In the current version of the paper, we proceed differently by identifying fundamentally unrelated industries using the customer-supplier relationship data (see answer to Comment 4 above). Therefore, we now use raw returns to test our model's predictions.

It is important to emphasize that, although completely different, both approaches that we use to identify fundamentally unrelated industry returns yield the same result. Namely, there exists attention-driven contagion in the U.S. equity market, as predicted by the model.

Comments on the Empirical Results

6. *[...] the model predicts higher attention results in faster transmission of news into returns and as a results in more volatile discount rates. Can the authors provide empirical evidence for the key mechanism of the model? One possible way is to show post earnings*

announcement drifts are shorter, or less pronounced in periods of high attention or for sectors to which investors pay lots of attentions.

Response. Following you suggestion, we show that the post-earnings-announcement drift (PEAD) is weaker when attention paid to the industry is relatively high. We discuss this finding in Section 4.1 and report the results in Table 4. For this analysis, we double-sort firms into 5×5 groups based on the level of earnings surprises as measured using their standardized unadjusted earnings (SUE) and the level of attention paid to their industry. We find that the PEAD is weaker subsequent to earnings announcement surprises (positive or negative) when attention paid to the industry is high. This finding is strongest for negative earnings surprises, which is consistent with Dellavigna and Pollet (2009) who show that the PEAD is weaker for earnings announced on Friday — when investor attention is likely lower.

7. *[...] an increase in attention to sector 1 increases the volatility of sector 2 more than the one sector 1 itself. I would love to see any evidence supporting this prediction. Evidence consistent with the prediction would also alleviate concerns other mechanisms might be at work such downside risk or similar (see discussion below). Given similar in-sample variances, my reading of Table 5 is that industries are more sensitive to own-industry attention rather than attention of other industries. This seems to contradict the model prediction and I would be curious to read a discussion of it in the paper.*

Response. Comparing Tables 2 and G1 shows that the relative impact of individual attentions on the volatility depends on the value of risk aversion in the model. While the volatility to stock i is more sensitive to changes in attention to stock j when risk aversion is equal to 3, the volatility of stock i becomes more sensitive to changes in attention to stock i when risk aversion is smaller than one.

We empirically test this prediction and report the results in Table G2; see also Section Appendix G for the discussion. Here, we regress industry i's return volatility change ($\Delta\sigma_{i,t}$) on industry i's and j's attention changes (resp., $\Delta\Phi_{i,t}$ and $\Delta\Phi_{j,t}$), as well as on their interacted terms with the dummy variable for periods of economic boom, $\mathbb{1}_t(\text{Boom})$.

The dummy variable $\mathbb{1}_t(\text{Boom})$ is equal to 1 when the GDP growth rate in month t is greater than its 5-year moving average, and 0 otherwise.

Column (2) of Table G2 shows that, in bad times (when $\mathbb{1}_t(\text{Boom}) = 0$), industry i's volatility reacts more to industry j's attention. Indeed, the coefficient on industry j's attention is equal to 0.032 and is statistically significant at the 5% level, whereas that on industry i's attention is insignificant. In contrast, industry i's volatility reacts more to industry i's attention in good times (when $\mathbb{1}_t(\text{Boom}) = 1$). Indeed, the coefficient on industry i's attention is equal to $-0.008 + 0.087 = 0.079$, whereas that on industry j's attention is equal to $0.032 - 0.008 = 0.024$.

These empirical results are consistent with our model's prediction that industry i's volatility is more sensitive to industry j's (resp., industry i's) attention when risk aversion is high (resp., low). The reason is that risk aversion is counter-cyclical (Brandt and Wang, 2003; Bollerslev et al., 2011), being larger in bad times than in good times. In particular, Bollerslev et al. (2011) show that risk aversion typically drops below one during high growth periods.

8. *I miss a discussion of potential concerns to the findings in the paper. I'm mainly worried of the following alternative story: we have one aggregate shock. Industries have differential exposure to the shock. Investor attention fluctuates as a function of the shock. I do not see how any of the findings in the paper can differentiate that story from the model proposed in the paper.*

Response. In our tests of the model's predictions, Tables 6 and 7 show that the effect of attention-driven return and volatility spillovers are robust to the inclusion of various macroeconomic variables (Columns (3) and (6)), as well as the inclusion of year-month fixed effects (Columns (2) and (5)). We believe that these tests help mitigate some of the concerns that our main findings are due to aggregate shocks. In fact, our results in Tables 6 and 7 show that the effect of changes in attention variables are generally stronger when we control for macro variables or year-month fixed effects. This suggests that the exclusion of aggregate and macro variables is more likely to bias us against finding the attention-driven volatility and return spillover results.

Nevertheless, as you mentioned in your comment above, industries may have differential exposure to aggregate shocks which is not controlled for in the standard panel-regression framework. To mitigate this concern, we re-estimate our regression models similar to those in Tables 6 and 7 using the linear mixed model with random coefficients. The results are reported in Table R2-1 at the end of this response letter. Here, we allow the regression coefficients on the macro control variables to be unique to each cross section in the panel. This allows for an aggregate macro shock to affect the volatility differently of one industry to the next. Similarly, an aggregate shock can also have a differential impact on the cross-return correlation across different industry pairs. Our results in Table R2-1 show that the coefficient estimates on the attention variables do not substantially change in magnitude and statistical significance when we allow industries to have heterogeneous exposures to macro shocks. We believe that this test helps mitigate the concern that our attention-driven contagion could be driven by industries' differential exposure to aggregate macro shocks.

Other Comments

9. *I would like to see attempts to disentangle the mechanism proposed in the current paper from other possible mechanisms such as asymmetric information and financial constraints or systemic risk or at least I would encourage the authors to provide verbal arguments why they think these channels cannot drive the results the paper provides (see Yuan (2005) and Pasquariello (2007)) [...] Is there a way to differentiate the explanation proposed in the current paper from models of downside risk or disappointment aversion (see Routledge and Zin (2010) and Delikouras (2016) for disappointment aversion, Ang et al. (2006) and Lettau et al. (2014) for downside risk).*

Response. At the end of Section 4.3, we mention that our empirical results are unlikely to be explained by alternative theories based on borrowing constraints (Yuan, 2005), downside risk (Ang et al., 2006; Lettau et al., 2014), systematic risk (Pasquariello, 2007), and disappointment aversion (Routledge and Zin, 2010; Delikouras, 2017). The reason is that borrowing constraints bind in bad times, downside risk is particularly high during market declines, systematic risk measures market risk, and disappointment events occur in bad times when aggregate consumption drops significantly. Each of these features are closely related to the business cycle and market risk, which our four control variables in Tables 6 and 7 (S&P500 return, S&P500 volatility, GDP growth, and inflation) capture.

10. *The authors motivate the process for the signal (see equation (3)) by referring to different, publicly available sources of information such as CNN Money, Financial Times, Bloomberg, etc. If the authors have indeed a large shock to one sector in mind driving attention which is unrelated to other sectors, then I would assume the headlines to be identical and I'm not sure whether this example captures the idea behind process (3). I would simply cut it and just refer to the literature as the authors anyways do at the bottom of page 8.*

    Response. We have cut this part and refer to the existing literature.

11. *Why would dividend surprises decades ago matter for today's attention?*

    Response. Because the dividend performance index is defined as a continuous time exponentially weighted moving average, the parameter ω determines the importance of current relative to past dividend surprise observations in the computation of today's attention (see Equations (5) and (6)). As shown in Table 1, the maximum likelihood estimation yields $\omega = 0.122$. As discussed in Section 2.4, this parameter value implies that the weight assigned to the past 15 years of dividend surprise observations in the determination of today's attention is about 85%. That is, dividend surprises observed more than 15 years ago have a weak impact on current attention.

12. *Looking at Figure 4, we see moving from zero attention to stock 1 to full attention to stock 1 changes the return correlation between stocks 1 and 2 by roughly 0.05 from 0.81 to 0.86. This seems like a rather small change in correlation for a large change in attention. How much data is needed to statistically differentiate extreme observations for attention using correlations only?*

    Response. The change in correlation implied by a change in attention to stock 1 is now depicted in Figure 2. The correlation varies from about 0.59 to 0.64, which represents an 8.5% increase.

Although this model-implied change in correlation might perhaps be perceived as being relatively small, we provide evidence that such a change is statistically detectable using standard methods. To do so, we simulate the model at monthly frequency over 50 years and report in Table 3 the results obtained by regressing changes in correlation on changes in attention to stock 1 and stock 2. The slope coefficients are positive and statistically significant at the 1% level. This shows that, although changes in correlation are also influenced by changes in the other state variables of the model, the impact of attention on correlation is strong enough to make it easily detectable using standard statistical methods.

13. *I would suggest to use a common smoothing parameter for variances and covariances. Then the issue of correlations larger than 1 in absolute value should also occur less frequently.*

    The authors should report how often they encounter correlations larger than 1 in absolute value.

    Response. We now follow your suggestion and use a common smoothing parameter (i.e., EWMA coefficient) for variances and covariances. This approach has eliminated the issue of finding correlations larger than 1. Descriptive statistics of our return correlations are shown in Appendix Table G3.

14. *The authors should cluster standard errors at the quarter level to account for common shocks. Ideally, they would double cluster at the industry and quarter level.*

    Response. For consistency in the main paper, we report Newey-West t-statistics for parameter estimates obtained from the model calibration (Table 1), the time-series regressions on model-simulated data (Tables 2, 3, and G1), the time-series regression on observed data (Figure 3), and the panel regressions on unrelated FF48 industries (Tables 6, 7, and G2). In Tables R2-2 and R2-3 (included at the end of this response letter), we report regression results with standard errors clustered at the industry-pair level, and double clustered at the industry-pair and year-month level. We report results from the most conservative regression specification, where industry-pair and year-month fixed effects are included.

We find that clustering at the industry-pair level slightly improves the statistical significance of the coefficient estimates relative the those obtained using Newey-West estimates. On the other hand, double clustering at the industry-pair and year-month level reduces statistical significance. Nevertheless, we find that statistical significance at the conventional level still applies to all of our coefficient estimates of interest, except those in Column (3) of Table R2-2 where their t-statistics are between 1.35–1.37. Therefore, we interpret our empirical results as being fairly robust to alternative methods of calculating standard errors.

15. *In Table 5, I would want to see a specification without additional covariates.*

    Response. Table 6 in the current version of the paper now reports the results that are related to your comment. In this Table, we report baseline regression results in Columns (1) and (4) where we exclude additional covariates.

16. *Why do the authors use NYSE/ NASDAQ as the proxy for the market? Do they mean the CRSP index? The latter also includes stocks traded on AMEX.*

    Response. We apologize for this typo. We were using the CRSP index which would include stocks traded on AMEX.

17. *The explanatory power is higher for EWMA volatility, because it is much smoother and less erratic compared to realized vol the way it is calculated in the paper.*

    Response. We now focus on the EWMA volatility only.

Table R2-1: Robustness Check: Heterogeneous Exposures to Macro Shocks

This table shows the robustness of our main panel regression results in Tables 6 and 7 when allowing each cross section to have different exposures to the four macro economic control variables: $\Delta\sigma_{sp500,t}$, $\text{Return}_{sp500,t}$, GDP $\text{growth}_{i,t}$, and Inflation $\text{growth}_{i,t}$. We report results from estimating a monthly panel of 18 fundamentally unrelated industry pairs from 1972 to 2015. Industries are defined according to the Fama-French 48 industry classifications. In Columns (1), (3), (5), and (7), the coefficient estimates on the macro variables are fixed across the 18 cross sections. These estimates are duplicates of the results shown in Tables 6 and 7, and are replicated here for your convenience. Columns (2), (4), (6), and (8) report results where the coefficient estimates on the macro variables can differ across the 18 cross sections, i.e., heterogeneous exposures to macro shocks. These results are obtained from estimating the linear mixed model with random coefficients on the macro variables. T-statistics are reported in parentheses below each estimate. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent var: $\Delta\sigma_{i,t+1}$				Dependent var: $\Delta\rho_{ij,t+1}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Change in Attentions								
$\Delta\Phi_{i,t}$	0.039**	0.039***			0.366*	0.367*		
	(2.10)	(2.63)			(1.88)	(1.70)		
$\Delta\Phi_{j,t}$	0.025**	0.025**			0.370***	3.71**		
	(2.37)	(2.12)			(2.45)	(2.11)		
Change in Total Attentions								
$\Delta\left(\Phi_{i,t}+\Phi_{j,t}\right)$			0.031***	0.031***			0.370***	0.371***
			(3.42)	(3.75)			(3.38)	(3.06)
Coefficients on macro vars	Fixed	Mixed	Fixed	Mixed	Fixed	Mixed	Fixed	Mixed
Lagged dependent var	✓	✓	✓	✓	✓	✓	✓	✓
Lagged attentions var	✓	✓	✓	✓	✓	✓	✓	✓
Industry-pair FE	✓	✓	✓	✓	✓	✓	✓	✓
No. cross sections	18				18			
Time-series length	516				516			

Table R2-2: Cross-Industry Volatility Spillover: Different Corrections for Standard errors

This table replicates our main regression results shown in Table 6 with different corrections for standard errors in the coefficient estimates. Year-month and Industry-pair fixed effects are included in all specifications. The dependent variable is $\Delta\sigma_{i,t+1}$, the monthly change in return volatility of industry i. Columns (1) and (4) report results with Newey-West t-statistics, which are adjusted for heteroskedasticity and autocorrelations in the regression residuals; they are duplicates of Columns (2) and (5) from Table 6 in the main paper. Columns (2) and (5) report results with robust t-statistics clustered at the industry-pair level. Columns (3) and (6) report results with robust t-statistics double-clustered at the industry-pair and year-month levels. T-statistics are reported in parentheses below each estimate. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent var: $\Delta\sigma_{i,t+1}$					
	Panel A			Panel B		
	(1)	(2)	(3)	(4)	(5)	(6)
Change in Attentions						
$\Delta\Phi_{i,t}$	0.034*	0.034**	0.034			
	(1.89)	(2.13)	(1.33)			
$\Delta\Phi_{j,t}$	0.020*	0.020*	0.020			
	(1.90)	(1.91)	(1.37)			
Change in Total Attentions						
$\Delta\left(\Phi_{i,t}+\Phi_{j,t}\right)$				0.025***	0.025***	0.025*
				(2.51)	(2.48)	(1.73)
Standard errors	Newey-West	Industry-pair Cluster	Industry-pair & Year-month Cluster	Newey-West	Industry-pair Cluster	Industry-pair & Year-month Cluster
Lagged dependent var	✓	✓	✓	✓	✓	✓
Lagged attentions var	✓	✓	✓	✓	✓	✓
Industry-pair FE	✓	✓	✓	✓	✓	✓
Year-month FE	✓	✓	✓	✓	✓	✓
No. cross sections	18			18		
Time-series length	516			516		
Adjusted R^2	39.4%			39.3%		

Table R2-3: Cross-Industry Return Correlation: Different Corrections for Standard errors

This table replicates our main regression results shown in Table 7 with different corrections for standard errors in the coefficient estimates. Year-month and Industry-pair fixed effects are included. The dependent variable is $\Delta\rho_{ij,t+1}$, the monthly change in return correlation between industries i and j from t to $t+1$. Columns (1) and (4) report results with Newey-West t-statistics, which are adjusted for heteroskedasticity and autocorrelations in the regression residuals; they are duplicates of Columns (2) and (5) from Table 7 in the main paper. Columns (2) and (5) report results with robust t-statistics clustered at the industry-pair level. Columns (3) and (6) report results with robust t-statistics double-clustered at the industry-pair and year-month levels. T-statistics are reported in parentheses below each estimate. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent var: $\Delta\rho_{ij,t+1}$					
	Panel A			Panel B		
	(1)	(2)	(3)	(4)	(5)	(6)
Change in Attentions						
$\Delta\Phi_{i,t}$	0.645***	0.645***	0.645**			
	(3.14)	(3.23)	(2.21)			
$\Delta\Phi_{j,t}$	0.686***	0.686***	0.686***			
	(3.47)	(3.56)	(2.88)			
Change in Total Attentions						
$\Delta\left(\Phi_{i,t}+\Phi_{j,t}\right)$				0.670***	0.670***	0.670***
				(4.17)	(4.24)	(2.94)
Standard errors	Newey-West	Industry-pair Cluster	Industry-pair & Year-month Cluster	Newey-West	Industry-pair Cluster	Industry-pair & Year-month Cluster
Lagged dependent var	✓	✓	✓	✓	✓	✓
Lagged attentions var	✓	✓	✓	✓	✓	✓
Industry-pair FE	✓	✓	✓	✓	✓	✓
Year-month FE	✓	✓	✓	✓	✓	✓
No. cross sections	18			18		
Time-series length	516			516		
Adjusted R^2	30.0%			29.9%		