Cash Flow News and Stock Price Dynamics

JF 2020.04

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汇报人：任宇卓
2020年 11月 11日

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Publications:

[1] Pettenuzzo D, Sabbatucci R, Timmermann A. Dividend suspensions and cash flow risk during the COVID-19 pandemic[J]. Available at SSRN 3628608, 2020.

[2] Korobilis D, Pettenuzzo D. Machine Learning Econometrics: Bayesian algorithms and methods[J]. Available at SSRN, 2020.

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Publications:

[1] Johansson A, Sabbatucci R, Tamoni A. Smart Beta Made Smart[J]. Available at SSRN 3594064, 2020.

[2] Parsons C A, Sabbatucci R, Titman S. Geographic lead-lag effects[J]. The Review of Financial Studies, 2020, 33(10): 4721-4770.

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Publications:

[1] Break Risk (with Simon Smith). Forthcoming in Review of Financial Studies.

[2] Grønborg N S, Lunde A, Timmermann A, et al. Picking funds with confidence[J]. Journal of Financial Economics, 2020.

[3] Smith S C, Timmermann A, Zhu Y. Variable selection in panel models with breaks[J]. Journal of econometrics, 2019, 212(1): 323-344.

Content

$$G_t = \frac{\sum_{i=1}^{N_t} I_t^i D_t^i}{\sum_{i=1}^{N_t} I_{\bar{t}}^i D_{\bar{t}}^i}. \tag{1}$$

$$\Delta d_{t+1} = \mu_{dt+1} + \xi_{dt+1} J_{dt+1} + \varepsilon_{dt+1}. \tag{2}$$

$$\begin{tikzcd}
\boxed{\mu_{dt}} \arrow[r] & \boxed{\Delta d_{dt+1}} \arrow[r] & \boxed{r_{dt+1}} \\
 & \boxed{\mu_{dt+1}} \arrow[u] &
\end{tikzcd}$$

Background

- Information extracted from firms' cash flow announcements is critical to understanding investors' cash flow expectations and, in turn, movements in stock prices.

- relatively few studies analyze the predictability of cash flows (Cochrane,2008), in most cases focusing instead on quarterly or annual changes in aggregate dividends or earnings (van Binsbergen and Koijen,2010;Kelly and Pruitt ,2013).

- On most days, a multitude of firms announces cash flow news, but the number of firms, as well as the industries they belong to, can vary greatly over time.

Literature

- Estimates the effect of new information on stock prices on days with news releases using event-study methodology.

  Cutler, Poterba, and Summers (1989), McQueen and Roley (1993)

- Estimate models of stock return dynamics with stochastic volatility and jumps.

  Cutler, Poterba, and Summers (1989), McQueen and Roley (1993)

- First, no existing study attempts to model the high frequency dynamics in dividends using such methods, let alone estimate and test a model as general as ours.

- Second, we test asset pricing implications implied by the present value model using a much higher data frequency (daily) than previously employed.

- Third, our paper models the transmission from daily cash flow news—in the form of mean, volatility, or jump components—to contemporaneous dynamics in stock market returns, including variation in the volatility and jump probability of returns.

Challenges

- First, individual firms' announced dividends can change by large amounts from one quarter to the next and display strong heterogeneity across firms.

- Second, the number and type of firms that announce dividends often changes substantially from day to day, leading to large composition shifts.

Both effects lead to lumpiness in the daily cash flow news process.

We address this lumpiness by decomposing news on dividend growth into a transitory “normal” shock whose volatility can vary over time, jumps that occur more rarely but whose magnitude tends to be much larger, and a persistent, smoothly evolving component that captures long-run predictive dynamics in the mean of the cash flow growth process.

Abstract

- We develop a new approach to modeling dynamics in cash flows extracted from daily firm-level dividend announcements.
- We decompose daily cash flow news into a persistent component, jumps, and temporary shocks.
- Empirically, we find that the persistent cash flow component is a highly significant predictor of future growth in dividends and consumption.
- Using a log-linearized present value model, we show that news about the persistent dividend growth component predicts stock returns consistent with asset pricing constraints implied by this model.
- News about the daily dividend growth process also helps explain concurrent return volatility and the probability of jumps in stock returns.

Data

Our sample includes all ordinary cash dividends(503,591) declared by firms with common stocks (share codes 10 and 11) listed on NYSE, NASDAQ, or AMEX from 1926 to 2016.

数据来源：CRSP（1926-2016年，101476 pre-1964， 402115 post-1964.）

- do not exclude special dividends, Costco declared two “special dividends” : per quarter \$7 per share(2012.11.08), and \$5 per share(2015.1.30). (usually around 30 cents per quarter)
- do not include, nonordinary dividends: M&A cash flows, buybacks, and new issues.

Year-over-year (gross) growth in aggregate dividends:

$$G_t = \frac{\boxed{\sum_{i=1}^{N_t} I_t^i D_t^i}}{\sum_{i=1}^{N_t} I_{\tilde{t}}^i D_{\tilde{t}}^i}. \tag{1}$$

total dollar value of dividends paid out on day *t*.

D_t^i : the total dividends declared by firm *i* on day *t*, calculated as the dividend per share times the number of shares outstanding.

I_t^i : indicator variable that equals 1 if company *i* announces quarterly dividends on day *t*, and 0 otherwise.

$\tilde{t}$: the same-quarter, prior-year dividend announcement date for firm *i*.

N_t : the number of (publicly traded) firms in existence on day *t*.

Only firms for which $I_i^t = I_i^{\tilde{t}} = 1$ are included in this calculation, which ensures that the samefirms are used in both the numerator and denominator of the ratio.

Figure 1. Distribution of dividend announcements within a quarter.（2014.Q2）

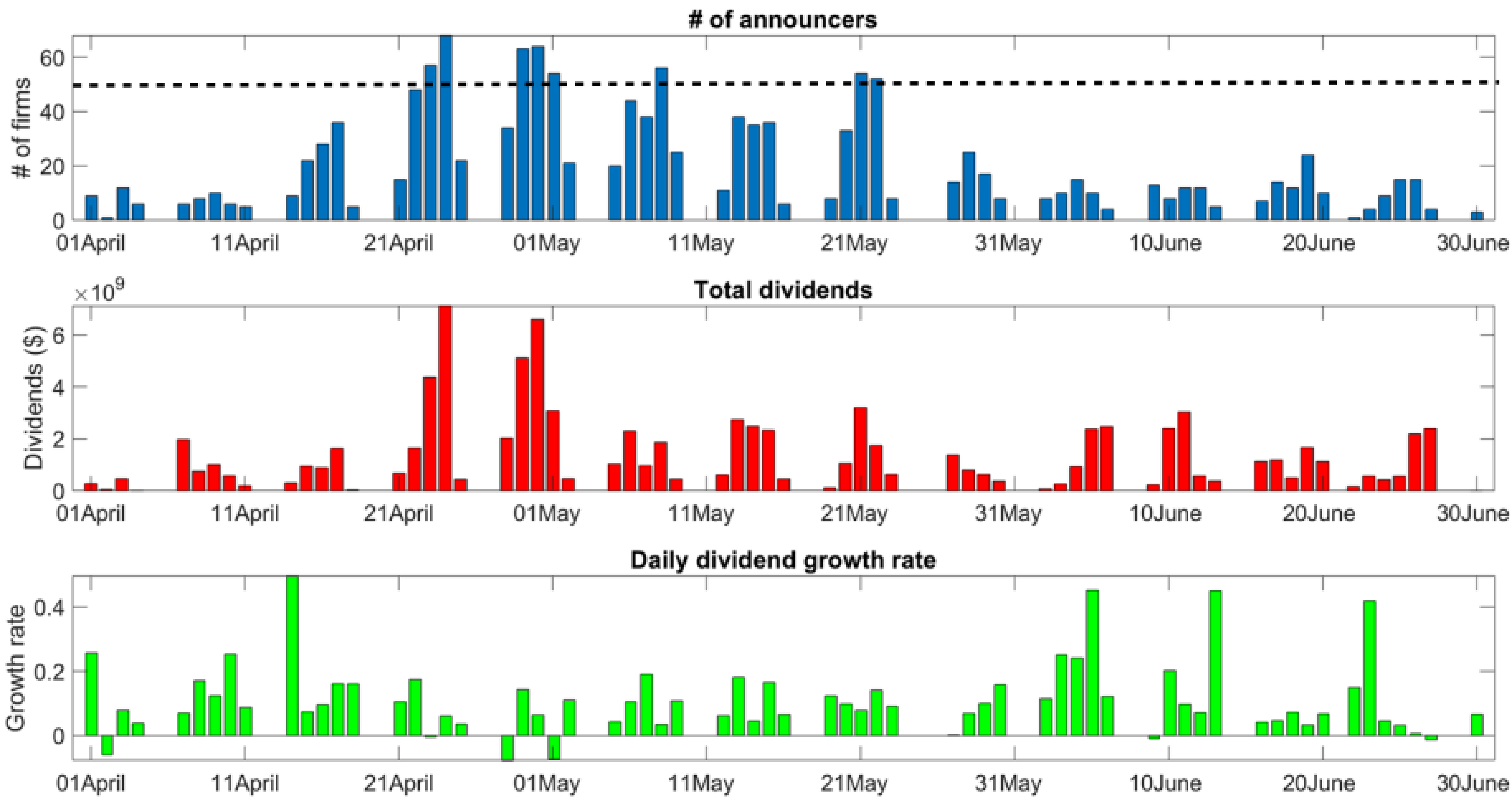
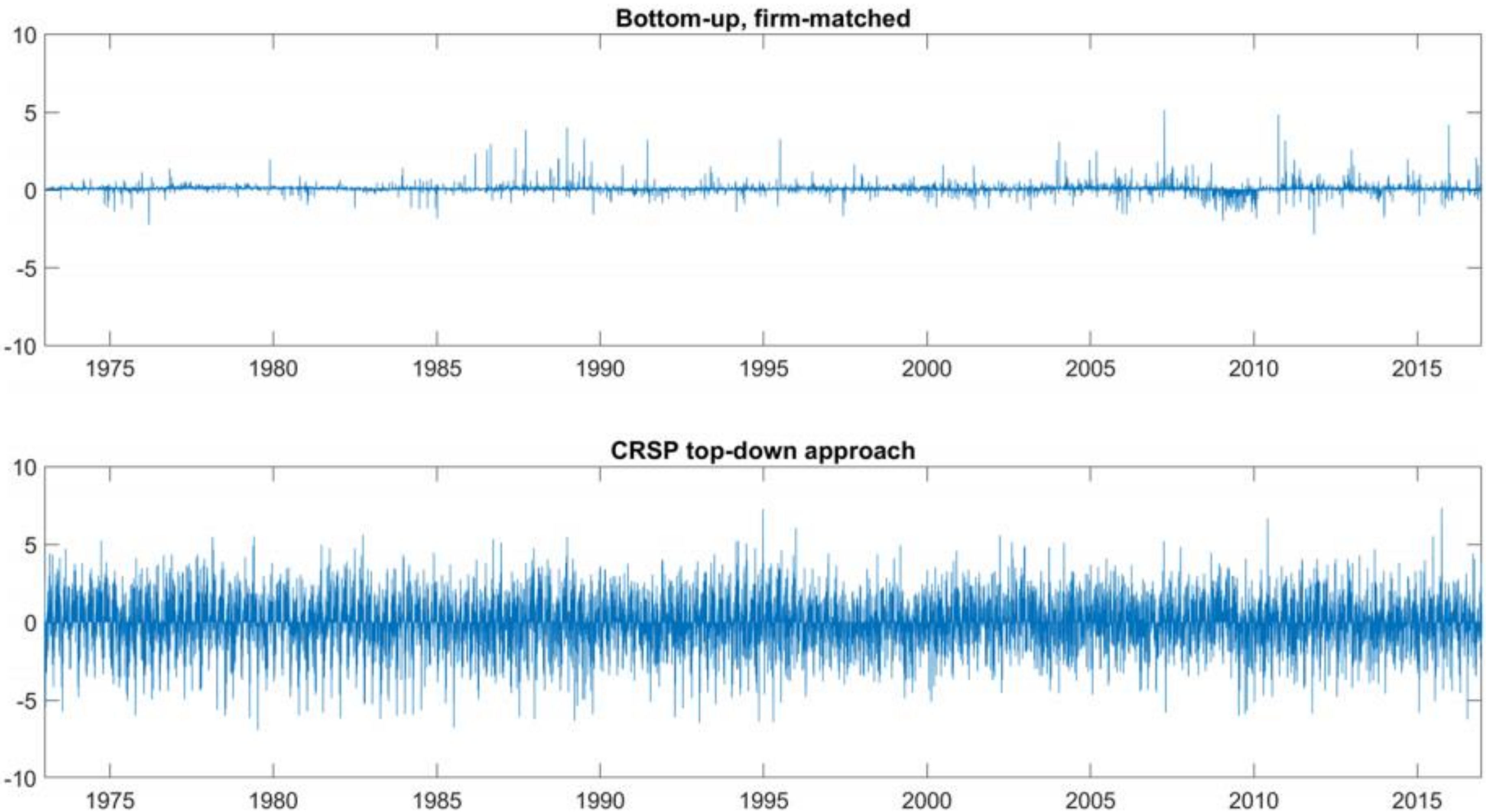


Figure 2. Comparison between our daily “bottom-up” dividend growth series versus a daily “top-down” dividend growth measure extracted from CRSP.



2. Econometric Model

A components model for daily dividend growth:

$$\Delta d_{t+1} = \mu_{dt+1} + \xi_{dt+1} J_{dt+1} + \varepsilon_{dt+1}. \tag{2}$$

Suppose the data-generating process for aggregate dividend growth:

$$\Delta d_{At+1} = \mu_{dt+1} + \sigma_A \varepsilon_{At+1}, \quad \varepsilon_{At+1} \sim \mathcal{N}(0, 1), \tag{3}$$

μ_{dt+1} : the conditional mean of the aggregate dividend growth process at time t + 1.

σ_A : the volatility of the daily shocks, εAt+1.

Assuming that μ_{dt+1} follows a mean-reverting first-order autoregressive process

$$\mu_{dt+1} = \mu_d + \phi_\mu(\mu_{dt} - \mu_d) + \sigma_\mu \varepsilon_{\mu t+1}, \quad \varepsilon_{\mu t+1} \sim \mathcal{N}(0, 1), \tag{4}$$

Firm i's year-over-year dividend growth rate on day $t + 1$,

$$\Delta d_{it+1} = \boxed{\beta_i} \Delta d_{At+1} + \sigma_i \varepsilon_{it+1}, \quad \varepsilon_{it+1} \sim \mathcal{N}(0, 1). \tag{5}$$

firm i's cash flow beta

Dividend growth on day $t + 1$,

$$\begin{aligned}
\Delta d_{t+1} &= \sum_{i=1}^{N_{dt+1}} \omega_{it+1} \Delta d_{it+1} = \sum_{i=1}^{N_{dt+1}} \omega_{it+1} [\beta_i \Delta d_{At+1} + \sigma_i \varepsilon_{it+1}] \\
&= \left[\sum_{i=1}^{N_{dt+1}} \omega_{it+1} \beta_i \right] \Delta d_{At+1} + \left[\sum_{i=1}^{N_{dt+1}} \omega_{it+1} \sigma_i \varepsilon_{it+1} \right] \\
&\equiv \beta_{t+1} \Delta d_{At+1} + \sigma_{dt+1} \varepsilon_{t+1}, \quad \varepsilon_{t+1} \sim \mathcal{N}(0, 1), \qquad (6)
\end{aligned}$$

β_{t+1}: weighted average of the cash flow betas of firms announcing dividends on day t + 1.

ω_{it} : weight on the dividends announced by firm i on day t.

The number of firms announcing dividends can be low on some days, Using (6), we can therefore write (7),

$$\Delta d_{t+1} \equiv \beta_{t+1} \Delta d_{At+1} + \sigma_{dt+1}\varepsilon_{t+1}, \quad \varepsilon_{t+1} \sim \mathcal{N}(0, 1), \tag{6}$$

$$\begin{aligned} \Delta d_{t+1} &= \bar{\beta}\Delta d_{At+1} + (\beta_{t+1} - \bar{\beta})\Delta d_{At+1} + \sigma_{dt+1}\varepsilon_{t+1} \\ &= \bar{\beta}\left[\mu_{dt+1} + \sigma_A \varepsilon_{At+1}\right] + (\beta_{t+1} - \bar{\beta})\left[\mu_{dt+1} + \sigma_A \varepsilon_{At+1}\right] + \sigma_{dt+1}\varepsilon_{t+1} \\ &\propto \mu_{dt+1} + \boxed{\frac{(\beta_{t+1} - \bar{\beta})}{\bar{\beta}}\mu_{dt+1}} + \left[1 + \boxed{\frac{\beta_{t+1} - \bar{\beta}}{\bar{\beta}}\Bigg]\sigma_A \varepsilon_{At+1}} + \boxed{\frac{\sigma_{dt+1}}{\bar{\beta}}\varepsilon_{t+1}}. \end{aligned} \tag{7}$$

$$\Delta d_{At+1} = \mu_{dt+1} + \sigma_A \varepsilon_{At+1},$$

Our model in (2) captures the effect of these components in Δd_{t+1} in two ways.

- First, the jump component, $\xi_{dt+1}J_{dt+1}$, can account for temporary composition shifts that lead to large variation in the daily cash flow beta of our composite dividend growth measure.The jump probability depend on the number of announcers,

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

The magnitude of the jumps: $\xi_{dt+1}\sim\mathcal{N}(0,\sigma_\xi^2)$

- Second, our model captures time-varying heteroskedasticity in Δd_{t+1} by modeling the variance of the residuals in the dividend growth process as a stochastic volatility process,

$$\varepsilon_{dt+1}\sim\mathcal{N}(0,e^{h_{dt+1}}),$$

$$h_{dt+1}=\mu_h+\phi_h(h_{dt}-\mu_h)+\sigma_h\varepsilon_{ht+1},\qquad \varepsilon_{ht+1}\sim\mathcal{N}(0,1)$$

Table I Parameter Estimates for the Dividend Growth Rate Model

$$\Delta d_{t+1} = \mu_{dt+1} + \xi_{dt+1} J_{dt+1} + \varepsilon_{dt+1}, \qquad h_{dt+1} = \mu_h + \phi_h (h_{dt} - \mu_h) + \sigma_h \varepsilon_{ht+1},$$

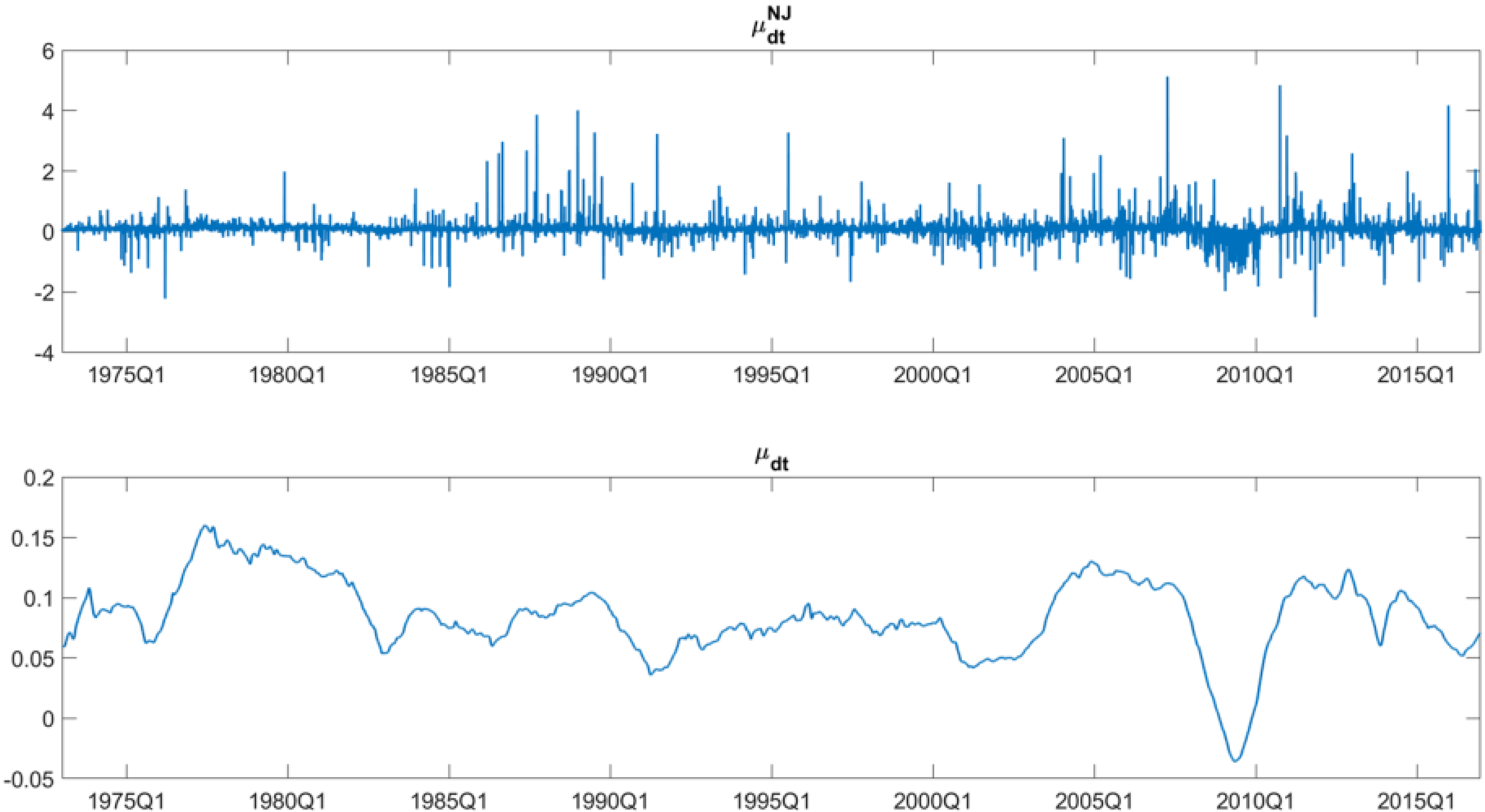
$$\mu_{dt+1} = \mu_d + \phi_\mu (\mu_{dt} - \mu_d) + \sigma_\mu \varepsilon_{\mu t+1}, \qquad \Pr(J_{dt+1} = 1) = \Phi(\lambda_1 + \lambda_2 N_{dt+1}),$$

$$\varepsilon_{dt+1} \sim \mathcal{N}(0, e^{h_{dt+1}}), \qquad \xi_{dt+1} \sim \mathcal{N}(0, \sigma_\xi^2),$$

Parameter Estimates

	1927 to 2016			1973 to 2016		
	Mean	Std	90% Credible Set	Mean	Std	90% Credible Set
μ_d	0.058	0.016	[0.035, 0.080]	0.080	0.012	[0.062, 0.097]
ϕ_μ	0.999	0.000	[0.999, 0.999]	0.998	0.001	[0.997, 0.999]
σ_μ	0.002	0.000	[0.002, 0.002]	0.002	0.000	[0.002, 0.002]
μ_h	−5.076	0.037	[−5.138, −5.014]	−5.337	0.045	[−5.415, −5.262]
ϕ_h	0.749	0.008	[0.735, 0.762]	0.833	0.008	[0.820, 0.846]
σ_h	1.320	0.031	[1.269, 1.369]	0.752	0.028	[0.706, 0.797]
σ_ξ	2.651	0.040	[2.584, 2.718]	2.761	0.040	[2.695, 2.829]
λ_1	−1.387	0.039	[−1.452, −1.323]	−1.354	0.045	[−1.428, −1.281]
λ_2	−0.054	0.006	[−0.064, −0.045]	−0.024	0.002	[−0.028, −0.021]

Figure 3.Time series of daily dividend growth and the persistent growth component.



To summarize, our dividend growth model in (2) accounts for a persistent mean-reverting component, time-varying volatility, and jumps.

$$\Delta d_{t+1} = \mu_{dt+1} + \xi_{dt+1} J_{dt+1} + \varepsilon_{dt+1}. \tag{2}$$

Comparing results from the general model in (2) to a simpler (no-jump) model

$$\Delta d_{t+1} = \mu_{dt+1}^{NJ} + \varepsilon_{dt+1}, \qquad \varepsilon_{dt+1} \sim \mathcal{N}(0, \sigma_d^2),$$

Figure 5. Jumps in the daily dividend growth series.

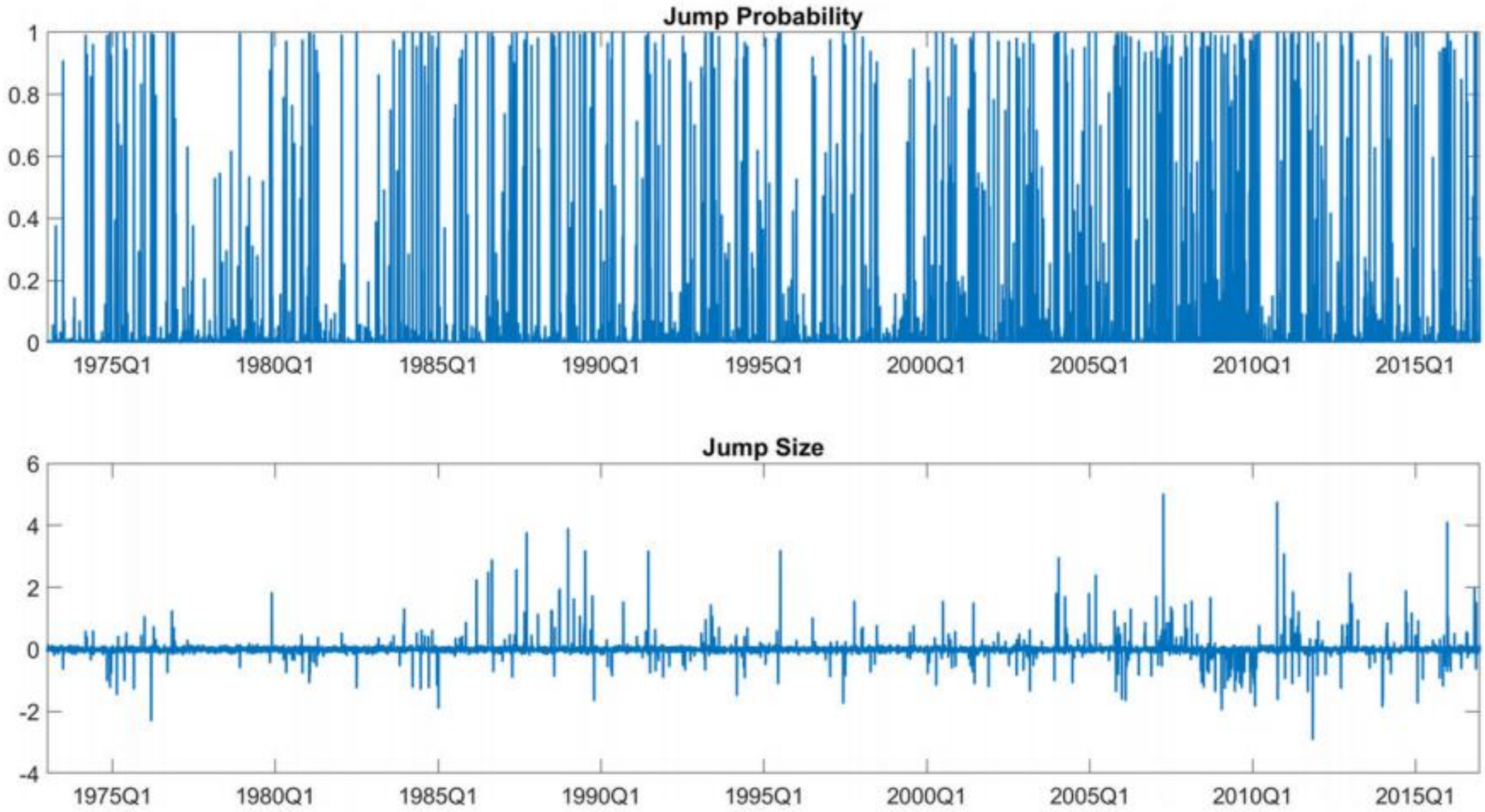


Figure 6. Jump intensities and the number of firms announcing dividend news.

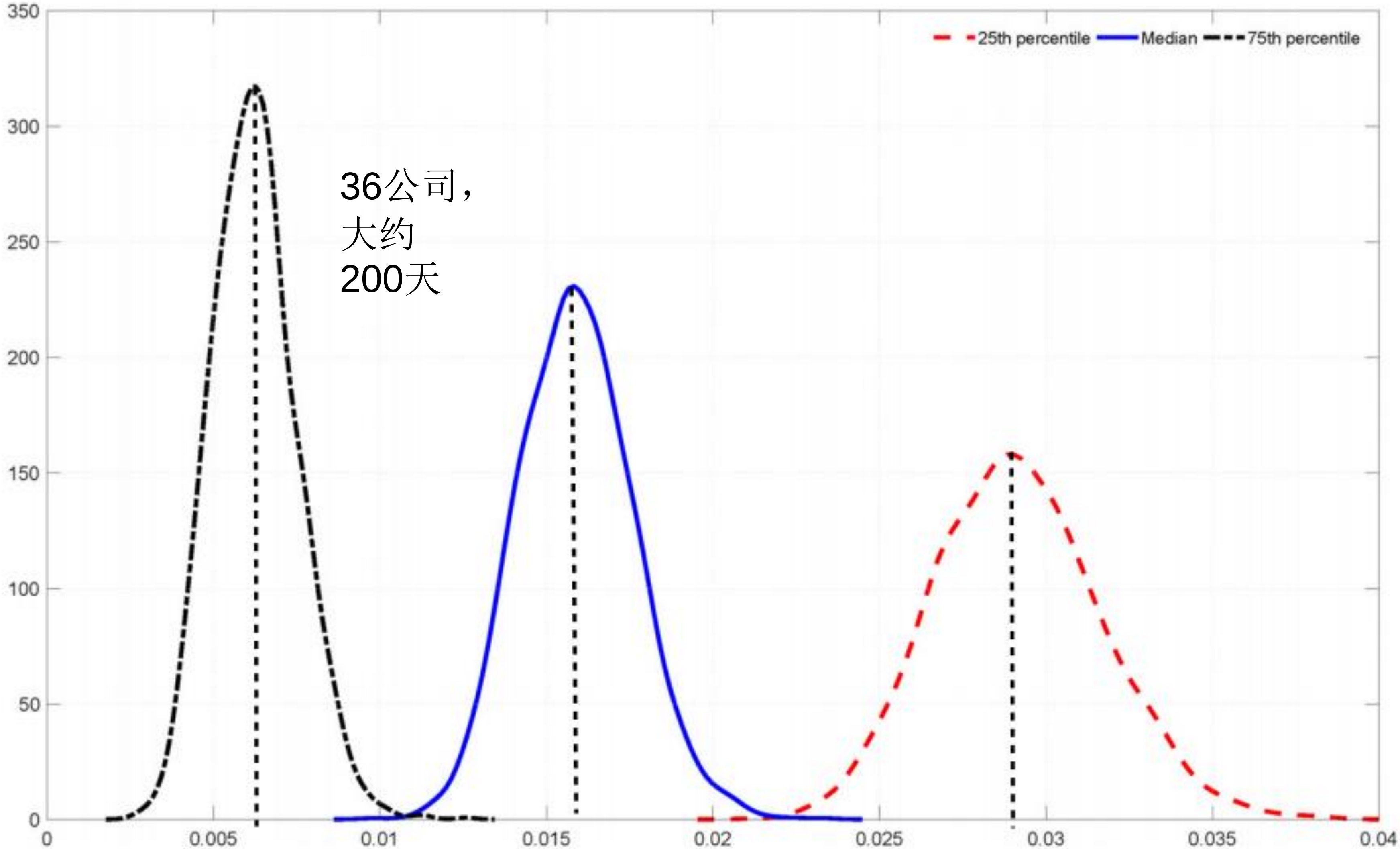
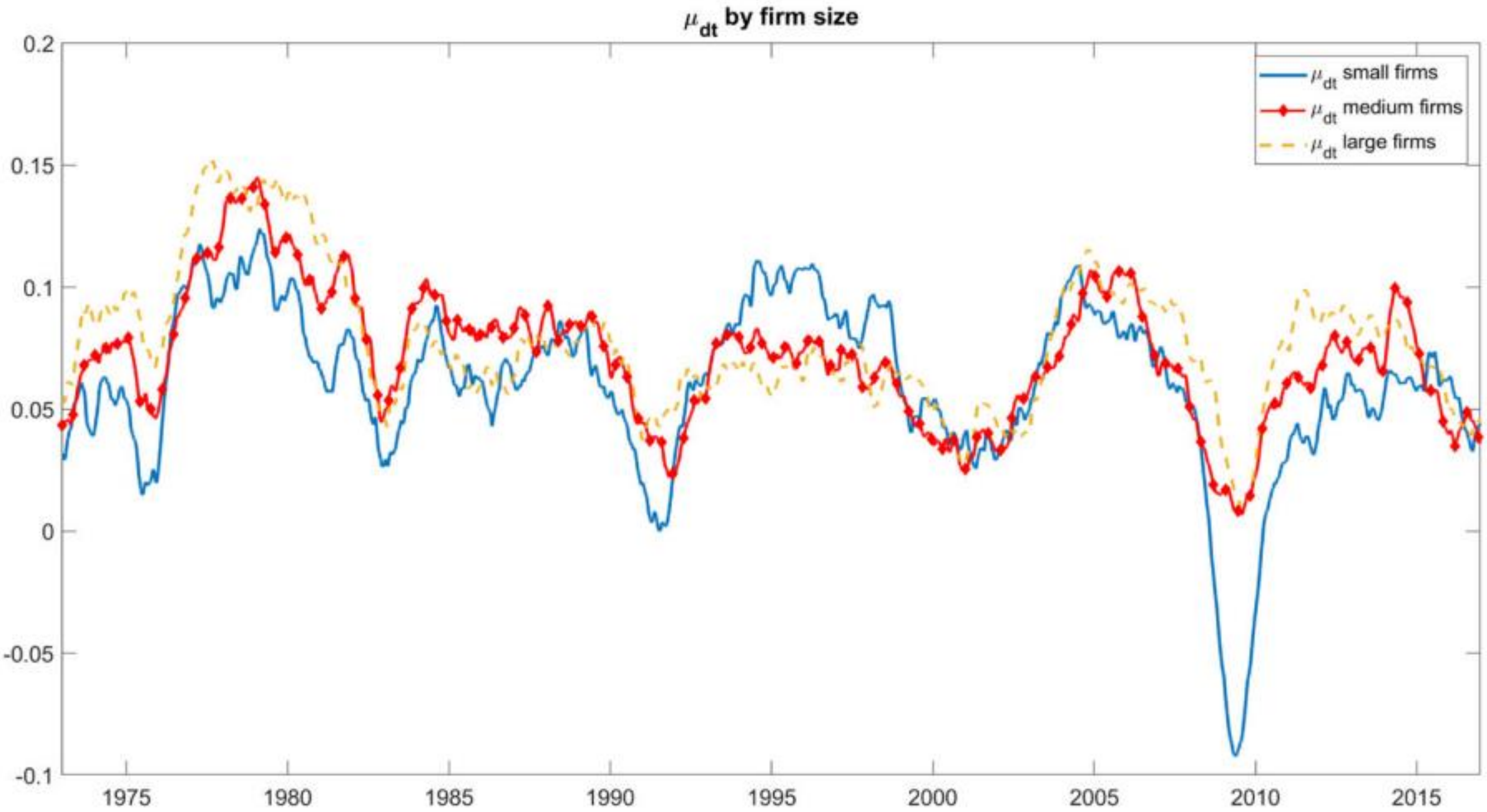


Figure 7. Heterogeneity in μdt and firm characteristics.

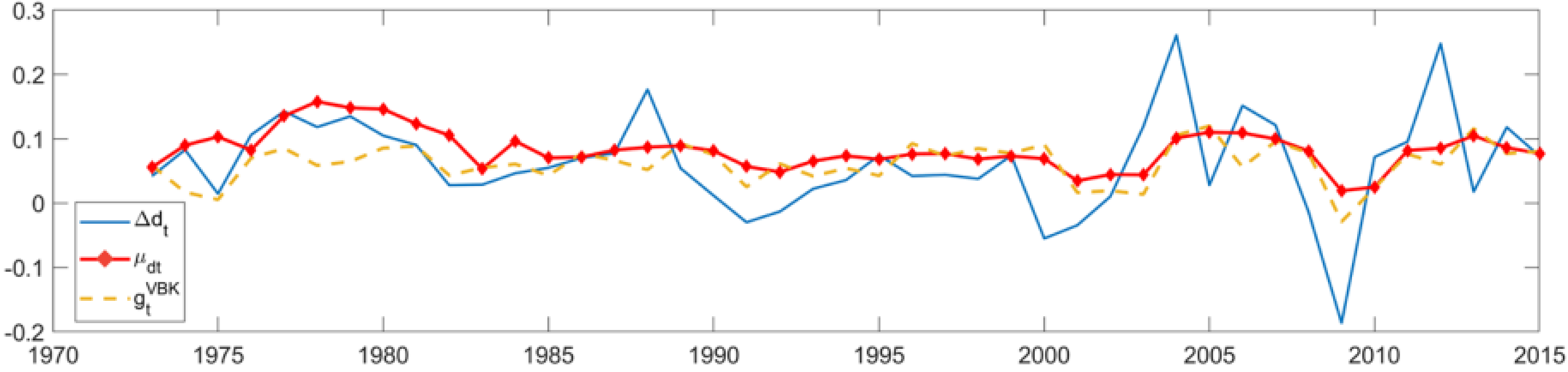


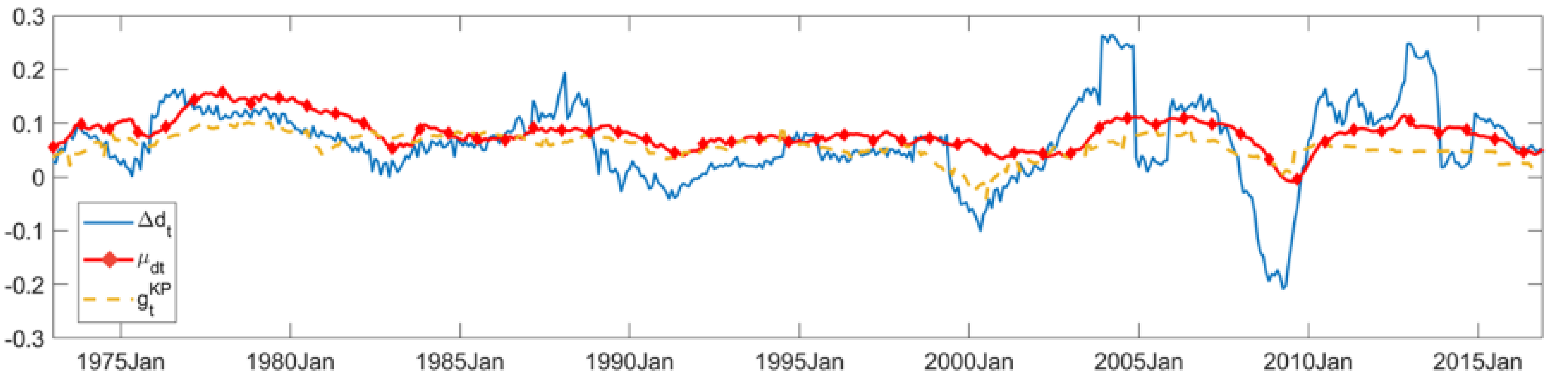
3. Predictability of Dividend Growth

Dividend Growth Regressions

Panel A: $\Delta d_{t+1}^{CRSP} = \alpha + \rho_i \sum_{i=1}^{3} \Delta d_{t+1-i}^{CRSP} + \beta \mu_{dt} + \gamma dp_t^{CRSP} + \varepsilon_{t+1}$				
	Quarterly (1)	Annual (2)	Quarterly (1927-) (3)	Annual (1927-) (4)
μ_{dt}	0.36***	2.50***	0.14**	0.96***
	[4.58]	[3.95]	[2.49]	[3.20]
dp_t	−0.01	0.03	−0.00	0.04
	[−1.29]	[0.50]	[−0.73]	[1.11]
Δd_t^{CRSP}	0.16**	−0.64***	0.34***	−0.16
	[2.20]	[−4.58]	[5.58]	[−1.07]
Δd_{t-1}^{CRSP}	0.07	−0.53***	0.22***	−0.12
	[1.39]	[−3.87]	[4.58]	[−0.84]
Δd_{t-2}^{CRSP}	0.03	−0.12	0.01	0.01
	[0.45]	[−0.78]	[0.26]	[0.05]
R^2	26.50%	27.45%	37.42%	6.31%
Observations	169	40	353	86

Figure 8. Actual versus predicted dividend growth under alternative modeling approaches.





Panel B: $\Delta d_{t+1}^{i} = \alpha + \beta\mu_{dt} + \gamma g_t^i + \varepsilon_{t+1}$

	Annual			Monthly		
	(1)	(2)	(3)	(4)	(5)	(6)
μ_{dt}	1.28***		1.10***	1.39***		1.16***
	[4.04]		[3.97]	[7.23]		[5.12]
g_t^{VBK}		0.90**	0.34			
		[2.16]	[0.91]			
g_t^{KP}					1.45***	0.43
					[6.41]	[1.58]
R^2	25.84%	13.14%	27.27%	31.65%	20.30%	32.67%
Observations	42	42	42	527	527	527

Panel C

$$\Delta d_{t+1}^{CRSP} = \alpha + \beta_1 \mu_{dt} + (1 - \beta_1) g_t^{VBK} + \varepsilon_{t+1},$$
$$\Delta d_{t+1}^{CRSP} = \alpha + \beta_1 \mu_{dt} + (1 - \beta_1) g_t^{KP} + \varepsilon_{t+1}. \tag{13}$$

β_1	0.87***	1.08***
p-Value	(0.00)	(0.00)
$1 - \beta_1$	0.13	−0.08
p-Value	(0.66)	(0.53)
β_1 (OOS)		1.25***
p-Value (OOS)		(0.00)
$1 - \beta_1$ (OOS)		−0.25***
p-Value (OOS)		(0.00)

Figure 9. Comparison of estimates of the persistent dividend growth component, μdt, extracted from data at the daily, monthly, quarterly, and annual frequencies.

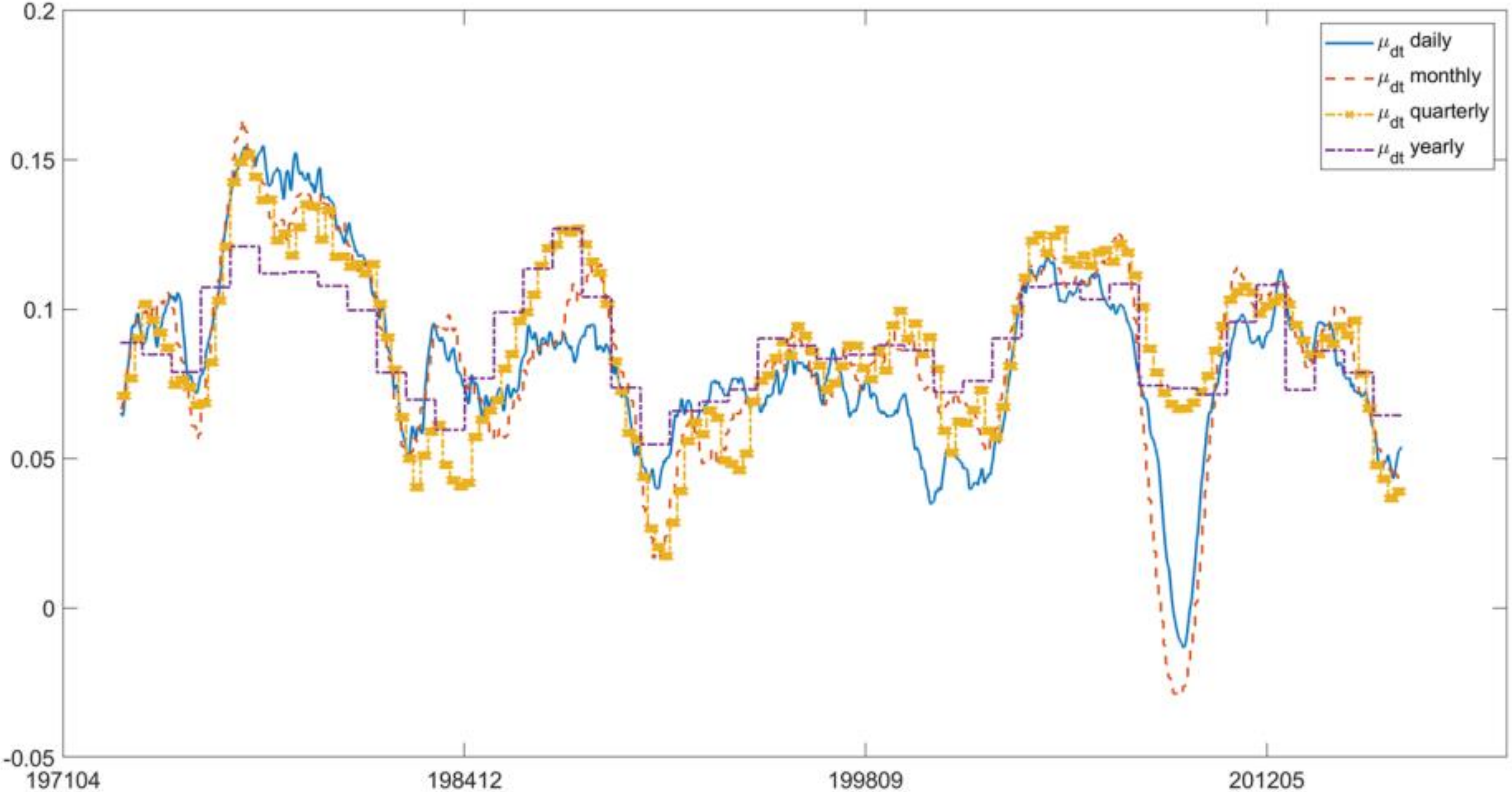


Table III Dividend Growth Regressions at Different Frequencies

$$\Delta d_{t+1}^{CRSP} = \alpha + \beta \mu_{dt}^{i} + \gamma dp_t^{CRSP} + \sum_{i=1}^{3} \rho_i \Delta d_{t+1-i}^{CRSP} + \varepsilon_{t+1}$$

	Monthly			Quarterly			Annual		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
μ_{daily}	0.17***		1.14***	0.36***		0.73***	2.50***		1.72
	[5.77]		[15.01]	[4.58]		[7.64]	[3.95]		[1.44]
$\mu_{monthly}$		0.14***	−0.14*						
		[6.51]	[−1.90]						
$\mu_{quarterly}$					0.22***	0.27***			
					[3.19]	[2.87]			
μ_{yearly}								2.64**	−0.72
								[2.58]	[−0.60]
dp_t	−0.00**	−0.00	−0.03***	−0.01	0.00	−0.02***	0.03	0.07	0.05
	[−2.49]	[−0.97]	[−9.86]	[−1.29]	[0.20]	[−2.79]	[0.50]	[1.12]	[0.73]
Δd_t^{CRSP}	−0.05	−0.05	−0.58***	0.16**	0.22**	−0.05	−0.64***	−0.52***	−0.52***
	[−0.97]	[−0.94]	[−4.77]	[2.20]	[2.59]	[−0.72]	[−4.58]	[−3.07]	[−2.81]
Δd_{t-1}^{CRSP}	−0.07*	−0.07**	−0.58***	0.07	0.10	−0.10	−0.53***	−0.36***	−0.39*
	[−1.96]	[−2.01]	[−5.69]	[1.39]	[1.65]	[−1.50]	[−3.87]	[−3.01]	[−2.03]
Δd_{t-2}^{CRSP}	0.20***	0.20***	−0.31***	0.03	0.06	−0.13*	−0.12	−0.08	−0.05
	[3.68]	[3.59]	[−3.99]	[0.45]	[1.05]	[−1.84]	[−0.78]	[−0.52]	[−0.26]
R^2	18.29%	17.80%		26.50%	21.76%		27.45%	22.14%	
Observations	525	525	525	169	169	169	40	40	40

Cash Flow News and Economic Activity

$$\Delta y_{t+1} = \alpha + \beta_1 \mu_{dt} + \beta_2 \Delta y_t + \varepsilon_{t+1}, \tag{14}$$

Table IV Predictive Regressions of GDP and Consumption Growth on the Persistent Dividend Growth Component

Panel C: $\Delta y_{t+1} = \alpha + \beta \mu_{quarterly} + \gamma \Delta y_t + \varepsilon_{t+1}$

	ΔGDP		$\Delta Consumption$	
	(1)	(2)	(3)	(4)
$\mu_{quarterly}$	0.08**	0.04	0.09***	0.02
	[2.06]	[1.44]	[2.65]	[1.63]
Δy_t		0.49***		0.74***
		[5.77]		[17.22]
R^2	5.85%	28.68%	9.36%	58.64%
Observations	171	171	171	171

Table V Correlations between the Persistent Dividend Growth Component μdt and Macroeconomic and Financial Activity Measures

Panel B: Persistent Dividend Growth and Indexes (Changes)						
	ΔVIX	ΔPU	ΔADS Index	ΔLiquidity	ΔInflation	$\Delta\mu_{dt}$
ΔVIX	1					
ΔPU	−0.02	1				
	(0.10)					
ΔADS Index	0.01	0.00	1			
	(0.65)	(0.94)				
ΔLiquidity	−0.01	0.05***	−0.00	1		
	(0.53)	(0.00)	(0.95)			
ΔInflation	0.03	−0.03	−0.00	−0.00	1	
	(0.24)	(0.27)	(0.89)	(0.94)		
$\Delta\mu_{dt}$	−0.02	−0.00	0.04	−0.01	0.10***	1
	(0.16)	(0.77)	(0.66)	(0.58)	(0.00)	

4. Implications for Return Predictability

Following Campbell and Shiller (1988a), consider the approximate log-linearized present value model

$$r_{t+1} \approx k + \rho(p_{t+1} - d^{cf}_{t+1}) + \Delta d^{cf}_{t+1} + (d^{cf}_t - p_t), \tag{15}$$

where $\rho = 1/(1+\exp(\overline{d-p})$ and $k = -\ln(\rho) - (1-\rho)\ln(1/\rho - 1)$ are log-linearization constants.

Advantages:

- Adopting a similar framework makes it easier to compare our findings to existing literature.
- Strong economic implications that directly link predictability of dividend growth to predictability of stock returns.
- The present value model has implications for return predictability at different horizons.

At the daily frequency, the average dividend yield is very small and so ρ = 0.99998 is extremely close to unity,

$$r_{t+1} \approx k + \rho(p_{t+1} - d_{t+1}^{cf}) + \Delta d_{t+1}^{cf} + (d_t^{cf} - p_t), \tag{15}$$

$$\Downarrow$$

$$r_{t+1} \approx k - \Delta\left(d_{t+1}^{cf} - p_{t+1}\right) + \Delta d_{t+1}^{cf}. \tag{16}$$

$$\Delta d_{t+1}^{cf} = \theta_0 + \theta_\mu \Delta\mu_{dt} + \theta_{dp}\left(\overline{d_t - p_t}\right) + \theta_d \Delta d_t^{cf} + \varepsilon_{dt+1}. \tag{18}$$

$$\Delta\left(d_{t+1}^{cf} - p_{t+1}\right) = \gamma_0 + \gamma_\mu \Delta\mu_{dt} + \gamma_{dp}\left(\overline{d_t - p_t}\right) + \gamma_d \Delta d_t^{cf} + \varepsilon_{t+1}^{cf}. \tag{19}$$

$$\begin{aligned} r_{t+1} \approx{}& k + \theta_0 - \gamma_0 + (\theta_\mu - \gamma_\mu)\Delta\mu_{dt} + \left(\theta_{dp} - \gamma_{dp}\right)\left(\overline{d_t - p_t}\right) \\ &+ (\theta_d - \gamma_d)\Delta d_t^{cf} + \varepsilon_{dt+1} - \varepsilon_{t+1}^{cf}. \end{aligned} \tag{20}$$

$$r_{t+1} \approx k + \theta_0 - \gamma_0 + (\theta_\mu - \gamma_\mu)\Delta\mu_{dt} + \left(\theta_{dp} - \gamma_{dp}\right)\left(\overline{d_t - p_t}\right) + (\theta_d - \gamma_d)\Delta d_t^{cf} + \varepsilon_{dt+1} - \varepsilon_{t+1}^{cf}. \tag{20}$$

$$r_{t+1} = \lambda_0 + \lambda_\mu \Delta\mu_{dt} + \lambda_{dp}(\overline{d_t - p_t}) + \lambda_d \Delta d_t^{cf} + \varepsilon_{rt+1}, \tag{21}$$

The present value model imposes the following cross-equation restrictions on the parameters of the return equation:

$$\begin{aligned} \lambda_0 &= k + \theta_0 - \gamma_0, \\ \lambda_\mu &= \theta_\mu - \gamma_\mu, \\ \lambda_{dp} &= \theta_{dp} - \gamma_{dp}, \\ \lambda_d &= \theta_d - \gamma_d. \end{aligned} \tag{22}$$

Table VI Parameter Estimates and Test Statistics for the Predictive Present Value Model Fitted to Daily Data

$$\Delta d^{cf}_{t+1} = \theta_0 + \theta_\mu \Delta\mu_{dt} + \theta_{dp}(\overline{d_t - p_t}) + \theta_d \Delta d^{cf}_t + \varepsilon_{dt+1},$$

$$\Delta(d^{cf}_{t+1} - p_{t+1}) = \gamma_0 + \gamma_\mu \Delta\mu_{dt} + \gamma_{dp}(\overline{d_t - p_t}) + \gamma_d \Delta d^{cf}_t + \varepsilon^{cf}_{t+1},$$

$$r_{t+1} = \lambda_0 + \lambda_\mu \Delta\mu_{dt} + \lambda_{dp}(\overline{d_t - p_t}) + \lambda_d \Delta d^{cf}_t + \varepsilon_{rt+1},$$

with the following restrictions implied by the model:

$$\lambda_0 = k + \theta_0 - \gamma_0,\ \lambda_\mu = \theta_\mu - \gamma_\mu,\ \lambda_{dp} = \theta_{dp} - \gamma_{dp},\ \lambda_d = \theta_d - \gamma_d.$$

	Const.	$\Delta\mu_{dt}$	$\overline{d_t - p_t}$	Δd^{cf}_t	R^2
Δd^{cf}_{t+1}	−0.24**	13.93	−0.04**	−0.36***	12.87%
	(−2.31)	(0.30)	(−2.54)	(−58.32)	
$\Delta(d^{cf}_{t+1} - p_{t+1})$	−0.23**	12.72	−0.04	−0.36***	12.87%
	(−2.31)	(0.28)	(−2.53)	(−58.32)	
ret_{t+1}	0.00	1.28***	0.00	−0.00	0.08%
	(0.86)	(3.31)	(0.27)	(−0.14)	
p-Value of restriction	0.37	0.87	0.13	0.75	

Return Predictability at Longer Horizons

Table VII Predictive Regressions for Stock Returns

	Return Horizon											
	r_{t+2}			$r_{t+2:t+4}$			$r_{t+2:t+6}$			$r_{t+2:t+22}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Δd_t	−0.00**			−0.00			−0.00			−0.00		
	[−2.19]			[−0.07]			[−0.17]			[−0.32]		
$\Delta\mu_{dt}^{NJ}$		−0.00**			−0.00			−0.00			−0.00	
		[−2.20]			[−0.00]			[−0.08]			[−0.26]	
$\Delta\mu_{dt}$			1.14***			3.17***			5.40***			21.60***
			[3.36]			[3.90]			[4.77]			[4.98]
$\xi_{dt} J_{dt}$			−0.00			0.00			0.00			0.00
			[−0.04]			[1.49]			[0.53]			[0.37]
$h_{dt}/2$			0.00			0.00			0.00			0.01
			[0.13]			[0.85]			[1.52]			[0.72]
ε_{dt+1}			−0.00			0.00			−0.00			−0.00
			[−1.16]			[0.37]			[−0.30]			[−0.77]
R^2	0.03%	0.03%	0.09%	0.00%	0.00%	0.22%	0.00%	0.00%	0.37%	0.00%	0.00%	1.27%
Observations	20,965	20,965	20,965	20,963	20,963	20,963	20,961	20,961	20,961	20,945	20,945	20,945

Table VIII Out-of-Sample Return Predictability

	Full Sample			Expansions			Recessions		
	$R^2_{OS}(\%)$	$p-val$	$\Delta U(\%)$	$R^2_{OS}(\%)$	$p-val$	$\Delta U(\%)$	$R^2_{OS}(\%)$	$p-val$	$\Delta U(\%)$
$\Delta\mu_{dt}$	0.43	0.14	1.28	−0.02	0.35	0.11	1.68	0.03	11.40
log(DP)	−1.98	0.97	−2.44	−3.06	0.99	−3.63	1.01	0.09	7.66
log(DY)	−2.01	0.96	−2.28	−3.25	0.99	−3.73	1.41	0.04	10.18
log(EP)	−0.85	0.67	0.74	−0.94	0.86	−1.17	−0.61	0.48	17.45
log(DE)	−2.04	0.80	−0.77	−1.29	0.99	−1.24	−4.13	0.65	3.19
SVAR	1.49	0.12	1.30	0.08	0.34	0.10	5.38	0.13	11.80
BM	−0.45	0.80	−0.77	−0.51	0.75	−0.96	−0.28	0.82	1.00
NTIS	−2.57	0.97	−1.37	−1.31	0.72	−0.23	−6.04	0.99	−11.33
TBL	−0.55	0.43	−0.57	0.42	0.12	0.93	−3.22	0.98	−13.20
LTY	−0.33	0.65	−0.14	−0.17	0.50	−0.17	−0.76	0.82	0.37
LTR	−0.20	0.31	−0.31	−0.28	0.33	−0.38	0.01	0.41	−0.04
TMS	−1.20	0.65	−1.33	−1.11	0.51	−0.22	−1.46	0.80	−11.35
DFY	−3.24	0.99	−4.13	−3.02	0.96	−2.66	−3.84	0.96	−17.29
DFR	−2.13	0.41	1.08	−2.17	0.49	−0.25	−2.00	0.41	12.41
INFL	−0.75	0.79	−1.06	−0.33	0.53	−0.30	−1.89	0.89	−7.62

V. Dividend News and Return Dynamics

A. Dividend News and Contemporaneous Stock Returns

a) First, decomposes daily stock returns into a weighted average of the capital gain and dividend yield,

$$r_{t+1} \approx k + \rho p_{t+1} - p_t + (1-\rho) d^{cf}_{t+1}$$
$$= k + \rho(p_{t+1} - p_t) + (1-\rho)(d^{cf}_{t+1} - p_t). \quad (23)$$

Next,

$$p_{t+1} - p_t = \pi_0 + \pi_\mu \Delta\mu_{dt+1} + \pi_{dp}(\overline{d_t - p_t}) + \varepsilon_{pt+1},$$
$$d^{cf}_{t+1} - p_t = \delta_0 + \delta_{dp}(\overline{d_t - p_t}) + \varepsilon^{cf}_{t+1}. \quad (24)$$

Last， combining the present value model in (23) with the regressions in (24),

$$r_{t+1} = \lambda_0 + \lambda_\mu \Delta\mu_{dt+1} + \lambda_{dp}(\overline{d_t - p_t}) + \varepsilon_{rt+1}, \quad (25)$$

where $\varepsilon_{rt+1} = \rho\varepsilon_{pt+1} + (1-\rho)\varepsilon^{cf}_{t+1}.$

Cross-equation restrictions,

$$\lambda_0 = k + \rho\pi_0 + (1-\rho)\delta_0,$$
$$\lambda_\mu = \rho\pi_\mu,$$
$$\lambda_{dp} = \rho\pi_{dp} + (1-\rho)\delta_{dp}.$$

b) Our second specification uses the present value model (15) with the key difference that we now use $\Delta\mu_{dt+1}$, instead of $\Delta\mu_{dt}$.

$$\Delta d_{t+1}^{cf} = \theta_0 + \theta_\mu \Delta\mu_{dt+1} + \theta_{dp}(\overline{d_t - p_t}) + \theta_d \Delta d_t^{cf} + \varepsilon_{dt+1},$$

$$\Delta\left(d_{t+1}^{cf} - p_{t+1}\right) = \gamma_0 + \gamma_\mu \Delta\mu_{dt+1} + \gamma_{dp}(\overline{d_t - p_t}) + \gamma_d \Delta d_t^{cf} + \varepsilon_{t+1}^{cf}, \qquad (27)$$

$$r_{t+1} = \lambda_0 + \lambda_\mu \Delta\mu_{dt+1} + \lambda_{dp}\left(\overline{d_t - p_t}\right) + \lambda_d \Delta d_t^{cf} + \varepsilon_{rt+1}$$

Cross-equation restrictions,

$$\lambda_0 = k + \theta_0 - \gamma_0,$$

$$\lambda_\mu = \theta_\mu - \gamma_\mu,$$

$$\lambda_{dp} = \theta_{dp} - \gamma_{dp},$$

$$\lambda_d = \theta_d - \gamma_d.$$

B. Empirical Findings

Table IX Estimates and Diagnostic Tests for the Contemporaneous Present Value Model Fitted to Daily Data

$$p_{t+1} - p_t = \pi_0 + \pi_\mu \Delta\mu_{dt+1} + \pi_{dp}(\overline{d_t - p_t}) + \varepsilon_{pt+1},$$

$$d^{cf}_{t+1} - p_t = \delta_0 + \delta_{dp}(\overline{d_t - p_t}) + \varepsilon^{cf}_{t+1},$$

$$r_{t+1} = \lambda_0 + \lambda_\mu \Delta\mu_{dt+1} + \lambda_{dp}(\overline{d_t - p_t}) + \varepsilon_{rt+1},$$

Panel A: Estimates and Tests for Present Value Model (I)

	Const.	$\Delta\mu_{d,t+1}$	$\overline{d_t - p_t}$	R^2
$p_{t+1} - p_t$	−0.00	$\boxed{1.55^{***}}$	−0.00	0.13%
	(−1.26)	(3.94)	(−1.62)	
$d^{cf}_{t+1} - p_t$	−4.13***		$\boxed{0.94^{***}}$	14.44%
	(−40.49)		(54.80)	
ret_{t+1}	−0.00	$\boxed{1.57^{***}}$	$\boxed{-0.01^{\dagger}}$	0.12%
	(−0.09)	(3.97)	(−0.63)	
p-Value of restriction	0.13	0.98	0.60	

$$\Delta d_{t+1}^{cf} = \theta_0 + \theta_\mu \Delta\mu_{dt+1} + \theta_{dp}(\overline{d_t - p_t}) + \theta_d \Delta d_t^{cf} + \varepsilon_{dt+1},$$

$$\Delta\left(d_{t+1}^{cf} - p_{t+1}\right) = \gamma_0 + \gamma_\mu \Delta\mu_{dt+1} + \gamma_{dp}(\overline{d_t - p_t}) + \gamma_d \Delta d_t^{cf} + \varepsilon_{t+1}^{cf},$$

$$r_{t+1} = \lambda_0 + \lambda_\mu \Delta\mu_{dt+1} + \lambda_{dp}\left(\overline{d_t - p_t}\right) + \lambda_d \Delta d_t^{cf} + \varepsilon_{rt+1}$$

Panel B: Estimates and Tests for Present Value Model (II)

	Const.	$\Delta\mu_{dt+1}$	$\overline{d_t - p_t}$	Δd_t^{cf}	R^2
$= \Delta d_{t+1}^{cf}$	−0.24**	30.28	−0.04**	−0.36***	12.87%
	(−2.31)	(0.66)	(−2.54)	(−58.32)	
$\Delta(d_{t+1}^{cf} - p_{t+1})$	−0.23**	28.86	−0.04	−0.36***	12.87%
	(−2.31)	(0.63)	(−2.54)	(−58.32)	
ret_{t+1}	0.00	1.45***	0.00	−0.00	0.11%
	(0.87)	(3.74)	(0.28)	(−0.14)	
p-Value of restriction	0.36	0.94	0.13	0.75	

From a theoretical perspective, we would expect the three dividend growth components in (2) to have a very different impact on stock prices.

$$r_{t+1} = \lambda_0 + \lambda_\mu \Delta\mu_{dt+1} + \lambda_{dp}(\overline{d_t - p_t}) + \lambda_\varepsilon \varepsilon_{dt+1} + \lambda_h \exp(h_{dt+1}) + \lambda_J J_{dt+1}\xi_{dt+1} + \varepsilon_{rt+1}. \quad (28)$$

We fail to reject the hypothesis that $\lambda_\varepsilon = \lambda_h = \lambda_J = 0$ and we also find that the estimated return effect of these additional terms is small.

These results suggest that news about the persistent dividend growth rate affects the first moment (mean) of same-day stock returns, while news about the temporary components does not.

$$\varepsilon_{rt+1}^2 = a_0 + a_1\varepsilon_{rt}^2 + a_2\sigma_{dt+1}^2 + a_3\Delta\mu_{dt+1} + \varepsilon_{\sigma t+1},$$

$$I_{t+1} = b_0 + b_1\xi_{dt+1}J_{dt+1} + b_2\sigma_{dt+1}^2 + b_3\Delta\mu_{dt+1} + \varepsilon_{t+1}^I.$$

Panel C: Heteroskedasticity Test

	Coeff.	Std. Err.	t-Stat	p-Value
Intercept	0.00***	0.00	11.81	0.00
$\varepsilon_{r,t}^2$	0.17***	0.06	3.11	0.00
σ_{t+1}^2	0.00***	0.00	5.56	0.00
$\Delta\mu_{dt+1}$	−0.03	0.02	−1.55	0.12

Panel D: Jump Test

	Coeff.	Std. Err.	t-Stat	p-Value
Intercept	0.04***	0.00	21.49	0.00
$\xi_{dt+1}J_{dt+1}$	−0.02*	0.01	−1.70	0.09
σ_{dt+1}^2	0.31***	0.05	6.82	0.00
$\Delta\mu_{dt+1}$	−23.98**	9.59	−2.50	0.01

Conclusion

- We find strong evidence that the persistent dividend growth component can be used to forecast stock market returns at both short horizons such as a single day and longer horizons such as a month.

- Positive news about the persistent dividend growth component is associated with higher mean stock returns, reduced stock market volatility, and a lower likelihood of a jump in stock returns on the same day.

- Finally, we find that greater uncertainty about cash flow growth translates into larger volatility for stock prices, and we identify news about our dividend growth components as a determinant of jumps in daily stock returns.

THANKS！