Cash Flow News and Stock Price Dynamics

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Abstract

We develop a new approach to modeling dynamics in cash flow data extracted from daily firm-level dividend announcements. We decompose the daily cash flow news series into a persistent component, jumps, and temporary shocks. Empirically, we find that the persistent cash flow growth component predicts future dividend growth and is significantly positively correlated with stock market returns. Cash flow dynamics have sizeable and long-lasting effects on the volatility and jump probability of stock returns through an uncertainty transmission channel. Finally, we find that news about the persistent cash flow growth component is correlated with a variety of cross-sectional risk factors.

Keywords: High-frequency cash flow news; predictability of dividend growth; jump risk; dynamics in stock returns; uncertainty transmission channel; Bayesian modeling

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1 Introduction

On most days, a multitude of firms announce cash flow news, but the number of firms, as well as the industries they belong to, can vary greatly over time. Such variation gives rise to a highly irregular cash flow news process and complicates investors’ attempt to infer the underlying growth rate of cash flows for individual firms, industries, and for the economy as a whole. This is important because the resulting cash flow growth estimates are a key driver of investors’ forecasts of future cash flows, their assessment of cash flow risks, and, ultimately, of their valuation of assets.¹

While information extracted from firms’ cash flow announcements is critical to understanding investors’ cash flow expectations and, in turn, movements both in individual and aggregate stock prices, relatively few studies analyze predictability of cash flows and, in most cases, focus on quarterly or annual changes in aggregate dividends or earnings.² However, data aggregated in this manner may conceal the rich dynamic patterns in cash flows recorded at a higher frequency which could reduce our ability to study important questions such as how strong and rapid cash flow growth responds to changes in the underlying state of the economy.

Several challenges complicate attempts to measure daily cash flow dynamics. First, most firms’ cash flows have a pronounced seasonal component related to weather patterns and holiday sales. Second, the number of firms announcing cash flow news on any given day can fluctuate between as little as zero to more than one hundred firms. Third, the particular date on which a firm announces dividends can vary widely from year to year, requiring that

¹Patton and Verardo (2012) develop a rational learning model to explain the patterns in firms’ betas observed around earnings announcements. Their model contains unobserved firm-specific and common earnings innovation terms and investors’ extraction of these components is modeled as a Kalman filtering problem. Savor and Wilson (2016) develop a learning model in which investors decompose cash flow news into firm-specific and market-wide components. Positive average covariances between the cash flow process of individual firms and of the broader market imply that bad (good) news on individual firms’ cash flows result in reduced (increased) forecasts of aggregate cash flows. In turn, this cash flow learning channel implies that the stock returns of the announcing firms and of the aggregate stock market are positively correlated, justifying an “announcement risk premium” for exposure to individual firms’ cash flows. These models do not allow for lumpiness in cash flows (“jumps”), although in practice this is an important feature of earnings and dividend data.

close attention be paid to constructing daily proxies that account for firm specific effects. Fourth, there is considerable heterogeneity across individual firms’ cash flow processes. The combined effect of these factors is that daily news on cash flows tends to be very lumpy.

To address these challenges, we develop a new approach to measure and model dynamics in high frequency (daily) cash flows. To deal with firm-level heterogeneity and seasonality effects, we take a bottom-up approach that starts from changes in individual firms’ dividends on a given day relative to their payments over the same quarter during the previous year. In contrast with conventional smoothed estimates, only data on those firms that announce dividend news on a given day are used to update the dividend growth estimate, ensuring that our measure is timely in picking up changes in the cash flow process. Moreover, by computing a dollar-weighted growth estimate, we account for variation in the size of the firms paying dividends on any given day. Our dividend growth measure uses dividend announcements as opposed to dividend payments which form the basis for the CRSP measure of dividend growth conventionally used in the finance literature. This is an important distinction because dividend announcements precede dividend payments by several weeks, giving our dividend measure a significant timing advantage and also more closely aligns our measure with movements in market prices following dividend news.

To account for the lumpiness in daily values of year-on-year changes in firm-matched cash flows, we decompose cash flow news into a slowly evolving component that picks up time variation (predictability) in the mean of the cash flow process, a transitory component whose volatility is allowed to change over time, and large jumps whose probability of occurring can depend on the number of firms that announce cash flow news on a given day. Empirically,

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3To illustrate the loss in information from the common practice of aggregating cash flow news over the most recent 12-month period and updating this on, say, a monthly basis, suppose that firms’ announcement dates are uniformly distributed across calendar dates. Every month when the cash flow estimate gets updated, the same weight is assigned to firms announcing cash flows close to the cutoff date and firms whose announcement date happened almost one year previously. This weighting automatically makes the resulting growth estimate stale and also introduces spurious serial correlation in the estimate – see, e.g., Working (1960).

4The daily horizon appears to be the highest frequency at which cash flow news can meaningfully be modeled; cash flow news is often announced after the regular trading sessions in the stock market have closed and so aggregating across firms that announced cash flows within a 24-hour interval – as opposed to modeling, say, hourly cash flow news – seems appropriate.

5Announced dividends precede actual dividend payments by approximately 42 days, on average.
all three components turn out to be important for capturing predictability in the dividend growth process and understanding the evolution in the uncertainty that surrounds growth in cash flows.

An important test of our approach is whether it can be used to generate more accurate forecasts of cash flows than existing methods. To evaluate this, we study the growth in dividends of publicly traded US firms which has been the focus of a large literature. Empirically, we find that our estimate of the persistent dividend growth component is a strong predictor of future dividend growth. Moreover, the predictive power of our approach compares favorably to alternative predictors of dividend growth proposed by van Binsbergen and Koijen (2010) and Kelly and Pruitt (2013). We also find that our measure of the persistent dividend growth component is a positive and significant predictor of future growth in GDP and aggregate consumption. In sharp contrast, “raw” dividend growth, as well as the individual jump or transitory shock components, are very noisy and turn out not to have any predictive power over future dividend growth as conventionally measured. Our results suggest that firms closely monitor the state of the economy and adjust their dividend policies in anticipation of changes in more slow-moving economic indicators such as GDP and consumption growth.

The availability of daily estimates of cash flows offers large benefits to empirical tests of asset pricing models. A key challenge for such tests is that while high-frequency data are available on movements in individual and aggregate stock prices (e.g., daily or even intra-daily returns), cash flows of individual firms are observed at much lower frequencies (typically quarterly). The absence of high-frequency cash flow data reduces researchers’ ability to estimate and test asset pricing models which rely on the joint dynamics of stock prices, expected returns and cash flow growth expectations.

The second part of our paper studies asset pricing implications of our new cash flow measures. Specifically, we develop a dynamic model that links dynamics in the daily dividend growth process to the mean, volatility and probability of a jump in stock market returns. This model offers two key insights. First, we find that it is crucial to distinguish between different components of the dividend process when analyzing the impact of dividend news on stock prices. While news about the persistent dividend growth component has a large,
positive and statistically significant effect on same-day stock returns, news about jumps or shocks to the temporary dividend growth component have a much smaller effect on mean stock returns. This is consistent with economic intuition that long-lasting cash flow shocks matter more to stock returns than shorter-lived shocks.

Second, we identify a new and important uncertainty transmission channel through which higher uncertainty about dividend growth spills over to the volatility and jump probability of stock returns. We find that higher volatility in the dividend growth process increases the volatility of stock returns not just on the day of the dividend shock, but for several weeks afterwards. Moreover, jumps in the dividend growth process have a sizeable and long-lasting effect on both the volatility and jump probability of stock returns. In particular, negative jumps in the cash flow process are associated with large increases to stock market volatility and a significantly higher chance of observing a contemporaneous jump in stock returns. The latter effect is particularly large when few firms announce dividend news, i.e., on days when little cash flow news is available to the markets. Positive jumps in cash flow growth have the reverse effect and tend to calm markets.

We also relate innovations to our new persistent dividend growth component to a variety of risk factors proposed in the literature on cross-sectional variation in stock returns. We find strong evidence of a significant correlation between shocks to persistent dividend growth and several risk factors. In particular, improved prospects for cash flow growth have a strongly positive correlation with the (relative) returns of small firms, value stocks, and firms with weak profitability. Thus, these types of firms tend to be more sensitive to dividend growth prospects and exposure to dividend growth appears to be priced in the cross-section.

Our paper is related to a literature that estimates the effect of news on stock prices on days with news releases using event-study methodology, see e.g., Cutler et al. (1989) and McQueen and Roley (1993). A limitation of this approach is that news stories are either of a qualitative nature (e.g., “world events”), heterogeneous across news categories (news on housing starts versus monetary policy shocks), or relatively rare (monetary policy shocks). In addition, the effect of these news may be state-dependent. For example, good news about the economy can be bad news to stock prices in a high-growth state (McQueen and Roley (1993)) and may depend on whether the economy is operating below trend with a
large negative output gap (Law et al. (2018)). Macroeconomic news can also be difficult to decipher because they comprise a bundle of information about cash flows and expected returns (Boyd et al. (2005)). In contrast, our daily dividend growth series allows us to construct a more direct measure of daily news on cash flow growth.

A second literature uses analyst expectations to gauge the news component from firms’ dividend or earnings announcements, using the difference between actual and expected cash flows as an estimate of the news. A limitation of this approach is that the estimated surprise is affected by biases in analyst estimates (e.g., Lim, 2001; Hong and Kubik, 2003) and by staleness in analysts’ updates of their estimates which can contaminate consensus estimates. Again, our approach is fundamentally different as it uses actual cash flow data which, unlike analyst expectations, are not affected by biases in subjective estimates.

The methodology developed in our paper is also related to papers in the asset pricing literature such as Chib et al. (2002) and Eraker et al. (2003) which estimate models of stock return dynamics with stochastic volatility and jumps. There are two key differences between our approach and these papers. First, to the best of our knowledge, no existing study has attempted to model the high-frequency dynamics in dividends using such methods, let alone estimate and test a model as general as ours. Second, our paper models the transmission (“ripple effects”) from daily cash flow news—in the form of mean, volatility, or jump components—to contemporaneous and future dynamics in stock market returns, including variation in the volatility and jump probability of returns.

The outline for the paper is as follows. Section 2 introduces our data and explains how we construct a daily cash flow index from dividend announcement data. Section 3 explains our econometric modeling approach for dealing with jumps and a persistent (predictable) cash flow component and reports estimates of our model. Section 4 analyzes the extent to which our approach can be used to predict conventional measures of dividend growth. Section 5 develops a model relating dynamics in stock returns to cash flow news, Section 6 links our dividend news measure to cross-sectional variation in stock returns, while Section 7 presents results from a set of robustness tests. Section 8 concludes.
2 Data

We start our analysis by explaining how we construct our daily dividend growth series and describing the data sources that we use. Our analysis of daily cash flows focuses on growth in dividends which, as pointed out by Kelly and Pruitt (2013), has been the focus of a large literature on asset pricing. Because earnings can be negative, defining growth in earnings poses challenges that are quite different from those arising when studying dividends.

The biggest effect of dividend news on asset prices is likely to come through their information content, so we focus on dividends as initially announced as opposed to the actual dividend payments. However, in Section 7.1.1 we also undertake an analysis of daily dividends viewed from the perspective of the payment date which allows us to compare the information effect to the direct cash flow effect from dividend payments.

2.1 Sample Construction

Our sample includes all ordinary cash dividends declared by firms with common stocks (share codes 10 and 11) listed on NYSE, NASDAQ, or AMEX from 1926 to 2016. We require firms to have valid stock prices and a valid figure for the number of shares outstanding when dividends are announced. Furthermore, we make sure there are no duplicate observations in the dataset and that each firm pays only one dividend at any point in time. Overall, our sample consists of 503,591 declared dividends.

Corporate dividends have a strong firm-specific component and often display pronounced seasonal variation. Our analysis therefore computes dividend growth by comparing same-firm, same-(fiscal) quarter, year-on-year changes in cash flows. To this

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7Ordinary cash dividends have CRSP distribution codes below 2000.

8There are instances in CRSP in which a company declares or pays multiple dividends on the same day, using different distribution codes but still classified as ordinary dividends. We aggregate such dividends to convert them into a single dividend. As an example, on November 23, 1983, PPL Corporation (permno 22517) declared two ordinary dividends of 39 and 21 cents.

9Following a recent update, CRSP no longer provides the dividend declaration date prior to 1962 and data until 1964 appear to be incomplete. Nonetheless, we also have an older version of the database in which the declared dividend dates start in 1926. As a consequence, we have 101,476 pre-1964 observations and 402,115 post-1964 observations.
end, let $D^i_{yr,s}$ be the total dividends declared by firm $i$ on day $s$ in year $yr$, calculated as the dividend per share times the number of outstanding shares. Moreover, let $I^i_{yr,s}$ be an indicator variable that equals one if company $i$ announces quarterly dividends on day $s$ in year $yr$, and otherwise takes a value of zero, while $\tilde{s}$ is the associated same-quarter, prior-year dividend announcement date for firm $i$.\(^{10}\) For example, a company may have declared dividends on May 17, 2014 while it declared the corresponding quarter’s prior-year dividends on May 9, 2013, in which case $s$ is May 17, 2014 and $\tilde{s}$ is May 9, 2013.

Aggregating across firms, the total dollar value of dividends paid out on day $s$ in year $yr$ is $\sum_{i=1}^{N_{yr}} I^i_{yr,s} D^i_{yr,s}$, where $N_{yr}$ is the number of (publicly traded) firms in existence in year $yr$. Similarly, the total value of dividends paid out by the same set of firms for the same fiscal quarter during the prior year is given by $\sum_{i=1}^{N_{yr}} I^i_{yr,s} D^i_{yr-1,\tilde{s}}$. Taking the ratio of these two numbers, we obtain a measure of the aggregate, year-on-year (gross) growth in dividends on day $s$ in year $yr$:\(^{11}\)

$$G_{yr,s} = \frac{\sum_{i=1}^{N_{yr}} I^i_{yr,s} D^i_{yr,s}}{\sum_{i=1}^{N_{yr}} I^i_{yr,s} D^i_{yr-1,\tilde{s}}}.$$  \hspace{1cm} (1)

Note that the number of firms used in this calculation – as well as their identity – changes on a daily basis and from year to year as firms shift their dividend announcement dates. Only firms for which $I^i_{yr,s} = 1$ are included in this calculation, ensuring that the same firms are used in both the numerator and denominator of the ratio. Equation (1) accounts for seasonal components in dividends and uses the dollar amount paid in dividends by individual firms, implicitly applying value weights since large firms tend to have larger dividend payouts.\(^{12}\)

As a first illustration of our data, Figure 1 provides a plot of the number of firms, as well

\(^{10}\)We use this notation to keep the exposition simple. More precisely, $\tilde{s}$ depends on both the firm $i$ and years $yr - 1$ and $yr$, so that a more precise notation would be $\tilde{s}(i, yr - 1, yr)$.

\(^{11}\)Only seven percent of individual firms’ year-on-year dividend growth observations in our sample are constant, suggesting that firms often change their dividends, even marginally, every year.

\(^{12}\)An alternative approach that more explicitly accounts for heterogeneity in firm size is to first define individual firms’ cash flow growth as

$$z^i_{yr,s} = \begin{cases} 
\frac{D^i_{yr,s}}{D^i_{yr-1,\tilde{s}}} & \text{if } I^i_{yr,s} = 1 \\
0 & \text{otherwise}
\end{cases}.$$  

In a second step we can use individual firms’ market capitalization to aggregate the cash flow growth rates across firms that pay dividends on day $s$ in year $yr$.
as the dollar dividend and the (net) growth rate from equation (1) during a single quarter (Q2 2014). The top panel shows substantial intra-quarter variation in the number of firms announcing dividends, consistent with the fact that firms tend to announce dividends around the same days. During this particular quarter, the maximum number of firms announcing dividends on any one day was 68 (on April 24), while the minimum number was zero (on June 22), and there were several days where more than 50 firms announced dividends.

The middle panel in Figure 1 shows the total value of dividends declared on individual days. This depends on the number of firms announcing dividends as well as on their size as large firms tend to announce bigger dividends.\(^1\)

Lastly, the bottom panel in Figure 1 shows the daily net dividend growth during the quarter, calculated as the log change \(\Delta d_{yr,s} = \ln(G_{yr,s})\). Peaks in this measure do not necessarily coincide with days where most firms announce dividends (top panel) or days in which the overall amount of dividends announced (middle panel) peaked. This is because the dividend growth rate depends on dividends announced by the same group of firms during the prior year as reflected in the denominator of equation (1). For example, the gross dividend growth rate on June 22 (1.15) is generated by a single firm announcing dividends on that day: the firm announced $155m in dividends in Q2, 2014 and $135m for Q2, 2013. Thus, the substantial variation in daily dividend growth rates reflects both heterogeneity across firms’ dividend behavior and variation in the number of firms announcing dividends on a given day.

\[ \hat{G}_{yr,s} = \sum_{i=1}^{N_{yr}} I_{yr,s}^i \omega_{yr,s}^i \hat{G}_{yr,s}^i, \text{ where} \\
\omega_{yr,s}^i = \frac{MktCap_{yr,s}^i \times I_{yr,s}^i}{\sum_{i=1}^{N_{yr}} MktCap_{yr,s}^i I_{yr,s}^i} \]

is the weight on company \(i\) in the daily year-on-year value-weighted dividend growth calculation. By construction, \(\sum_{i=1}^{N_{yr}} \omega_{yr,s}^i = 1\) on all days in the sample. Results based on this alternative measure are qualitatively similar to those based on the measure in equation (1) and are, therefore, not reported here.

\(^1\)The largest amount of dividends declared during Q2 2014, $7.12bn, happened on April 24, while only $3.6m of dividends were announced on June 30.
2.2 Features of daily dividend growth

Our data spans the period 1927-2016, but the first part of the sample is dominated by the Great Depression. For robustness, we therefore split the sample into halves and study both the full sample and the second half of the sample from 1973 to 2016. Figure 2 (top panel) plots $\Delta d_{yr,s}$ from 1973 to 2016.\footnote{On days with no dividend announcements, we set the series to zero.} The daily dividend growth series is very spiky and is dominated by days with unusually large or small dividend growth. There is also evidence of a sustained decline in dividends during the financial crisis.

The features displayed by our daily series of year-on-year growth in dividends in Figure 2 can be summarized as follows: (i) the daily dividend growth series is very lumpy. This reflects both variation in individual firms’ cash flow growth and variation in the composition of firms that, on any given day, announce their cash flows; (ii) daily dividend news also appears to be driven by a persistent component which was particularly pronounced during the financial crisis of 2008/09; (iii) the volatility of daily cash flow news changes over time with unusually calm periods interchanged with more volatile periods.

2.3 Comparison with the standard CRSP measure of dividend growth

The conventional alternative to our bottom-up approach is to extract dividends top-down using market returns with and without dividends as published by the Center for Research in Security Prices (CRSP). Three limitations render this alternative approach unattractive.

First, the daily CRSP index accounts for dividends distributed on a particular day but does not show when those dividends were announced. This distinction is crucial as firms typically announce dividends several days prior to the payment date and it is the news effect of announced dividends that we would expect to be important for movements in stock market returns and volatility.

Second, the set of firms announcing or paying dividends on any given day is generally different from the set of firms announcing dividends on the same day one year earlier. As a consequence, year-on-year estimates of dividend growth from daily values of the CRSP index
are difficult to interpret as they do not control for firm fixed effects and so may get distorted due to changes in the composition of the set of firms paying dividends on a given calendar day, confounding dividend growth information with shifts in firm fixed effects.\footnote{Changes in the composition of the dividend-paying firms has a far smaller effect on dividend growth measured at longer time intervals such as a quarter or a year.}

Third, the CRSP index contains many different assets such as ETFs and mutual funds \cite{Sabbatucci2017} whose dividends may follow a pattern different from that of individual firms.

These points turn out to make a crucial difference to daily dividend growth. To see this, the bottom panel of Figure 2 plots the daily dividend growth rate constructed using the conventional top-down CRSP approach over the sample 1973-2016.\footnote{To replicate our methodology as closely as possible, the daily dividend CRSP measure shown here computes the growth rate as the change in aggregate dividends paid on a given day relative to aggregate dividends paid on the same day (or whichever day is closest) during the previous year. However, the time-series looks very similar if, instead, we plot the annualized growth rate by comparing dividends paid on day $t$ relative to dividends paid on day $t-1$.} While the daily dividend growth series based on our bottom-up methodology (top panel) is affected by occasional jumps, it clearly contains a persistent component which appears to be linked to the state of the economy as evidenced by the marked decline during 2008-2009. In contrast, the daily dividend growth series constructed from the CRSP return indexes is very noisy throughout the sample.

\section{Econometric model}

To match the features of the dividend growth data noted above, an econometric model for daily dividend growth must incorporate multiple components that display very different behavior. We accomplish this as follows. First, we account for lumpiness by allowing for a jump component in daily cash flow growth. Since the lumpiness introduced by firm-level heterogeneity in dividend payments is more likely to be diversified away if a large number of firms announce dividends on the same day, we allow the jump intensity to depend on the number of firms announcing dividends. Second, we incorporate a persistent component in the mean growth equation. Third, we account for time-varying volatility by modeling the non-jump shock to daily dividend growth as a stochastic volatility process.
This decomposition is not only of interest because it can better capture the dynamics in daily cash flow news. It is also crucial for understanding and interpreting the effects of different types of cash flow news on movements in stock prices. For example, we would expect a change in the longer-lasting, persistent cash flow component to have a stronger effect on stock prices than a change in the transitory components.

We next introduce our econometric approach. To simplify notations, we use the daily indicator $t$ in place of the more cumbersome $yr,s$ notation used in equation (1). Thus, $\Delta d_t = \ln(G_{yr,s})$ denotes the year-on-year growth in dividends on day $t$.

### 3.1 A components model for daily dividend growth

Our econometric model decomposes the daily dividend growth process, $\Delta d_{t+1}$, into three parts, namely (i) a persistent term, $\mu_{dt+1}$, which captures a smoothly evolving mean component; (ii) a jump component, $\xi_{dt+1}J_{dt+1}$, where $J_{dt+1} \in \{0, 1\}$ is a jump indicator that equals unity in case of a jump in dividends and otherwise is zero, while $\xi_{dt+1}$ measures the magnitude of the jump; (iii) a temporary cash flow shock, $\varepsilon_{dt+1}$, whose volatility is allowed to be time-varying. Adding up these terms, we have

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

We next introduce our assumptions on the individual components. We capture any persistence that may be present in the dividend growth process by assuming that $\mu_{dt+1}$ follows a mean-reverting first-order autoregressive process

$$\mu_{dt+1} = \mu_d + \phi_\mu (\mu_{dt} - \mu_d) + \sigma_\mu \varepsilon_{\mu t+1}, \quad \varepsilon_{\mu t+1} \sim \mathcal{N}(0, 1), \quad (3)$$

where $|\phi_\mu| < 1$ and $\varepsilon_{\mu t+1}$ and $\varepsilon_{dt+1}$ are assumed to be uncorrelated. In the special case where $\phi_\mu = 0$, $d_{t+1}$ follows a random walk process whose changes, $\Delta d_{t+1}$, are unpredictable.

Turning to the jump component, empirically we find a systematic relation between the probability of observing a jump in $\Delta d_{t+1}$ and the number of firms that announce dividends on a given day, $N_{dt+1}$. In particular, days with few firms announcing dividend news tend to have a higher chance of jumps in $\Delta d_{t+1}$, as the effect of diversifying outlier observations
across multiple firms is smaller on such days. To account for this effect, we assume that the probability of a jump depends on the number of firms announcing their dividends on any given day. We capture this through a Probit model of the form

\[ \Pr (J_{dt+1} = 1) = \Phi (\lambda_1 + \lambda_2 N_{dt+1}) , \] \hspace{1cm} (4)

where \( \Phi \) is the CDF of a standard normal distribution. The magnitude of the jumps is modeled as \( \xi_{dt+1} \sim \mathcal{N} (0, \sigma^2_\xi) \).

Finally, we capture time-varying uncertainty about the temporary cash flow news component, \( \varepsilon_{dt+1} \), by means of a stochastic volatility process:

\[ \varepsilon_{dt+1} \sim \mathcal{N}(0, e^{h_{dt+1}}), \] \hspace{1cm} (5)

where \( h_{dt+1} \) is the log-variance of \( \varepsilon_{dt+1} \) which is assumed to follow a mean-reverting process,

\[ h_{dt+1} = \mu_h + \phi_h (h_{dt} - \mu_h) + \sigma_h \varepsilon_{ht+1}, \quad \varepsilon_{ht+1} \sim \mathcal{N}(0, 1), \] \hspace{1cm} (6)

where \( \varepsilon_{ht+1} \) is uncorrelated with both \( \varepsilon_{dt+1} \) and \( \varepsilon_{\mu t+1} \).

To summarize, our dividend growth model accounts for a persistent mean-reverting component, time-varying volatility, and jumps. We evaluate the importance of these features of the model by comparing results from the general model in (2) to a simpler (no-jump) model that ignores jump dynamics and stochastic volatility and so takes the form

\[ \Delta d_{t+1} = \mu_{djt+1} + \varepsilon_{dt+1}, \quad \varepsilon_{dt+1} \sim \mathcal{N}(0, \sigma^2_d) \] \hspace{1cm} (7)

where \( \mu_{djt+1} \) follows the mean-reverting process in equation (3). This comparison allows us to gauge the importance of incorporating jump dynamics and stochastic volatility.

### 3.2 Estimation

We adopt a Bayesian approach that uses Gibbs sampling to estimate the model parameters. Details of our estimation procedure are provided in Internet Appendix A while Internet Appendix B documents the convergence properties of our estimation algorithm.
It is worth briefly describing the priors that underlie our model. We choose standard normal-gamma conjugate priors which simplify the process of drawing from the conditional distributions of the model parameters in the Gibbs samplers. Moreover, we specify independent priors for the parameters of both the mean, variance, and jump processes. As for the prior hyperparameters, for almost all of the parameters we use loose and mildly uninformative priors. The main exceptions are the persistence parameters, $\phi_\mu$ and $\phi_h$, whose priors we center on 0.99. Further details are provided in Internet Appendix A.

3.3 Empirical estimates

We next present estimates of the parameters of our econometric model and evaluate empirically the behavior of the three components in the dividend growth process.

Table 1 presents parameter estimates for our general dividend growth model in equations (2)-(6) for both the short sample (1973-2016) and the full sample (1927-2016). We focus our discussion on the parameter estimates for the short sample but note that the estimates for the longer sample are very similar.

First consider the parameters determining the mean of the dividend growth process in equation (3). The long-run mean estimate $\mu_d = 0.084$ corresponds to an 8% annualized nominal dividend growth rate which is close to the mean of the standard dividend growth measure (extracted from CRSP data) of 7.8% over the same sample period—a figure well within the 90% credible set of [0.064, 0.104]. The persistence parameter for the mean reverting component of the dividend growth process, $\phi_\mu$, is centered on 0.998, corresponding to a half-life of 350 trading days. While highly persistent, shocks to the mean-reverting component (3) are very small as shown by the estimate $\sigma_\mu = 0.002$. Our model thus identifies a small, but highly persistent component in the dividend growth process.

The top and bottom panels in Figure 3 plot the persistent dividend growth component, $\mu_{dt}$, extracted using either the no-jump model (equation 7, top panel) or the general jump model (equation 2, bottom panel). The $\mu_{nt}^{XJ}$ series evolves on the same scale as the daily dividend growth series from which it is extracted (shown in the top panel of Figure 2) and, thus, erroneously, assigns large daily spikes in the observed series to the persistent
component, $\mu_{dt}$. In contrast, the jump model succeeds in separating the temporary spikes (noise) in the daily dividend series from the persistent component $\mu_{dt}$ which, consequently, is far smoother. Indeed, values of the persistent dividend growth component extracted from the general model fall on a far narrower scale than the unfiltered dividend growth series, ranging from just below zero to 0.15. As expected, the financial crisis in 2008-09 is associated with a notable drop in mean dividend growth which, for the only time in our sample, turns negative, followed by a notable bounce-back in the second half of 2009 and 2010.

The stochastic volatility process in equation (6) is quite persistent as evidenced by the estimate of $\phi_h$ whose mean is 0.963 with a standard deviation of 0.002. The negative estimates of the jump intensity parameters ($\lambda_1$ and $\lambda_2$) imply that a jump occurs every sixty days on average with jump probabilities tending to be lower on days where a large number of firms announce dividends.

Figure 4 provides details of the jump component estimated from our model (2)-(6). The jump probability indicator, $J_{dt}$, in the top panel shows that the spikes in daily dividend growth are attributed mostly to jumps rather than to clusters with unusually high volatility from the transitory component, $\varepsilon_{dt}$, in equation (2). Moreover, on many days, the jump indicator variable is close to one. On such days we attribute, with a very high likelihood, much of the dividend growth shock to a jump. Jumps can be very large in magnitude, as shown in the bottom panel, which displays the estimated jump size, $\xi_{dt}$. Indeed, the estimated standard deviation of the jump size ($\sigma_{\xi}$) has a mean of 1.43 which is seven times larger than the estimated mean of $\sigma_h$ (0.20), so shocks to daily dividend growth originating from the jump component tend to be far bigger than the regularly occurring $\varepsilon_{dt}$ shocks.

While Figure 3 and 4 show the evolution in the different dividend components, further insights can be gained by focusing on how our model decomposes the total variation in the dividend growth rate into temporary “normal”, jump, and slowly mean-reverting components. Figure 5 performs this analysis for two days in our sample, namely December 8, 2009 (in the middle of the global financial crisis), and August 5, 2010. The first day experienced a large negative shock to dividend growth. Our decomposition attributes this to small negative shocks to the persistent and transitory components and a large negative jump. Conversely, on August 5, 2010, the dividend growth news was small and positive.
which gets attributed to small positive realizations of the persistent component and the
transitory shock and no jump.

To get a sense of how sensitive the dividend growth jump probability is to the number of
firms announcing dividends on a given day, \( N_{dt} \), Figure 6 plots the jump intensities for three
values of \( N_{dt} \) chosen to match the 25th, median and 75th percentiles of the distribution of
the daily number of announcing firms. On days with a large number of announcing firms
(75th percentile, or 36 firms on average), the jump intensity distribution is centered on a
number a little over 0.005, corresponding to a jump on average every 200 days. On days with
a typical number of announcing firms (median, or 22 firms), the jump intensity is centered
around its average value near 0.016, implying a jump every 60 days. Finally, on days with a
small number of announcing firms (25th percentile, or 12 firms), the probability of a jump
is centered just below 0.03, corresponding to a jump in dividend growth every 35 days.

4 Predictability of dividend growth

Predictability of dividend growth has featured prominently in discussions of asset pricing
models. Cochrane (2008) finds little evidence of predictability of US dividends, while
studies such as van Binsbergen and Koijen (2010) and Kelly and Pruitt (2013) argue that
dividend growth is, to some extent, predictable.\footnote{A recent literature uses dividend futures to estimate the term structure of dividends. In particular, van Binsbergen et al. (2012) and van Binsbergen and Koijen (2017) recover prices of dividend strips and show that their expected returns are higher than those on the underlying index. Kragt et al. (2015) estimate a model for the term structure of discounted risk-adjusted dividend growth using dividend derivatives for four major stock markets.} The parameter estimates from our
dividend model show that the daily dividend growth process contains a small, but highly
persistent component and this section explores the implications of those results for
predictability in dividend growth.

Existing studies on dividend growth predictability use time-aggregated dividends
measured over longer horizons than our daily interval. To explore whether our estimate of
the persistent dividend growth component is capable of predicting dividends—and to make
our results directly comparable to existing ones—we use the conventional top-down
approach to construct monthly and annual measures of dividend growth from CRSP data,
denoted $\Delta d_{t}^{CRSP}$.

### 4.1 Predictive regressions

We estimate a predictive regression of future dividend growth, $\Delta d_{t+1}^{CRSP}$, on the persistent dividend component measured at the end of the previous period, $\mu_{dt}$, the log dividend-price ratio extracted from CRSP, $dp_t$, and current and lagged dividend growth:

$$\Delta d_{t+1}^{CRSP} = \alpha + \beta \mu_{dt} + \gamma dp_t + \sum_{j=1}^{3} \rho_j \Delta d_{t+1-j}^{CRSP} + \varepsilon_{t+1}. \quad (8)$$

We include the log dividend-price ratio in the regression because this has been suggested as a predictor of cash flow growth in a variety of studies (e.g., Cochrane (1992), Cochrane (2008), and Lettau and Nieuwerburgh (2008)).

Panel A of Table 2 shows that the persistent component of dividend growth, $\mu_{dt}$, has strong predictive power over future dividend growth recorded at the quarterly horizon. In the shorter post-1973 sample, the lagged persistent dividend growth component obtains a t-statistic of 4.5 after accounting for the effect of lagged dividend growth and the lagged dividend-price ratio. Moreover, at 0.28 the $R^2$ is quite high. These findings are not sensitive to the sample period. Starting the sample in 1927, the coefficient on $\mu_{dt}$ obtains a t-statistic of 4.3 and the predictive regression has an $R^2$ value of 0.41. Interestingly, the coefficient on the lagged dividend-price ratio is not significant in any of these regressions, while the first two lags of dividend growth are significant in some of the models, but not always with the expected (positive) sign.

The predictive power of $\mu_{dt}$ over future dividend growth is somewhat weaker at the annual than at the quarterly horizon. This is perhaps not surprising considering the mean reversion in $\mu_{dt}$ which reduces its predictive power at long horizons. Still, $\mu_{dt}$ remains highly statistically significant at the annual horizon and this result is robust to the inclusion of lagged dividend growth and the dividend-price ratio in the predictive regression.

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18 Most researchers extract aggregate dividends, $D_t$, from CRSP as the difference between the cum-dividend return (VWRETD), $R_{t}^{cum}$, and the ex-dividend return (VWRETX), $R_{t}^{ex}$, multiplied by the previous ex-dividend index level, $P_{t-1}^{ex}$, i.e., $D_t = (R_{t}^{cum} - R_{t}^{ex}) \times P_{t-1}^{ex}$. Using the resulting aggregate dividend series, the log dividend growth rate can be computed as $\Delta d_{t}^{CRSP} = \ln \left( \frac{D_t}{D_{t-1}} \right)$. 

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4.2 Comparison with alternative predictors of dividend growth

Our study is not the first to use filtering methods to model predictability in dividend growth. For example, van Binsbergen and Koijen (2010) use a latent variables approach to estimate a log-linearized present value model consisting of expected returns and expected dividend growth rates for the aggregate stock market.\(^\text{19}\) van Binsbergen and Koijen (2010) find that annual dividend growth rates are less persistent but more predictable than stock returns.

Kelly and Pruitt (2013) assume that individual firms’ stock returns and log cash flow growth rates are a linear function of a set of unobserved common factors which can be estimated using a three-pass regression (partial least squares) methodology. In turn, cash flow growth can be projected on the common factors to generate a dividend growth forecast. Empirically, Kelly and Pruitt (2013) find strong in-sample evidence of predictability in annual cash flow growth while their out-of-sample results are somewhat mixed; in the Depression-era (1930-1940), dividend growth appears to be highly unstable and hard to predict while out-of-sample predictability is stronger over the sample 1940-2010.

We next compare our dividend growth estimates to results based on the approaches of van Binsbergen and Koijen (2010) and Kelly and Pruitt (2013).\(^\text{20}\) To this end, the top panel in Figure 7 plots realized values of annual dividend growth against the persistent growth component estimated from our model, \(\mu_{dt}\), (sampled annually) and the van Binsbergen and Koijen (2010) measure, \(g_{t}^{\text{VBK}}\). The bottom panel repeats the exercise, plotting monthly dividend growth against our persistent dividend growth series, \(\mu_{dt}\), (sampled monthly) and the Kelly and Pruitt (2013) estimate, \(g_{t}^{\text{KP}}\). While the different dividend growth estimates are clearly correlated, there are also some notable differences. Notably, our persistent dividend growth measure shows a sharper decline during the global financial crisis compared with the two alternative estimates.

To conduct a more formal comparison, Panel B in Table 2 reports results from regressions of the observed future dividend growth on the growth estimate implied by the three approaches we are comparing. Note that van Binsbergen and Koijen (2010) study

\(^{19}\)Because the expected value of dividend growth rates is unobserved, van Binsbergen and Koijen (2010) use Kalman filtering methods to extract the underlying series and generate forecasts of cash flows.

\(^{20}\)We are grateful to Seth Pruitt for sharing data and computer code which allowed us to replicate the results in Kelly and Pruitt (2013).
cash-reinvested, annual dividend growth while Kelly and Pruitt (2013) use monthly dividend growth extracted from CRSP so their growth estimates are not directly comparable. We therefore report separate results for the annual and monthly frequencies used in the two studies.

In the univariate regressions, all three growth estimates clearly have predictive power over future dividends. For example, the growth estimate of van Binsbergen and Koijen (2010) obtains a t-statistic of 2.94 with an $R^2$ value of 14% in the annual sample from 1946 to 2015. For comparison, the t-statistic on our $\mu_{dt}$ estimate is 5.77 and the associated $R^2$ value is 39%. Including both the $\mu_{dt}$ and $g_{t}^{VBK}$ measures in the regression, we obtain a very large t-statistic on $\mu_{dt}$ (6.03), while the t-statistic on the estimate of van Binsbergen and Koijen (2010) remains significant but drops to 2.03. The $R^2$ value of this regression is 44%. This is notably higher than the value obtained when only $g_{t}^{VBK}$ is used as a predictor, thus demonstrating the extra predictive power possessed by our estimate of the persistent growth component.

In monthly dividend growth regressions from 1940 to 2016, the growth estimate of Kelly and Pruitt (2013) generates a t-statistic of 4.86 and an $R^2$ value of 13%. For comparison, the t-statistic obtained when instead we use our $\mu_{dt}$ component is 9.96 and the $R^2$ value is 32%. Including both $\mu_{dt}$ and $g_{t}^{KP}$ as predictors in the regression, $\mu_{dt}$ obtains a t-statistic of 8.09 while the t-statistic of the growth estimate of Kelly and Pruitt (2013) remains significant but declines to 2.06.

These results show that the persistent component in dividend growth extracted from daily dividend announcements possesses strong predictive power over actual dividend growth at both the monthly and annual frequencies. Moreover, our estimate adds substantial predictive power to existing dividend growth estimates.

To formally test and compare the predictive power of the three dividend growth estimates, we run a pair of forecast encompassing regressions:

$$\Delta d_{t+1}^{CRSP} = \alpha + \beta_1 \mu_{dt} + (1 - \beta_1)g_{t}^{VBK} + \varepsilon_{t+1},$$

$$\Delta d_{t+1}^{CRSP} = \alpha + \beta_1 \mu_{dt} + (1 - \beta_1)g_{t}^{KP} + \varepsilon_{t+1}. \quad (9)$$
The larger is $\beta_1$, the greater the weight on our dividend growth estimate and the smaller the weight on the competing model estimate. Specifically, a value of $\beta_1 = 1$ suggests that $\mu_{dt}$ dominates (encompasses) either $g_{t}^{VBK}$ (top regression) or $g_{t}^{KP}$ (bottom regression).\footnote{Note that $g_{t} = E_t \Delta d_{t+1}$ is the forecast of dividend growth next period.}

The first two rows of Panel C in Table 2 show that the estimate of $\beta_1$ equals 0.81 in the encompassing regression that includes $\mu_{dt}$ and $g_{t}^{VBK}$, so that the persistent dividend growth estimate from our model obtains a weight of 81% while the weight on the van Binsbergen and Koijen (2010) estimate equals 19%. Moreover, the estimated weight on $\mu_{dt}$ is statistically significant at the 1% level while the weight on the van Binsbergen and Koijen (2010) estimate is significant at the 10% level. Similar results are obtained from the second regression. Here the weight on $\mu_{dt}$ is 77%, while the weight on the Kelly and Pruitt (2013) dividend growth estimate is 23%, with both being significant at the 1% level.

We conclude from these regressions that our dividend growth estimate adds significant predictive value to existing state-of-the-art alternatives from the literature.

4.2.1 Out-of-sample forecasts

The results listed so far use the full data sample up to 2016. From the perspective of most efficiently using all available data, this is the appropriate estimation strategy (see Hansen and Timmermann (2015)). However, the analysis does not address whether our approach could have been used in real time to generate accurate forecasts of dividend growth.

To address this point, we conduct an out-of-sample forecasting experiment that only uses historically available data to estimate the parameters of our model and generate forecasts. Specifically, using an expanding estimation window and an initial warm-up period from 1973-1986, we re-estimate our model every week and construct real-time, out-of-sample daily forecasts over the 1986-2016 sample. Each month, we then take the last daily value of our forecast and compare this to the monthly out-of-sample forecasts generated using the approach of Kelly and Pruitt (2013). Finally, we evaluate the accuracy of these forecasts using either univariate regressions or the forecast encompassing regressions in (9).

A univariate regression of dividend growth on our out-of-sample, real-time estimate, $\mu_{dt}$, generates an $R^2$ of 27.76% ($t$-stat of 6.70), while the same regression using the out-of-sample
forecast of Kelly and Pruitt (2013) produces an $R^2$ of 2.88% ($t$-stat of 2.38).\footnote{22} Similarly, in the forecast encompassing regression, the weight on the $\mu_{dt}$ series increases from 0.77 to 1.38 with a $t$-statistic of 12, while the weight on the Kelly and Pruitt (2013) forecast is -0.38. These results suggest that our dividend growth forecasts perform very well even out-of-sample.\footnote{23}

4.3 Cash flow news and economic activity

We next examine the relation between our estimate of the persistent component of dividend growth news and two measures of macroeconomic growth, namely GDP and consumption growth, both of which have been examined by authors such as Liew and Vassalou (2000) and Bansal and Yaron (2004).\footnote{24} Figure 8 plots quarterly GDP and consumption growth against our $\mu_{dt}$ measure sampled quarterly. We observe a clear and positive relation between the persistent dividend growth component and consumption or GDP growth.

To evaluate the statistical significance of these relations, we estimate predictive regressions

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

(10)

where $\Delta y_{t+1}$ is the future change in either log GDP or log consumption. We include one lag of the dependent variable, $\Delta y_t$, to control for persistence in consumption or GDP growth. Table 3 reports the results from the regression in (10). In the univariate regressions, our persistent dividend growth measure, $\mu_{dt}$, generates positive coefficients of 0.14 and 0.13 with $t$-statistics of 4.57 and 4.72 for GDP growth and consumption growth, respectively. Moreover, with $R^2$ values of 21% and 26%, $\mu_{dt}$ clearly has strong predictive power over future GDP and consumption activity.

We conclude from this evidence that our persistent cash flow measure $\mu_{dt}$ helps predict

\footnote{22}Results ending in 2007, excluding the recent financial crisis, are qualitative identical with a $R^2$ of 25.47% ($t$-stat of 9.01) for our measure, and a $R^2$ of 4.05% ($t$-stat of 2.15) for Kelly and Pruitt (2013).

\footnote{23}Since our out-of-sample forecasts are generated recursively, our findings are not overly sensitive to the Great Recession which produced a considerable amount of cash flow news, see, e.g., Campbell et al. (2013).

\footnote{24}The Gross Domestic Product series is downloaded from FRED and is seasonally adjusted, see \url{https://fred.stlouisfed.org/series/GDP}. Consumption expenditures are the sum of non-durable consumption plus services from Table 2.3.5 of the National Income and Product Accounts (NIPAs) and are available on the Bureau of Economic Analysis (BEA) website.
variation in macroeconomic growth. This is consistent with our earlier finding that $\mu_{dt}$ predicts future dividend growth and shows that this result carries over to broader measures of economic growth. In broader terms, our findings suggest that firms adjust their dividend payments in anticipation of changes in economic conditions measured by slow-moving economic indicators such as GDP and consumption growth.

4.4 Relation to other activity measures

Our daily dividend growth measure reflects general macroeconomic conditions and so can be viewed as an economic indicator similar to existing measures such as the macroeconomic uncertainty measure of Jurado et al. (2015), the economic policy uncertainty measure of Baker et al. (2016), the ADS business conditions index of Aruoba et al. (2009), the credit spread indicator of Gilchrist and Zakrajsek (2012), and “noise” in the Treasury market (Hu et al. (2013)). Previous research has addressed whether these measures can be used to predict the state of the economy, especially during recessions and financial crises, so we next explore the relation between $\mu_{dt}$ and these alternative measures.

Panel A of Table 4 shows estimates of the correlations between the persistent dividend component $\mu_{dt}$ and these daily measures of financial and macroeconomic conditions. Our persistent dividend growth measure has a highly significant negative correlation of -0.53 with the VIX, suggesting that dividend growth is lower in times with high uncertainty, which tends to coincide with economic recessions. Confirming this finding, $\mu_{dt}$ also has a significantly negative correlation of -0.23 with the policy uncertainty index of Baker et al. (2016) and a negative correlation of -0.59 with the liquidity noise index of Hu et al. (2013), indicating that firm payouts are lower in times with greater uncertainty. Finally, our cash flow index has a significantly positive correlation of 0.32 with the ADS index of Aruoba et al. (2009) and with the daily inflation index of Cavallo and Rigobon (2016) (correlation of 0.78). These findings show that our persistent dividend growth measure is significantly negatively correlated with

\[25\] Aruoba et al. (2009) measure economic activity at the daily frequency using a variety of stock and flow data observed at mixed frequencies. Their approach extracts the state of the business cycle from a latent factor that affects all observed variables. Jurado et al. (2015) provide econometric estimates of time-varying macroeconomic uncertainty and show that important uncertainty episodes appear far more infrequently than indicated by popular uncertainty proxies. However, when such episodes do occur, they tend to be larger, more persistent, and more correlated with real economic activity.
risk proxies, e.g., stock market volatility and policy uncertainty, but positively correlated with economic growth and inflation.

Panel A in Table 4 uses levels and so the correlation estimates described above are driven by common, persistent factors reflecting the state of the economy. Panel B highlights short-run correlations by reporting the correlations between daily changes in the underlying indexes. Changes in our daily dividend growth index are significantly positively correlated both with changes in the ADS index and changes in daily inflation, suggesting that our measure in part captures fundamental information reflected in other macroeconomic variables.

5 Return dynamics and cash flow news

A key motivation for our daily dividend growth measure is that it can shed light on the drivers of movements in daily stock prices. From a theoretical perspective, we would expect the three dividend growth components to have a very different impact on stock prices. For example, purely temporary shocks to the cash flow process \(\varepsilon_{dt}\) should have very little effect on stock prices, whereas shocks to the persistent dividend growth component \(\mu_{dt}\) should have a larger impact. Similarly, shocks to the volatility of dividend growth might influence the mean and volatility of aggregate stock market returns, as investors attempt to learn about the underlying cash flow process, and hence affect returns through a risk premium channel. Documenting the importance of these effects is important as the sources of daily movements in stock prices are poorly understood.

To address these points, we next use our daily dividend growth estimates to conduct an analysis of the relation between stock market returns and news about the dividend growth process. We first develop a new dynamic model that is sufficiently flexible to allow the distribution of stock market returns to incorporate cash flow news. We then develop a set of hypotheses linking movements in stock market returns to our estimates of dividend growth dynamics. Finally, we report estimates of our return model and results from empirical tests of the hypotheses.
5.1 Stock returns and cash flow dynamics

A long-standing debate in the asset pricing literature is concerned with how important time variation in expected future cash flows is for explaining variation in stock market returns. Some studies argue that dividend growth is largely unpredictable. If dividend growth is not predictable, time variation in risk premia become more important to explaining movements in stock returns. Conversely, variation in the predictable component of dividend growth should impact stock prices by more than shocks to temporary components of dividend growth. Our dividend growth model in (2)-(6) allows us to easily compute forecasts of future cash flows and so can readily be used to estimate the importance of time variation in cash flow expectations.

To analyze the effect of dividend news on stock returns, we develop a new dynamic model for daily stock returns. Our approach takes advantage of the timing of firms’ dividend announcement. Firms generally determine their dividends several days prior to observing the aggregate returns on the day of the dividend announcement. Given this timing, we can treat the estimated dividend components as being pre-determined relative to aggregate stock market returns.

As in earlier studies such as Eraker et al. (2003), we allow for stochastic volatility effects and jumps in stock returns, but our model generalizes existing approaches by linking stock market volatility and jumps to the corresponding components in the cash flow process. We accomplish this using a two-stage approach that first estimates the dividend growth rate model, then includes the extracted components in the model for stock market returns.

Our model for daily stock market returns takes the following form:

\[ r_{t+1} = \mu_{rt+1} + \xi_{rt+1} J_{rt+1} + \beta_1 \Delta \mu_{dt+1} + \beta_2 \exp (h_{dt+1}/2) + \beta_3 \xi_{dt+1} J_{dt+1} + \beta_4 \varepsilon_{dt+1} + \varepsilon_{rt+1}. \] (11)

Analogously with the dividend growth model, \( \mu_{rt+1} \) captures a persistent component in returns, \( \xi_{rt+1} J_{rt+1} \) represent jumps in returns with \( J_{rt+1} \in \{0,1\} \) being a jump indicator and \( \xi_{rt+1} \) measuring the magnitude of a jump, while \( \varepsilon_{rt+1} \sim \mathcal{N}(0, e^{h_{rt+1}}) \) is a diffusion term with time-varying log-volatility \( h_{rt+1} \). The four additional components, \( \beta_1 \Delta \mu_{dt+1}, \)

\[ \]
\[ \beta_2 \exp (h_{dt+1}/2), \ \beta_3 \xi_{dt+1} J_{dt+1}, \ \text{and} \ \beta_4 \varepsilon_{dt+1} \] capture spillover effects on returns from the conditional mean, conditional volatility, jump, and diffusion components of the dividend growth process. We discuss the economic interpretation of these terms below.

The mean of the return process, \( \mu_{rt+1} \), is assumed to follow a mean-reverting process:

\[ \mu_{rt+1} = \mu_r + \phi_{\mu_r} (\mu_{rt} - \mu_r) + \sigma_{\mu_r} \varepsilon_{r\mu t+1}, \ \varepsilon_{r\mu t+1} \sim \mathcal{N}(0,1), \] (12)

where \( \varepsilon_{r\mu t+1} \) is uncorrelated at all times with \( \varepsilon_{rt+1} \), and \( |\phi_{\mu_r}| < 1 \).

The log variance of \( \varepsilon_{rt+1} \) is also assumed to evolve according to a mean-reverting, autoregressive process modified to include the volatility and jump components extracted from the dividend process:

\[ h_{rt+1} = \mu_h + \phi_h (h_{rt} - \mu_h) + \gamma_1 \Delta \mu_{dt+1} + \gamma_2 h_{dt+1} + \gamma_3 \xi_{dt+1} J_{dt+1} + \sigma_h \varepsilon_{rht+1}, \] (13)

where \( \varepsilon_{rht+1} \sim \mathcal{N}(0,1) \) is uncorrelated at all times with both \( \varepsilon_{rt+1} \) and \( \varepsilon_{r\mu t+1} \).

Finally, we allow the jump intensity of returns to depend on the number of firms announcing dividends on any given day, \( N_{dt} \), as well as on the jumps in the dividend growth process:

\[ \Pr (J_{rt+1} = 1) = \Phi (\lambda_1^r + \lambda_2^r N_{dt+1} + \lambda_3^r \xi_{dt+1} J_{dt+1}) . \] (14)

The magnitude of the jump, \( \xi_{rt+1} \), is modeled as \( \xi_{rt+1} \sim \mathcal{N}(0, \sigma_{\xi}^2) \).

Our return model can be compared to specifications adopted in previous studies in the asset pricing literature such as Chib et al. (2002) and Eraker et al. (2003). Chib et al. (2002) model daily returns on the S&P 500 index using an additive jump process in the return equation of a discrete-time stochastic volatility (SV) model, while Eraker et al. (2003) compare several SV models with additive jump components in both the return and variance equations applied to daily returns on the S&P 500 and Nasdaq indexes. Eraker et al. (2003) find that allowing for jumps in both the mean and the variance processes generate quite different price dynamic compared to a strategy of adding diffusion factors or only allowing for jumps in returns.\(^{27}\)

\(^{27}\) Chan and Grant (2016b,a) discuss and compare various SV models that are widely used in the literature to model financial and macroeconomic time series with and without jumps in the mean equation and outline efficient algorithms for fitting these models that build on fast band matrix routines.
Several key differences set our specification apart from models used in earlier studies. First, and most importantly, we include the components extracted from the daily dividend growth process in the specification of mean returns dynamics (11). Second, we allow for a mean reverting component, $\mu_{rt}$, in stock returns. Third, we allow the volatility of stock market returns to be affected by both the volatility and jumps of the dividend growth process, (13). Finally, the jump probability of returns in our model can depend not only on the number of firms announcing dividends on a given day but also on jumps in news about dividend growth, (14). These are features that have not previously been explored when modeling stock returns.

5.2 Economic hypotheses

We next develop a set of economic hypotheses that we use to guide our empirical analysis. Note that the direction of causality is well-determined in our setting: It is highly unlikely that the dividends announced by firms on any given day could be affected by stock returns on that day as corporate boards determine dividend payments well in advance of the announcement day. Conversely, stock prices are expected to react quickly to cash flow news announcements.

Our first hypothesis is that news about the permanent component of cash flows, $\Delta \mu_{dt+1}$, has a significantly positive and larger effect on same-day stock returns than a shock to the transitory cash flow component, $\varepsilon_{dt+1}$, or jumps in the cash flow process, $\xi_{dt+1} J_{dt+1}$. These observations translate into the following hypothesis about the parameters in equation (11):

**Hypothesis 1.** *Stock returns tend to be higher on days with positive news about the persistent dividend growth component, while temporary shocks to dividend growth should not have any effect on stock returns:*

$$H_1 : \beta_1 > 0 \text{ and } \beta_3 = \beta_4 = 0.$$  

Our second hypothesis is that higher cash flow volatility is associated with a positive risk premium as it indicates an environment with higher uncertainty about fundamental growth. We formulate this hypothesis as a statement about the effect of $\exp(h_{dt+1}/2)$ on stock returns, noting that this term will be dominated by variation in the conditional variance of $\varepsilon_{dt+1}$ due

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to the high persistence in the $h_{dt+1}$ process.

**Hypothesis 2.** *Stock returns tend to be higher in periods with greater uncertainty as manifested by higher dividend growth volatility:*

$$ H_2 : \beta_2 > 0. $$

Our third hypothesis is that higher cash flow volatility and jumps in cash flows are drivers of the return volatility process. Specifically, we expect positive news about $\Delta \mu_{dt+1}$ to be associated with lower return volatility as it indicates stronger fundamentals which are traditionally associated with a less uncertain environment. Conversely, we expect higher cash flow volatility and large negative jumps to be associated with more volatile stock returns as they indicate greater uncertainty about cash flows and potentially worse growth prospects. In the context of the return volatility equation (13), this suggests the following hypothesis:

**Hypothesis 3.** *Return volatility tends to be higher on days with negative news about the persistent dividend growth rate, higher dividend growth volatility, and negative jumps in the dividend process:*

$$ H_3 : \gamma_1 < 0, \gamma_2 > 0 \text{ and } \gamma_3 < 0. $$

Finally, we expect that jumps in cash flows will increase the probability of observing same-day jumps in stock returns. Jumps in cash flows increase uncertainty and make it more likely to see large movements in stock prices. Moreover, in the same way that negative news increases stock market volatility more than positive news through a leverage effect, we would expect a negative jump, i.e., a sharp downward adjustment in the cash flow process, to be associated with a particularly high chance of observing a jump in returns. Days with fewer signals about fundamentals, i.e., days with fewer firms announcing their dividends, can also be expected to be more uncertain, increasing the chance of observing a jump in stock returns. These hypotheses translate into the following parameter restrictions in equation (14):

**Hypothesis 4.** *The probability of a jump in stock returns is higher if there is little
information about dividend growth (few firms announce dividends) and if there is a large negative jump in dividend growth:

\[ H_4 : \lambda_2^r < 0 \text{ and } \lambda_3^r < 0. \]

### 5.3 Empirical results

Table 5 reports posterior means and credible sets for the parameters of the daily stock return model in equations (11)-(14).\(^\text{28}\) Our model identifies highly persistent, mean reverting components in both the conditional mean and volatility of returns with mean estimates \(\phi_{\mu r} = 0.989\) and \(\phi_{hr} = 0.990\) so that 99% of the daily value of the persistent mean or log-volatility component carries over to the following day. The jump intensity parameters suggest an average jump probability of 7.2%, corresponding to a jump in stock returns occurring every 14 days. These features of our model for stock returns are consistent with those identified in earlier studies such as Eraker et al. (2003).

Figure 9 shows the time series of \(h_{rt+1}\), \(J_{rt+1}\) and \(\xi_{rt+1}\), extracted from daily stock returns using our return model. The volatility of stock returns (top panel) rose markedly during the 2008-09 financial crisis as we would expect. The jump intensity (middle panel) and jump size (bottom panel) were also notably higher during the financial crisis of 2008-09.

Turning to the tests of the economic hypotheses laid out above, consistent with \(H_1\) the estimate of \(\beta_1\) is highly statistically significant with the expected positive value, so that positive news about the persistent dividend growth component is associated with higher stock returns on the same day. The coefficient on the jump component, \(\beta_3\), is positive and significant at the 90% confidence level but is insignificant at the 95% level. Thus, there is some evidence to suggest that jumps in the dividend growth process affect stock returns, contrary to \(H_1\).\(^\text{29}\) Finally, the small and insignificant value of \(\beta_4\) suggests that temporary shocks to dividend growth do not directly affect same-day returns, consistent with \(H_1\).\(^\text{30}\)

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\(^{28}\)As with the econometric model of Section 3, we provide full details of our estimation procedure and convergence statistics in Internet Appendix A and Internet Appendix B.

\(^{29}\)A possible explanation of this finding is that the risk premium on stocks rises on days with negative jumps in the dividend growth process, leading to a downward adjustment in the stock price on such days.

\(^{30}\)Including the market cap of the daily announcers, measured as a proportion of the aggregate market, does not affect the coefficients of the other variables in our return specification, (16). Moreover, the coefficient
Our second hypothesis is that higher uncertainty about cash flow growth translates into lower aggregate stock returns. Consistent with this hypothesis, our estimate of $\beta_2$ is positive and statistically significant so that returns are higher on average on days with higher cash flow volatility. Importantly, this result is driven by an expected volatility effect: splitting the actual volatility $\exp(h_{dt+1}/2)$ into an expected term, given information on day $t$, and the surprise component (i.e., the unanticipated change in volatility on day $t+1$), we find that only the expected cash flow volatility $\exp(h_{dt+1|t}/2)$ has a significant correlation with returns on day $t+1$.

Consistent with $H_3$, positive news about the persistent cash flow growth component tends to dampen return volatility ($\gamma_1 < 0$ in (13)). Conversely, higher cash flow volatility or a negative jump in the cash flow growth rate are associated with significantly higher return volatility as $\gamma_2 > 0$ and $\gamma_3 < 0$.

Finally, our probit estimates of the probability of jumps in stock market returns (14) show that, consistent with $H_4$, the probability of observing a jump in returns is higher on days where few firms announce dividends ($\lambda^r_2$ is negative) and on days with a negative jump in dividends (negative $\lambda^r_3$). Hence, a negative jump in the dividend growth process increases the probability of observing a jump in stock returns on the same day.

To evaluate the economic magnitude of how variation in $N_{dt+1}$ and $\xi_{dt+1}J_{dt+1}$ affect the probability of a jump in stock returns, we compute the jump probabilities from the Probit model (14) for different percentiles of these variables. Setting the variables at their 25th percentiles, we find a daily jump probability of 9%, corresponding to a jump every 11 days. Conversely, setting the variables at their 75th percentiles, the daily jump probability is 5.7%. Hence, the chance of observing a jump in stock returns is notably higher on days where fewer firms announce dividends and negative jumps hit the dividend process.

We conclude from this evidence that the three components of the dividend growth process have distinctly different effects on the dynamics in the mean, volatility and jump probability of stock returns. News about the persistent component of dividend growth is associated with higher mean returns, whereas news about the temporary components has a much smaller effect on mean returns. Moreover, there is strong evidence that uncertainty surrounding the

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on the relative market cap (t-stat of 1.38) is statistically insignificant.
dividend growth process impact the corresponding uncertainty measures of stock returns as the volatility and jump probability of the dividend growth process are significant drivers of the volatility and jump processes of returns. We next explore this uncertainty transmission mechanism in more detail.

5.4 Cash flow news, volatility and jump dynamics in stock returns

The parameter estimates in Table 5 can, as shown above, be used to conduct inference and test the four hypotheses laid out in subsection 5.2. However, they do not provide insights into the economic importance of how shocks to the dividend growth process affect not only the mean of stock market returns but the full distribution of returns. This is what we next address.

In particular, we proceed to compute the impulse responses of daily stock returns, volatilities, and jump probabilities from a one standard deviation shock to the corresponding components of the dividend process, $\Delta \mu_{dt}$, $\exp(h_{dt}/2)$, $\xi_{dt}J_{dt}$, and $\varepsilon_{dt}$.

The conventional approach to evaluating the importance of cash flow news for movements in stock returns uses the log-linearization methodology in Campbell (1991) to decompose the variance of unexpected returns into the variance of cash flow news plus the variance of expected return news minus twice their covariance. This approach uses a vector autoregression to project stock returns on a set of predictor variables and calculate the discounted value of future expected returns. Cash flow news is then backed out residually from unexpected plus expected return news, see Campbell and Ammer (1993) and Vuolteenaho (2002).

While this approach is useful for getting diagnostics on the average importance of variation in expected returns versus variation in cash flow news, it also has some well-known shortcomings. First, the approach uses a linear decomposition and does not account for non-linear effects of news on returns. This is particularly important in our context because we find strong evidence of non-linear effects of dividend news on daily stock market returns. Second, the approach is only as good as the instruments used to identify variation in expected returns. For example, weak instruments will capture very little variation in returns and indicate (by default) that return variation is largely driven by
cash flow news. Conversely, an over-fitted model with high predictive power over stock returns might suggest that time-varying expected returns account for most of the variation in stock prices. Third, the approach only considers the effect of expected return news on the unconditional variance and does not address how news affect the conditional variance or the probability of a jump in returns.

To address these shortcomings, we next present a new approach. In particular, we compute impulse responses that account for the highly nonlinear effects identified in our model for daily stock returns in (11)–(14). Accomplishing this is far from simple. As discussed in Gallant et al. (1993) and Koop et al. (1996), impulse responses of a nonlinear model are both history- and shock-dependent and so their computation requires special care. To deal with this, we follow the approach in Gallant et al. (1993), and compute “representative”, or average, impulse response sequences using Monte Carlo integration. In particular, we begin by initializing all the conditioning variables at their sample means and proceed by perturbing, one at a time, the various components of the dividend process by one standard deviation. Next, for each component of the dividend process, we simulate $B$ realizations of stock returns, volatilities, and jump probabilities, denoted by $\{r^j_{t+H}\}_{j=1}^B$, $\{\exp(h^j_{t+H}/2)\}_{j=1}^B$, and $\{J^j_{t+H}\}_{j=1}^B$, where $j = 1, ..., B$ indexes the simulation and $H$ is the horizon. Our framework accounts for parameter uncertainty since all parameters and latent states in the model (including the mean, volatility, and jump components) are treated as random variables. In particular, instead of iterating forward on the various processes by setting the parameter estimates of the return model at their respective posterior means, we follow Koop (1996) and draw from the entire (posterior) distribution of these parameters. Finally, we compute the net effect of the impulse by averaging the sequences across the $B$ simulations and comparing the resulting average profiles to a baseline constructed, in a similar fashion, by iterating forward the processes for stock returns, volatilities, and jump probabilities after initializing all conditioning variables at their sample means.

Our dynamic return model allows shocks to the dividend process to affect both the conditional volatility of returns in (13) as well as the probability of a jump, (14). First, consider the effect of dividend shocks on the volatility of stock market returns. These are shown, measured in percent of the initial volatility level, in Figure 10. Because stock market
volatility follows a smooth and highly persistent process, we would expect the effect of individual dividend shocks on the per-period stock return volatility to be small. However, small shocks to a highly persistent process can have a large cumulative effect so we plot the impulse responses as a function of the horizon, $H$, measured in number of days since the shock occurred.

Indeed, the top left panel in Figure 10 shows that although a one standard deviation shock to $\Delta \mu_{dt+1}$ only reduces short-run stock market volatility by -0.15%, the effect is still below -0.10% after 50 days, so that good news about the persistent dividend growth component reduces stock market volatility over the subsequent months by a sizeable amount.

Similarly, a one standard deviation rise in the volatility of dividend growth, $h_{dt+1|t}$, (top right panel) has a small initial effect on return volatility. Interestingly, the volatility effect grows larger over time, peaking at 0.3% after 50 days after which it starts to slowly taper off, although it remains above 0.05 even after 250 days. Thus, while cash-flow volatility shocks have only a modest initial effect on return volatility, they are highly persistent and, as indicated by the standard error bands, remain statistically significant for a long time.31

A one standard deviation jump in the cash flow process (bottom left panel), i.e., a positive (negative) one standard deviation shock to $\xi_{dt}J_{dt}$ conditional on $J_{dt} = 1$, reduces short-run return volatility by 7%. Although the effect is close to zero after 250 days, it remains high (about 5%) after 50 days. This effect is notably larger than the effect on return volatility arising from shocks to $\Delta \mu_{dt+1}$ or $h_{dt+1}$. It should be recalled, however, that while $\Delta \mu_{dt+1}$ and $h_{dt+1}$ are perturbed every day, the dividend growth process is only affected by a jump on average every 60 or so days. Hence, dividend jumps affect stock return volatility relatively infrequently, but when they do occur, they tend to be very important.

Finally, a one standard deviation shock to the dividend jump component ($\xi_{dt}J_{dt}$) has a notable effect on the probability of experiencing a jump in aggregate stock returns (bottom right panel). In particular, a positive, one standard deviation dividend jump reduces the average jump probability for stock returns from 6.8% to 1.45%, a sharp reduction in the jump probability which corresponds to a jump occurring every 69 days instead of every 15 days.

31The non-monotonic shape of the impulse response function for $h_{dt+1}$ reflects the dual persistence in the volatility processes for stock returns and dividend growth.
Conversely, a negative, one-standard deviation jump increases the average jump probability to 28.6%, corresponding to a jump being expected to occur every 3.5 days.

These impulse responses illustrate the rich set of channels through which dynamics in the daily dividend growth process affect the level of aggregate stock market returns as well as stock market volatility and the probability of observing jumps in market returns. In all cases we find that the effects are statistically and economically significant. To the best of our knowledge, the findings that jumps to the dividend growth process have (i) a big, and long-lasting, effect on the volatility of stock returns and (ii) a notable effect on the probability of observing a jump in the return process have not previously been documented.

6 Cross-sectional effects of dividend shocks

Our analysis of daily dividend growth so far focused on the aggregate stock market by (i) extracting cash flow news from all publicly traded firms; and (ii) studying the effect of dividend news on aggregate stock returns. In this section, we take a more disaggregate perspective and focus on how daily dividend news is linked to observable characteristics which have been highlighted in the asset pricing literature. First, following Vuolteenaho (2002), we study dividend dynamics of firms with different book-to-market ratios. Second, we analyze whether innovations to our new persistent dividend growth component, $\mu_{dt}$, are related to a range of important cross-sectional asset pricing factors that have been studied in the finance literature.

6.1 Dividend news and book-to-market ratios

To include as broad a cross-section of firms as possible in our daily dividend measure, so far we ignored possible cross-sectional differences in individual firms’ dividend payment behavior. Applying our approach to the firm level is, of course, not feasible because individual firms do not announce dividend news on most days. However, we can readily

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32Our finding that cash flow news are associated with jumps in stock returns is consistent with the evidence in Andersen et al. (2007) that macroeconomic news are associated with jumps in stock, bond and forex returns. However, we establish this using a very different approach—Andersen et al. (2007) use five-minute data to study high-frequency futures returns around macroeconomic news announcements.
apply our methodology to construct measures of cash flow news for subsets of firms, provided that there are sufficiently many dividend-paying firms in each subset to generate a cash flow process without too many missing observations. In turn, we can use these to explore differences in the dividend growth process of firms with different characteristics.

Heterogeneity in the cash flow process across firms with different characteristics have previously been noted. For example, Cohen et al. (2009) link firm book-to-market ratios to cross-sectional variation in the sensitivity of individual firms’ cash flows with respect to market cash flows and find that value stocks have higher cash flow betas than growth stocks.

Building on this finding, each month we sort all firms in our sample by their book-to-market (BM) ratios and form two portfolios consisting of firms whose BM ratios are above or below the median BM ratio. We then use equation (1) to compute a daily cash flow index and estimate the dividend growth components model (2)-(6) for each of the resulting series. Figure 11 shows the dividend growth measure for the high and low BM portfolios (top panels) along with the estimates of the persistent component, $\mu_{d_t}$, (bottom panels).

For high BM ratio (value) stocks, the persistent dividend growth component, $\mu_{d_t}$, turns negative during the recent financial crisis. In contrast, (growth) firms with a low BM ratio experience a relatively minor decline in the persistent dividend component. Moreover, the $\mu_{d_t}$ series is more volatile for value stocks than for growth stocks. This evidence is consistent with the finding in Cohen et al. (2009) that the cash flows of value stocks are more sensitive to aggregate (market) cash flows than are the cash flows of growth stocks.

These results demonstrate that our methodology for extracting a persistent component from a daily dividend growth series can be used to identify cross-sectional differences in firms’ dividend payments.

6.2 Cross-sectional effects of dividend shocks

Our finding that the behavior of the persistent component of the dividend growth process, $\mu_{d_t}$, varies across firms with different book-to-market ratios suggests that shocks to this

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33Firms with BM ratios above the median value go into the “high” BM portfolio, while firms whose BM ratio is below the median value are assigned to the “low” BM portfolio. To be included in the sort in a given month, a stock needs to have a reported book and market value and to be traded on the NYSE, AMEX or NASDAQ.
component may be related to cross-sectional risk factors tied to firm or stock characteristics.

To see if this holds, we next investigate whether \( \mu_{dt} \) is related to existing risk factors that have been found in the empirical asset pricing literature to capture cross-sectional variation in stock returns. These include the market (MRP), size (SMB), book-to-market (HML), profitability (RMW), quality (CMA) and momentum (UMD) factors. Each of these factors is formed as the return spread on long-short portfolios of firms sorted by firm characteristics. Data are obtained from Ken French’s website.

The first step in our analysis extracts the daily innovation \( \varepsilon_{\mu t+1} \) in the persistent cash flow component \( \mu_{dt+1} \) from equation (3). In a second step, we perform a set of univariate regressions of returns on the individual risk factors \( F_{t+1} \) on an intercept and the innovation \( \varepsilon_{\mu t+1} \):

\[
F_{t+1} = \alpha + \beta_{\mu t} \varepsilon_{\mu t+1} + u_{t+1}.
\]  

(15)

Results from these regressions are reported in Table 6. The estimated value of \( \alpha_i \) shows the unconditional mean risk premium of the individual factors. This ranges from highs of 7.4% and 6.3% for the momentum and market factors, respectively, to a low of 1.8% for the size factor (SMB). Our main interest is of course in the estimate of \( \beta_{\mu dt} \) which reflects the sensitivity of the daily factor returns with respect to daily shocks to the persistent dividend growth component. Dividend shocks, \( \varepsilon_{\mu t+1} \), are significantly linked to a number of return factors. Most notably, shocks to the persistent dividend growth component are positively and significantly correlated \( (t\text{-stat of } 2.10) \) with market returns. Days with above-normal stock market returns are thus associated with days with positive shocks to persistent cash flow growth. Similarly, we find a highly significant and positive correlation between dividend shocks and returns on the size (SMB) factor \( (t\text{-stat of } 3.07) \). Returns on small firms thus tend to be higher on days with positive shocks to cash flow growth and small firms are more sensitive to changes in aggregate cash flows than large firms. The negative and highly significant coefficient \( (t\text{-stat of } -4.35) \) on the profitability factor (RMW) suggests that returns on firms with weak profitability tend to have higher (relative) returns than firms with robust profitability on days where dividend growth prospects improve.

Overall, these results show that our new daily cash flow growth measure can help explain
the daily returns not only of the aggregate market, but also of (spread) risk factors. In particular, our findings suggest that improved cash flow prospects (positive shocks to $\Delta \mu_{dt+1}$) disproportionately benefit small firms, value stocks as well as firms with weak profitability. Conversely, large firms, growth stocks and firms with robust profitability benefit less from higher prospective cash flow growth.

7 Robustness analysis

This section conducts a set of tests designed to verify the robustness of the previous analysis. First, we report the outcome of simple regressions of daily stock returns on different measures of cash flow news. Second, we use these regressions to study the relation between stock returns and dividends on dividend payment days, rather than on days where dividends get announced. Third, we estimate regressions of different measures of stock market volatility on the persistent cash flow component extracted from our dividend growth decomposition.

7.1 Stock returns and cash flow news

Our return model in equations (11)-(14) provides a structured framework for analyzing the dynamic relation between cash flow news and stock market returns. We next explore whether our findings stand up in the context of a set of simple return regressions which can be used to establish the robustness of the relation between stock returns and dividend growth news.

Because dividend growth news announced on day $t$ could arrive after markets have closed on that day, such news can affect aggregate stock market returns on day $t$ or day $t+1$ and so, for added robustness, we measure trading day returns as the sum of the close-on-close returns on days $t$ and $t+1$, denoted $r_{t:t+1}$.\textsuperscript{34} To understand which, if any, of a set of alternative dividend growth measures are correlated with stock returns, we consider three different specifications. The first specification simply regresses stock returns on dividend growth news on day $t$, $\Delta d_t$:

\textsuperscript{34}We use the simpler one-day return measure in our dynamic model in Section 5 due to the overlap created by a two-day horizon which complicates simulations of dynamic effects.
\[ r_{t,t+1} = \alpha + \beta_1 \Delta d_t + \varepsilon_{t,t+1}. \] (16)

This regression uses a very noisy measure of cash flow news, mixing up temporary and persistent components in the dividend growth process. To separate these components, our second return regression uses changes in the persistent component from the no-jump model, \( \Delta \mu_{\text{NJ}}^{\text{dt}} \), in equation (7) as the regressor:

\[ r_{t,t+1} = \alpha + \beta_1 \Delta \mu_{\text{NJ}}^{\text{dt}} + \varepsilon_{t,t+1}. \] (17)

The estimate of \( \mu_{\text{NJ}}^{\text{dt}} \) extracted from the no-jump model remains very noisy which might confound this regression. To address this issue, our final model regresses returns on the different dividend growth components extracted from the general model:

\[ r_{t,t+1} = \alpha + \beta_1 \Delta \mu_{\text{dt}} + \beta_2 \xi_{\text{dt}} J_{\text{dt}} + \beta_4 \varepsilon_{\text{dt}} + \varepsilon_{t,t+1}. \] (18)

Results from the return regressions in (16)-(18) are presented in Table 7.\textsuperscript{35} The regression of daily stock market returns on the daily dividend growth rate, \( \Delta d_t \), uncovers no evidence of a statistically significant positive relation between stock returns and cash flow news. This conclusion carries over to the regression of returns on the change in the persistent cash flow component extracted from the simple model that ignores jumps, \( \Delta \mu_{\text{NJ}}^{\text{dt}} \). In contrast, we find a positive and significant (t-statistic of 2.09) relation between stock returns and changes in the persistent cash flow component, \( \Delta \mu_{\text{dt}} \), extracted from the general model that allows for jumps.

Consistent with the empirical results in the previous section, we continue to find only weak evidence (one instance with significance at the 10% level) that the jump or diffusion components are significantly correlated with stock returns.

7.1.1 Dividend Payments versus Announced Dividends

Our results up to this point show that movements in aggregate stock returns and market volatility are related to dividend news on the announcement date. This relation plausibly

\textsuperscript{35}We focus on the shorter sample, 1973-2016, but results are similar for the longer sample, 1927-2016.
reflects how investors re-assess equity prices following cash flow news. We can test this hypothesis by exploiting the fact that we have data on both the date of the dividend announcement and the date where a dividend is paid out, with the payment date typically occurring several days after the announcement date. If the news effect hypothesis is correct, we would expect to find a substantially smaller impact of dividend growth on stock returns on the payment date as compared to the return effect on the announcement date.

To see if this is the case, we estimate daily return regressions of the form in (18), but use the dividend payment date as opposed to the dividend announcement date. The results, presented in columns 4-6 of Table 7, show that the t-statistic on $\mu_{dt}$ drops from 2.09 to 0.89. This is consistent with the cash flow news effect being what matters to movements in aggregate stock market prices, rather than any liquidity effects associated with payment of dividends.

The final column of Table 7 shows estimates based on the daily dividend growth measure extracted from CRSP, computed as a daily year-on-year growth rate series. Once again, this measure, which uses information on dividend payments as opposed to announced dividends, has no significant explanatory power over aggregate stock returns.

### 7.1.2 Analyst surprises and stock returns

Our dividend growth model produces forecasts of daily cash flow growth from past dividend announcements, but there are also alternative estimates of dividend growth. In particular, we can adopt the approach of Patton and Verardo (2012) and Doyle et al. (2006) to data on analyst forecasts to construct estimates of dividend surprises. Specifically, we construct a sample that includes all announced dividends per share (DPS) available from IBES from July 1984 to January 2016. To keep as many observations as possible and limit the impact of outliers, we winsorize the data at the 1% level and assume at least two dividend forecasts are reported. Overall, our sample consists of 39,918 dividend surprises. Each day, we construct our aggregate daily dividend surprise measure $SUD_t$ by value-weighting individual firms’

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36 The announcement date is the `annndats_act` variable in the “ Announcement Date of the Actual” field in the Detail Actuals File.
dividend surprises, as defined by

\[ SUD_t = \frac{Actual\ DPS_t - Medest\ DPS_t}{P_{t-7}}, \]  

(19)

where Medest DPS\(_t\) is the last available median analyst DPS forecast prior to the dividend announcement date, and \(P_{t-7}\) is the stock price seven days before the actual DPS announcement.\(^{37}\)

Next, we regress aggregate stock returns, \(r_{t,t+1}\) on \(SUD_t\) and \(\Delta \mu_{dt}\):

\[ r_{t,t+1} = \alpha + \beta_1 SUD_t + \beta_2 \Delta \mu_{dt} + \varepsilon_{t,t+1}. \]  

(20)

Results from this regression reveal that our \(\mu_{dt}\) measure continues to be positively and significantly correlated with stock market returns after controlling for analysts’ dividend expectations. Conversely, the \(SUD\) measure fails to explain same-day stock market returns and is statistically insignificant.\(^{38}\)

### 7.2 Stock market volatility and dividend news

Our empirical analysis in Section 5 shows that dividend growth dynamics affect not only the mean of stock returns but also impact the volatility and jump probability of the return process with positive news about the persistent dividend growth component reducing stock market volatility.

To explore the robustness of this finding, we investigate the relation between daily stock market volatility and cash flow news using two different measures of market volatility. First, we use the VIX obtained from options prices which reflects market expectations of short-run (30-day) volatility in stock prices. Second, we use a realized variance (RV) measure of daily

\(^{37}\)Using the stock price seven days prior to the dividend announcement date avoids the confounding effect of the announcement surprise on the stock price (Patton and Verardo (2012)).

\(^{38}\)This finding is perhaps not surprising as dividend surprises mainly have a cross-sectional effect: a daily dividend surprise announced by an individual firm can affect the stock itself – as well as stock prices of other companies within the same industry or geographical areas – by a lead-lag relationship (e.g., Parsons et al. (2017)), but does not seem to drive the return of the aggregate stock market. Hence, movement in the aggregate stock market appears not to be explained by the \(SUD\) value of individual stocks.
stock market volatility based on intra-day movements in the price on the S&P500 index sampled every 5 minutes.\textsuperscript{39} Data on the VIX are available starting in 1990, while data on realized volatility begin in 2000.

We first consider the contemporaneous relation between daily stock market volatility and news about the persistent dividend growth component. Panel A in Table 8 shows that there is a significant and negative correlation between movements in the persistent dividend growth component and stock market volatility measured by either the VIX or the RV, consistent with positive news about long-run dividend growth reducing stock market volatility.

Next, we consider whether dividend growth news helps predict future stock market volatility. Following Paye (2012), we use the level of volatility in our regressions, but account for the high persistence in this variable by including either a single lag of volatility or an average of lagged volatility as proposed in the cascade model of Corsi (2009). Specifically, we use the following two regression specifications for the volatility on day \( t \), \( VOL_t \):

\[
VOL_{t+1} = \alpha + \beta_1 VOL_t + \beta_2 \mu_{dt} + \varepsilon_{t+1}, \tag{21}
\]

\[
VOL_{t+1} = \alpha + \beta_d RV^d_t + \beta_w RV^w_t + \beta_m RV^m_t + \beta \mu_{dt} + \varepsilon_{t+1}, \tag{22}
\]

where \( RV^d \), \( RV^w \) and \( RV^m \) are daily, weekly, and monthly volatility averages, respectively, as defined in Corsi (2009).

Panel B in Table 8 shows the results from these regressions using the VIX (left column) or the realized volatility (right column). Regardless of whether we use the specification in (21) or (22), we find strong evidence of persistence in the volatility process.

Turning to the predictive content of the persistent dividend component, \( \mu_{dt} \), over stock market volatility, for both specifications in Panel B we find that the coefficient on \( \mu_{dt} \) is negative and highly statistically significant with t-statistics of -4.40 and -9.27, respectively. While these t-statistics drop to -2.31 and -2.21 in the cascade model, they remain significant at the 5% level. This suggests that positive news about persistent dividend growth lead to

\textsuperscript{39}Our data come from the Oxford-Man Institute of Quantitative Finance, see http://realized.oxford-man.ox.ac.uk/data/download.
lower stock market volatility, while negative news tend to increase stock market volatility.\footnote{We also analyze whether the stochastic volatility and jump components extracted from the jump model have any contemporaneous or predictive effect on the aggregate volatility but find that the effects are negligible and not statistically significant.}

8 Conclusion

This paper develops a new methodology for constructing a daily “bottom-up” measure of aggregate cash flow growth based on firms’ dividend announcements. In constructing this measure, we address two key 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 of firms that announce dividends often changes substantially from day to day. Both effects cause lumpiness in the daily cash flow news process.

We handle 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. We find that these components are well identified in the dividend growth data. Importantly, the persistent mean component captures predictable dynamics in dividend growth which is easily overlooked in the raw dividend growth series that is dominated by the highly volatile temporary jump and shock components. We show empirically that this persistent dividend growth component can be used to produce more accurate forecasts of future dividend growth than alternative approaches from the existing finance literature.

While our empirical analysis uses high-frequency (daily) dividend announcements, it also offers new insights into the drivers of stock price dynamics at longer horizons. Indeed, shocks to the persistent dividend growth component identified by our model are long-lasting—with a half life close to 18 months—and lead measures of economic activity traditionally used as proxies for “fundamentals” such as GDP and consumption growth. Moreover, our estimates of persistent dividend growth can be used to produce more accurate forecasts of dividend growth than existing studies at both monthly and annual horizons. Consistent with the view that investors regard variation in dividend growth as being important to stock prices, we
find that shocks to the persistent dividend growth component are significantly correlated with a variety of risk factors that have been used to explain cross-sectional variation in stock returns, including firm size, book-to-market ratios, and profitability.

We use our dividend growth rate series to provide novel insights into the transmission mechanism from cash flow news to movements in aggregate stock prices. To this end, we propose a dynamic model that allows us to quantify the effect of different dividend growth news components on the full conditional distribution of stock market returns. We find that positive news about the persistent component of dividend growth is associated with significantly higher average stock returns, while news about the temporary components has a much smaller effect on returns. Reduced prospects for the predictable (persistent) cash flow component, higher cash flow volatility, and negative jumps in the dividend growth process are also associated with higher stock market volatility. Moreover, negative jumps in the dividend growth process are associated with a higher probability of observing a jump in aggregate stock returns. Hence, our analysis shows how uncertainty about cash flow growth prospects transmits into dynamics in stock prices, providing a better understanding of the sources of time-varying volatility and jumps in stock prices.
References


Parameter estimates

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Table 1: Parameter estimates for the dividend growth rate model. This table shows parameter estimates for a model fitted to the daily dividend growth series. The equations for the components model, further described in Section 3.1, take the following form:

\[
\Delta d_{t+1} = \mu_{d_{t+1}} + \xi_{d_{t+1}} J_{d_{t+1}} + \varepsilon_{d_{t+1}},
\]

\[
\mu_{d_{t+1}} = \mu_d + \phi_\mu (\mu_{d_{t}} - \mu_d) + \sigma_\mu \varepsilon_{\mu_{d_{t+1}}},
\]

\[
\varepsilon_{d_{t+1}} \sim \mathcal{N}(0, \sigma^2_{\mu}),
\]

\[
h_{d_{t+1}} = \mu_h + \phi_h (h_{d_{t}} - \mu_h) + \sigma_h \varepsilon_{h_{d_{t+1}}},
\]

\[
\Pr (J_{d_{t+1}} = 1) = \Phi (\lambda_1 + \lambda_2 N_{d_{t+1}}),
\]

\[
\xi_{d_{t+1}} \sim \mathcal{N} \left( 0, \sigma^2_\xi \right),
\]

where \( \mu_{d_{t+1}} \) captures the mean of the smooth component of the underlying dividend process, \( J_{d_{t+1}} \in \{0, 1\} \) is a jump indicator that equals unity in case of a jump in dividends and otherwise is zero, \( \xi_{d_{t+1}} \) measures the jump size, \( \varepsilon_{d_{t+1}} \) is a temporary cash flow shock, \( \varepsilon_{\mu_{d_{t+1}}} \sim \mathcal{N}(0,1) \) is assumed to be uncorrelated at all times with the innovation in the temporary dividend growth component, \( \varepsilon_{d_{t+1}} \), and \( |\phi_\mu| < 1 \). \( h_{d_{t+1}} \) denotes the log-variance of \( \varepsilon_{d_{t+1}} \), and \( \varepsilon_{h_{d_{t+1}}} \sim \mathcal{N}(0,1) \) is uncorrelated at all times with both \( \varepsilon_{d_{t+1}} \) and \( \varepsilon_{\mu_{d_{t+1}}} \). \( N_{d_{t+1}} \) denotes the number of firms announcing dividends on day \( t+1 \), while \( \Phi \) stands for the CDF of a standard Normal distribution and \( \xi_{d_{t+1}} \sim \mathcal{N} \left( 0, \sigma^2_\xi \right) \) captures the magnitude of the jumps. The columns report the posterior mean, standard deviation and 90% credible sets for the parameter estimates.
### PANEL A: \( \Delta d_{t+1}^{CRSP} = \alpha + \mu_t \sum_{i=1}^{3} \Delta d_{t+1-i}^{CRSP} + \beta \mu dt + \gamma dp_t^{CRSP} + \varepsilon_{t+1} \)

<table>
<thead>
<tr>
<th></th>
<th>Quarterly</th>
<th>Annual</th>
<th>Quarterly (1927)</th>
<th>Annual (1927)</th>
</tr>
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<tbody>
<tr>
<td>( \mu dt )</td>
<td>.32***</td>
<td>2.00**</td>
<td>.20***</td>
<td>.84***</td>
</tr>
<tr>
<td></td>
<td>[4.48]</td>
<td>[2.26]</td>
<td>[4.29]</td>
<td>[2.76]</td>
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<tr>
<td>( dp_t )</td>
<td>-.00</td>
<td>.05</td>
<td>.00</td>
<td>.05</td>
</tr>
<tr>
<td></td>
<td>[-0.60]</td>
<td>[0.81]</td>
<td>[0.63]</td>
<td>[1.25]</td>
</tr>
<tr>
<td>( \Delta d_t^{CRSP} )</td>
<td>.14*</td>
<td>-6.3***</td>
<td>.26***</td>
<td>-2.2</td>
</tr>
<tr>
<td></td>
<td>[1.77]</td>
<td>[-4.65]</td>
<td>[4.14]</td>
<td>[1.23]</td>
</tr>
<tr>
<td>( \Delta d_{t-1}^{CRSP} )</td>
<td>.05</td>
<td>-.49***</td>
<td>.16***</td>
<td>-1.7</td>
</tr>
<tr>
<td></td>
<td>[0.83]</td>
<td>[-3.82]</td>
<td>[3.45]</td>
<td>[-1.03]</td>
</tr>
<tr>
<td>( \Delta d_{t-2}^{CRSP} )</td>
<td>.01</td>
<td>-.07</td>
<td>-.03</td>
<td>-.00</td>
</tr>
<tr>
<td></td>
<td>[0.20]</td>
<td>[-0.49]</td>
<td>[-0.56]</td>
<td>[-0.05]</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>27.47%</td>
<td>27.84%</td>
<td>41.02%</td>
<td>7.31%</td>
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<tr>
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<td>165</td>
<td>39</td>
<td>353</td>
<td>86</td>
</tr>
</tbody>
</table>

### PANEL B: \( \Delta d_{t+1} = \alpha + \beta \mu_{dt+1} + \gamma g_t^{i} + \varepsilon_{t+1} \)

<table>
<thead>
<tr>
<th></th>
<th>Annual</th>
<th>Monthly</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \mu dt )</td>
<td>1.02***</td>
<td>.92***</td>
</tr>
<tr>
<td></td>
<td>[5.77]</td>
<td>[6.03]</td>
</tr>
<tr>
<td>( g_t^{VBK} )</td>
<td>.96***</td>
<td>.58**</td>
</tr>
<tr>
<td></td>
<td>[2.94]</td>
<td>[2.03]</td>
</tr>
<tr>
<td>( g_t^{KP} )</td>
<td>1.00***</td>
<td>.39**</td>
</tr>
<tr>
<td></td>
<td>[4.86]</td>
<td>[2.06]</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>39.35%</td>
<td>14.31%</td>
</tr>
<tr>
<td>Observations</td>
<td>69</td>
<td>69</td>
</tr>
</tbody>
</table>

### PANEL C: \( \Delta d_{t+1} = \beta_1 \mu_{dt+1} + (1 - \beta_1) \gamma g_t^{i} + \varepsilon_{t+1} \)

<table>
<thead>
<tr>
<th></th>
<th>Annual</th>
<th>Monthly</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \beta_1 )</td>
<td>.81***</td>
<td>.77***</td>
</tr>
<tr>
<td>( p\text{-value} )</td>
<td>(0.00)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>( 1 - \beta_1 )</td>
<td>.19*</td>
<td>.23***</td>
</tr>
<tr>
<td>( p\text{-value} )</td>
<td>(0.10)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>( \beta_1 ) (OOS)</td>
<td>1.38***</td>
<td></td>
</tr>
<tr>
<td>( p\text{-value} ) (OOS)</td>
<td>(12.04)</td>
<td></td>
</tr>
<tr>
<td>( 1 - \beta_1 ) (OOS)</td>
<td>-0.38***</td>
<td></td>
</tr>
<tr>
<td>( p\text{-value} ) (OOS)</td>
<td>(-3.29)</td>
<td></td>
</tr>
</tbody>
</table>

**Table 2: Dividend growth regressions.** Panel A reports results from predictive regression of the conventional dividend growth measure extracted from CRSP data, \( \Delta d_{t+1}^{CRSP} \), on the persistent component \( \mu dt \) estimated from our daily dividend growth model and the log dividend price ratio, \( dp_t \), at quarterly and annual frequencies. Panel B compares the predictive power of our persistent dividend growth component to that of two alternative dividend growth variables. The first measure, \( g_t^{VBK} \), is taken from van Binsbergen and Koijen (2010) and uses cash reinvested dividend growth, measured annually over the extended sample period 1946-2015. The second measure, \( g_t^{KP} \), is taken from Kelly and Pruitt (2013) and uses monthly data over the extended sample period 1940-2016. Panel C reports results from forecast encompassing regressions which compare the predictive power of our \( \mu dt \) measure to the two alternative measures, both in-sample and out-of-sample (available only for Kelly and Pruitt (2013)). Square brackets report t-statistics computed using Newey-West standard errors with three lags.
\[ \Delta y_{t+1} = \alpha + \beta \mu_{dt} + \gamma \Delta y_t + \varepsilon_{t+1} \]

<table>
<thead>
<tr>
<th></th>
<th>( \Delta GDP )</th>
<th></th>
<th>( \Delta Consumption )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \mu_{dt} )</td>
<td>.14***</td>
<td>.08***</td>
<td>.13**</td>
</tr>
<tr>
<td></td>
<td>[4.57]</td>
<td>[2.72]</td>
<td>[4.72]</td>
</tr>
<tr>
<td>( \Delta y_t )</td>
<td>.39***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[4.39]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( R^2 )</td>
<td>21.15%</td>
<td>32.82%</td>
<td>25.93%</td>
</tr>
<tr>
<td>Observations</td>
<td>171</td>
<td>171</td>
<td>171</td>
</tr>
</tbody>
</table>

Table 3: Predictive regressions of GDP and consumption growth on the persistent dividend growth component. This table reports estimates from quarterly predictive regressions of future GDP and consumption growth, \( \Delta y_{t+1} \), on the persistent dividend growth component, \( \mu_{dt} \), estimated from our dynamic cash flow model. Square brackets show t-statistics computed using Newey-West standard errors with three lags. The sample period used for these regressions is 1973-2015.
Table 4: Correlations between the persistent dividend growth component $\mu_{dt}$ and macroeconomic and financial activity measures. This table reports correlations between the persistent dividend growth component $\mu_{dt}$ extracted from our daily cash flow model and the following daily macroeconomic variables/indicators: the VIX index, the policy uncertainty index of Baker et al. (2016), the ADS index of Aruoba et al. (2009), the liquidity noise index of Hu et al. (2013), and the daily inflation index of Cavallo and Rigobon (2016). Panel A correlates the levels of these variables, while Panel B correlates changes in the variables.
Table 5: Parameter estimates for the dynamic model for stock returns. The table shows parameter estimates of the return model in Section 5.1 which relates dynamics in stock returns to the components extracted from our daily dividend growth model. The parameters listed in the table are taken from the following model specification:

\[
\begin{align*}
\gamma_{t+1} &= \mu_{\gamma_{t+1}} + \xi_{\gamma_{t+1}} J_{\gamma_{t+1}} + \beta_1 \Delta \mu_{dt+1} + \beta_2 \exp \left( \frac{h_{dt+1}}{2} \right) + \beta_3 \xi_{dt+1} J_{dt+1} + \beta_4 \varepsilon_{dt+1} + \varepsilon_{\gamma_{t+1}} \\
\mu_{\gamma_{t+1}} &= \mu_\gamma + \phi_\mu (\mu_{t+1} - \mu_t) + \sigma_\mu \varepsilon_{\mu_{t+1}} \\
h_{t+1} &= \mu_h + \phi_h (h_{t+1} - \mu_h) + \gamma_1 \Delta \mu_{dt+1} + \gamma_2 h_{dt+1} + \gamma_3 \left( \xi_{dt+1} J_{dt+1} \right) + \sigma_h \varepsilon_{ht_{t+1}} \\
\Pr (J_{\gamma_{t+1}} = 1) &= \Phi (X_1 + X_2 N_{dt+1} + X_3 \xi_{dt+1} J_{dt+1}) \\
\xi_{\gamma_{t+1}} &\sim \mathcal{N} \left( 0, \sigma_{\xi_\gamma}^2 \right)
\end{align*}
\]

where \(\mu_{\gamma_{t+1}}\) captures the persistent component in stock returns, \(\xi_{\gamma_{t+1}} J_{\gamma_{t+1}}\) represent jumps in stock returns with \(J_{\gamma_{t+1}} \in \{0,1\}\) being a jump indicator, while \(\varepsilon_{\gamma_{t+1}} \sim \mathcal{N} \left( 0, \sigma_{\varepsilon_{\gamma_{t+1}}}^2 \right)\) is a diffusion term with time-varying log variance \(h_{t+1}\). \(\beta_1 \Delta \mu_{dt+1}\) captures the effect of persistent cash flow news on stock returns, while the three additional components, \(\beta_2 \exp \left( \frac{h_{dt+1}}{2} \right), \beta_3 \xi_{dt+1} J_{dt+1}\) and \(\beta_4 \varepsilon_{dt+1}\) capture spillover effects on returns from the conditional volatility, jumps and idiosyncratic shocks in the dividend growth process. \(\varepsilon_{\mu_{t+1}} \sim \mathcal{N} \left( 0, \sigma_{\varepsilon_{\mu}}^2 \right)\) is assumed to be uncorrelated at all times with the innovation in the temporary return component, \(\varepsilon_{\gamma_{t+1}}\), and \(|\phi_\mu| < 1\). \(h_{dt+1}\) denotes the time-varying variance extracted from the dividend model, while \(J_{dt+1}\) and \(\xi_{dt+1}\) denote the time-varying jump probability and jump magnitude obtained from the dividend growth rate model. \(\varepsilon_{ht_{t+1}} \sim \mathcal{N} \left( 0, 1 \right)\) is uncorrelated at all times with both \(\varepsilon_{\gamma_{t+1}}\) and \(\varepsilon_{\mu_{t+1}}\). \(N_{dt+1}\) is the number of firms announcing dividends on day \(t+1\). Columns 1-3 report the posterior mean, standard deviation and 90% credible sets of the parameter estimates, respectively. The \(\sigma\) estimates have been multiplied by 1,000 (or by 100 in the case of estimates with the \(\dagger\) symbol) for readability. The model is estimated using daily data over the sample period 1973-2016.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Mean</th>
<th>Std</th>
<th>90% Credible Set</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\beta_1)</td>
<td>1.336</td>
<td>0.420</td>
<td>[0.645, 2.018]</td>
</tr>
<tr>
<td>(\beta_2)</td>
<td>0.144(\dagger)</td>
<td>0.080</td>
<td>[0.016, 0.271]</td>
</tr>
<tr>
<td>(\beta_3)</td>
<td>0.034(\dagger)</td>
<td>0.019</td>
<td>[0.003, 0.066]</td>
</tr>
<tr>
<td>(\beta_4)</td>
<td>-0.023(\dagger)</td>
<td>0.027</td>
<td>[-0.068, 0.021]</td>
</tr>
<tr>
<td>(\mu_r)</td>
<td>0.022(\dagger)</td>
<td>0.023</td>
<td>[-0.015, 0.061]</td>
</tr>
<tr>
<td>(\phi_{\mu_r})</td>
<td>0.989</td>
<td>0.001</td>
<td>[0.987, 0.990]</td>
</tr>
<tr>
<td>(\mu_{hr})</td>
<td>-9.554</td>
<td>0.056</td>
<td>[-9.648, -9.462]</td>
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<tr>
<td>(\phi_{hr})</td>
<td>0.990</td>
<td>0.000</td>
<td>[0.990, 0.990]</td>
</tr>
<tr>
<td>(\gamma_1)</td>
<td>-17.916</td>
<td>1.286</td>
<td>[-20.010, -15.768]</td>
</tr>
<tr>
<td>(\gamma_2)</td>
<td>0.050(\dagger)</td>
<td>0.013</td>
<td>[0.029, 0.072]</td>
</tr>
<tr>
<td>(\gamma_3)</td>
<td>-0.109</td>
<td>0.011</td>
<td>[-0.127, -0.091]</td>
</tr>
<tr>
<td>(\lambda_1)</td>
<td>-1.206</td>
<td>0.076</td>
<td>[-1.330, -1.084]</td>
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<tr>
<td>(\lambda_2)</td>
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<td>0.002</td>
<td>[-0.013, -0.007]</td>
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<tr>
<td>(\lambda_3)</td>
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<td>0.298</td>
<td>[-1.119, -0.139]</td>
</tr>
<tr>
<td>(\sigma_{\mu})</td>
<td>0.182</td>
<td>0.017</td>
<td>[0.156, 0.211]</td>
</tr>
<tr>
<td>(\sigma_h)</td>
<td>9.999</td>
<td>0.000</td>
<td>[9.999, 10.000]</td>
</tr>
<tr>
<td>(\sigma_{\xi_r})</td>
<td>0.541</td>
<td>0.055</td>
<td>[0.457, 0.639]</td>
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</table>
### PANEL A: Cross-sectional analysis

<table>
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<tr>
<th></th>
<th>MRP</th>
<th>SMB</th>
<th>HML</th>
<th>RMW</th>
<th>CMA</th>
<th>UMD</th>
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</thead>
<tbody>
<tr>
<td>$\alpha$ (annualized)</td>
<td>6.32%</td>
<td>1.83%</td>
<td>5.01%</td>
<td>3.51%</td>
<td>4.27%</td>
<td>7.40%</td>
</tr>
<tr>
<td>t-stat</td>
<td>2.51</td>
<td>1.39</td>
<td>3.95</td>
<td>3.71</td>
<td>4.81</td>
<td>4.16</td>
</tr>
<tr>
<td>$\beta_{\mu dt}$</td>
<td>1.15</td>
<td>0.80</td>
<td>0.29</td>
<td>-0.80</td>
<td>0.08</td>
<td>-0.47</td>
</tr>
<tr>
<td>t-stat</td>
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<td>3.07</td>
<td>1.01</td>
<td>-4.35</td>
<td>0.48</td>
<td>-1.20</td>
</tr>
</tbody>
</table>

Table 6: Return spreads and shocks to the persistent dividend growth component. This table reports the estimated intercept and slope coefficients from regressions of daily returns on spread portfolios tracking a variety of risk factors (MRP, SMB, HML, RMW, CMA and UMD) on a constant and daily shocks to the persistent component in the dividend growth process extracted from our dynamic dividend growth rate model. We also report t-statistics computed using Newey-West standard errors. Sample period: 1973-2016.
<table>
<thead>
<tr>
<th></th>
<th>Dividend announcement days</th>
<th>Dividend payment days</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta d_t$</td>
<td>.00</td>
<td>-.00</td>
</tr>
<tr>
<td></td>
<td>[0.40]</td>
<td>[-0.54]</td>
</tr>
<tr>
<td>$\Delta \mu^N_{dt}$</td>
<td>.00</td>
<td>1.23</td>
</tr>
<tr>
<td></td>
<td>[0.40]</td>
<td>[0.99]</td>
</tr>
<tr>
<td>$\Delta \mu_{dt}$</td>
<td>2.31**</td>
<td>1.12</td>
</tr>
<tr>
<td></td>
<td>[2.09]</td>
<td>[0.89]</td>
</tr>
<tr>
<td>$\xi_{dt} J_{dt}$</td>
<td>.00*</td>
<td>-.00</td>
</tr>
<tr>
<td></td>
<td>[1.81]</td>
<td>[-0.16]</td>
</tr>
<tr>
<td>$h_{dt}/2$</td>
<td>-.00</td>
<td>.00</td>
</tr>
<tr>
<td></td>
<td>[-0.03]</td>
<td>[1.65]</td>
</tr>
<tr>
<td>$\Delta d_t^{CRSP}$</td>
<td>.00</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>[0.31]</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.00%</td>
<td>0.00%</td>
</tr>
<tr>
<td></td>
<td>0.10%</td>
<td>0.00%</td>
</tr>
<tr>
<td></td>
<td>0.02%</td>
<td>0.07%</td>
</tr>
<tr>
<td></td>
<td>0.00%</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
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<td>9,068</td>
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<td>9,068</td>
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<tr>
<td></td>
<td>8,185</td>
<td></td>
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</tbody>
</table>

Table 7: Daily regressions of stock returns on dividend news. This table reports estimates from regressions of daily stock market returns on 1) daily aggregate dividend growth measure, $\Delta d_t$; 2) the change in the persistent dividend growth component, $\Delta \mu^N_{dt}$, extracted from a dividend growth model without jumps and stochastic volatility; or 3) the change in the persistent component, $\Delta \mu_{dt}$, extracted from the dynamic dividend growth model that accounts for jumps and stochastic volatility. In each case, the dependent variable is the two-day cumulative log stock market return on days $t$ and $t+1$, $r_{t:t+1}$. Columns 1-3 consider stock returns on the dates of the dividend news announcements, while columns 4-7 relate stock returns to dividend news on the days where the dividend payments are actually made. The final column reports results from regressing returns on a daily dividend growth series, $\Delta d_t^{CRSP}$, computed from CRSP data using a top-down approach based on dividend payments. Square brackets report t-statistics using Newey-West standard errors with three lags. Sample period: 1973-2016
Table 8: Relation between the persistent dividend component, VIX, and realized stock market volatility. Panel A in this table reports estimates from daily regressions of the VIX (left column) or the realized volatility based on the S&P500 index (right column) on the contemporaneous value of the persistent dividend growth component $\mu_{dt}$ extracted from our components model. Panel B reports similar results, relating the VIX or realized volatility to the lagged value of $\mu_{dt}$ as well as a single lag of the dependent variable or multiple lags based on the Corsi (2009) model. The dependent variables in Panel A are standardized. Square brackets show t-statistics using Newey-West standard errors computed using three lags.
Figure 1: Distribution of dividend announcements within a quarter. This figure plots time-series of dividend announcements for Q2 2014. For every day within this quarter, the top panel shows the number of firms announcing dividends. The middle panel shows the overall nominal amount of dividends announced by those firms (in billion dollars), while the bottom panel shows the daily (net) dividend growth rate.
Figure 2: Comparison between our daily “bottom-up” dividend growth series vs. a daily “top-down” dividend growth measure extracted from CRSP. The top panel plots the log of the daily dividend growth series \( G_{yr,s} \) defined in Eq.1. The bottom panel plots the CRSP-extracted daily dividend growth, calculated as dividends (paid out) on an given day divided by dividends distributed on the same day, one year earlier. Both plots use daily data over the sample 1973-2016.

Figure 3: Time series of daily dividend growth and the persistent growth component. The top panel plots the persistent dividend growth component, \( \mu_{dt} N_t \) extracted from a model without jumps and stochastic volatility. The bottom panel plots the persistent dividend growth component, \( \mu_{dt} \), extracted from the daily dividend series using a model that accounts for jumps and stochastic volatility. All plots use daily data over the sample 1973-2016.
Figure 4: Jumps in the daily dividend growth series. The top panel plots the probability of a jump in the daily dividend growth series while the bottom panel plots the magnitude of such jumps. Both plots use daily dividend data over the sample 1973-2016.

Figure 5: Decomposition of aggregate dividend growth. For two days in our sample (December 8, 2009 and August 5, 2010), this figure shows how the dividend growth rate gets decomposed into (i) a persistent mean component $\mu_t$; (ii) a normal component with stochastic volatility $\sigma_t$; and (iii) a jump component.
Figure 6: Jump intensities and the number of firms announcing dividend news. This figure shows the sensitivity of the dividend growth jump probability to the number of firms announcing dividends on a given day, $N_{dt}$, chosen to match the 25th, median and 75th percentiles of the distribution of the daily number of firms announcing dividends. On days with a large number of announcing firms (black, dashed curve), the jump intensity distribution is centered around 0.005, corresponding to a jump on average every 200 days. On days with a typical (median) number of announcing firms (blue curve), the jump intensity is centered around 0.016, implying a jump roughly every 60 days. Finally, on days with a small number of announcing firms (red, dotted curve), the probability of a jump is 0.03, corresponding to a jump on average every 35 days.
Figure 7: Actual versus predicted dividend growth under alternative modeling approaches. The top panel plots the actual dividend growth, $\Delta d_t$, against the persistent dividend growth component extracted from our model, $\mu_{dt}$, and the measure proposed by van Binsbergen and Koijen (2010), $g_{t}^{VBK}$. The latter assumes cash reinvested dividend growth. The bottom panel plots actual dividend growth against our persistent dividend growth component and the measure of Kelly and Pruitt (2013), $g_{t}^{KP}$. In both cases we have extended the sample period originally used by the papers after replicating their results.

Figure 8: GDP growth, consumption growth and the persistent dividend growth component, $\mu_{dt}$. This figure plots quarterly GDP and consumption growth along with the persistent dividend growth component $\mu_{dt}$, extracted from our daily cash flow model over the sample 1975-2015.
Figure 9: Decomposition of daily stock returns into stochastic volatility and jumps. The top panel shows the stochastic volatility component extracted from the dynamic model for stock returns (eq. 11). The middle and bottom panels plot the probability and magnitude of jumps in daily stock returns.

Figure 10: Impulse responses of stock returns following shocks to different components of the dividend growth process. The first three panels in this figure plot the impact on the volatility of stock market returns (measured in percent of the initial volatility level) of a one standard deviation shock to the first difference of the persistent dividend growth component (top left panel), the dividend growth volatility (top right panel), and the jump in dividend growth (bottom left panel). Days since the date of the shock are shown on the horizontal axis in these three plots. The bottom right panel shows the effect of a one standard deviation shock to the cash flow jump process on the probability of a jump in stock returns.
Figure 11: Heterogeneity in $\Delta d_t$ and $\mu_{dt}$. This figure plots the log growth rate, $\Delta d_t$, and the persistent dividend growth component, $\mu_{dt}$, for firms with high book-to-market ratios (left panels) and firms with low book-to-market ratios (right panels). The plots use daily data and cover the sample 1973-2016.
Internet Appendix A  MCMC Algorithm

In this Appendix, we provide the analytical derivations needed to compute the posterior
distribution of all parameters and latent states of the most general model we employ in the
paper.

A.1 The Model

We start by rewriting both the model as well as the priors distributions for all model
parameters. Starting with the observation equation and time-varying mean and volatility
processes, we have

\[ y_{t+1} = \mu_{t+1} + \xi_{t+1}J_{t+1} + \beta'X_{t+1} + \varepsilon_{yt+1}, \]  
\[ \mu_{t+1} = \mu_y + \phi_\mu (\mu_t - \mu_y) + \sigma_\mu \varepsilon_{\mu t+1}, \]  
\[ h_{t+1} = \mu_h + \phi_h (h_t - \mu_h) + \beta_h'X_{t+1}^h + \sigma_h \varepsilon_{ht+1} \]  

where \( y_{t+1} \) denotes either the cash flow growth rate or the stock return at time \( t + 1 \), while
\( \varepsilon_{yt+1} \sim \mathcal{N}(0, e^{h_{t+1}}) \), \( \varepsilon_{\mu t+1} \sim \mathcal{N}(0, \sigma^2_\mu) \), and \( \varepsilon_{ht+1} \sim \mathcal{N}(0, \sigma^2_h) \) independent among each other
and across time. The jump process intensity and size follow

\[ Pr(J_{t+1} = 1) = \Phi(XX'_{t+1}^J) \]  

and

\[ \xi_{t+1} \sim \mathcal{N}(0, \sigma^2_\xi) \]
with $X_{t+1}$, $X_h^t$, and $X_j^t$ exogenous. Finally, the initial conditions for $\mu$ and $h$ are as follows:

$$\mu_1 \sim \mathcal{N}\left(\mu_y, \frac{\sigma^2_\mu}{1 - \phi^2_\mu}\right)$$  \hspace{1cm} (A.6)

and

$$h_1 \sim \mathcal{N}\left(\mu_h + \frac{\beta_h X_1^h}{1 - \phi_h}, \frac{\sigma^2_h}{1 - \phi^2_h}\right).$$  \hspace{1cm} (A.7)

### A.2 Priors

The model in (A.1)-(A.7) includes 10 parameters, namely $\mu_y$, $\phi_\mu$, $\sigma^2_\mu$, $\mu_h$, $\phi_h$, $\sigma^2_h$, $\lambda$, $\sigma^2_\xi$, $\beta$, and $\beta_h$. We specify the following prior distributions:

$$\mu_y \sim \mathcal{N}(\mu_{y0}, V_{\mu_y}), \quad \phi_\mu \sim \mathcal{N}(\phi_{\mu0}, V_{\phi_\mu})I(|\phi_\mu| < 1), \quad \sigma^2_\mu \sim \mathcal{IG}(V_{\mu}, S_{\mu})$$  \hspace{1cm} (A.8)

$$\mu_h \sim \mathcal{N}(\mu_{h0}, V_{\mu_h}), \quad \phi_h \sim \mathcal{N}(\phi_{h0}, V_{\phi_h})I(|\phi_h| < 1), \quad \sigma^2_h \sim \mathcal{IG}(V_{\mu_h}, S_{\mu_h})$$  \hspace{1cm} (A.9)

$$\lambda \sim \mathcal{N}(\mu_\lambda, V_\lambda)$$  \hspace{1cm} (A.10)

$$\sigma^2_\xi \sim \mathcal{IG}(V_\xi, S_\xi)$$  \hspace{1cm} (A.11)

$$\beta \sim \mathcal{N}(\beta_0, V_\beta)$$  \hspace{1cm} (A.12)

$$\beta_h \sim \mathcal{N}(\beta_{h0}, V_{\beta_h}).$$  \hspace{1cm} (A.13)

### A.3 Posteriors

We now describe how to obtain posterior estimates for all model parameters ($\mu_y$, $\phi_\mu$, $\sigma^2_\mu$, $\mu_h$, $\phi_h$, $\sigma^2_h$, $\lambda$, $\sigma^2_\xi$, $\beta$, $\beta_h$), as well as latent state vectors $\mathbf{u} = \{\mu_t\}_{t=1}^T$, $\mathbf{h} = \{h_t\}_{t=1}^T$. 
\( J = \{ J_t \}_{t=1}^T \), and \( \xi = \{ \xi_t \}_{t=1}^T \). While the joint posterior distribution of all model parameters and latent state variables is highly non-linear, we can employ a Gibbs sampler algorithm augmented with a number of Metropolis-Hastings steps to draw recursively from the conditional posteriors of all model parameter and state variables. In particular, we break the evaluation of the joint posterior distribution in five different blocks, namely:

1. \( \mu | h, \xi, J, \mu_y, \phi_\mu, \sigma_\mu^2, \beta, D^T \)
2. \( J | \mu, \xi, \beta, h, D^T \)
3. \( \xi | \mu, J, \beta, h, \sigma_\xi^2, D^T \)
4. \( h | \mu, \xi, J, \mu_h, \phi_h, \sigma_h^2, \beta, D^T \)
5. \( \mu_y, \phi_\mu, \sigma_\mu^2, \mu_h, \psi_h, \sigma_h^2, \lambda, \sigma_\xi^2, \beta, \beta_h | \mu, h, \xi, J, D^T \)

The last block is further broken down into 10 separate sub-blocks, one for each element of the parameter vector. We now describe in details all steps of the Gibbs sampler algorithm.

**A.3.1 \( \mu | h, \xi, J, \mu_y, \phi_\mu, \sigma_\mu^2, \beta, D^T \)**

Start by rewriting the observation equation in (A.1) as follows:

\[
y^* = X_\mu \mu + \epsilon_y \quad \epsilon_y \sim \mathcal{N}(0, \Sigma_y) \tag{A.14}
\]

where

\[
y^* = \begin{bmatrix} y_1 - \xi_1 J_1 - \beta' X_1 \\ \vdots \\ y_T - \xi_T J_T - \beta' X_T \end{bmatrix}, \tag{A.15}
\]

\[
X_\mu = \begin{bmatrix} 1 \\ \ddots \\ 1 \end{bmatrix}, \quad \mu = \begin{bmatrix} \mu_1 \\ \vdots \\ \mu_T \end{bmatrix}, \quad \epsilon_y = \begin{bmatrix} \epsilon_{y1} \\ \vdots \\ \epsilon_{yT} \end{bmatrix}. \tag{A.16}
\]
and

\[ \Sigma_y = \begin{bmatrix} e^{h1} & & \\ & \ddots & \\ & & e^{hT} \end{bmatrix}. \] (A.17)

Next, combine the state equation for \( \mu \) in (A.2) with the initial condition in (A.6) into:

\[ H_\mu \mu = \tilde{\delta}_\mu + \epsilon_\mu \quad \epsilon_\mu \sim N(0, \Sigma_\mu) \] (A.18)

where

\[ H_\mu = \begin{bmatrix} 1 & 0 & \ldots & \ldots & 0 \\ -\phi_\mu & 1 & 0 & \ldots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & \ldots & 0 & -\phi_\mu & 1 \end{bmatrix} \quad \tilde{\delta}_\mu = \begin{bmatrix} \mu_y \\ (1 - \phi_\mu)\mu_y \\ \vdots \\ (1 - \phi_\mu)\mu_y \end{bmatrix} \] (A.19)

and

\[ \Sigma_\mu = \begin{bmatrix} \sigma^2_\mu \\ \cdot \\ \cdot \\ \sigma^2_\mu \\ \sigma^2_\mu \end{bmatrix}. \] (A.20)

It is easy to show that

\[ \mu = \delta_\mu + H_\mu^{-1} \epsilon_\mu \] (A.21)

where \( \delta_\mu = H_\mu^{-1} \tilde{\sigma}_\mu \). It follows that

\[ \mu \sim N\left(\delta_\mu, H_\mu^{-1} \Sigma_\mu \left( H_\mu^{-1} \right)' \right) \] (A.22)

or

\[ \mu \sim N\left(\delta_\mu, (H_\mu' \Sigma_\mu^{-1} H_\mu)^{-1} \right) \] (A.23)
Finally, combining (A.14) and (A.23) leads to the following posterior:

$$
\mu | h, \xi, J, \mu_y, \phi, \beta, D^T \sim \mathcal{N}(\mu, V) \quad (A.24)
$$

where

$$
V = [H^{\prime} \Sigma_{\mu}^{-1} H + X^{\prime} \Sigma_{y}^{-1} X]^{-1}
\mu = V [H^{\prime} \Sigma_{\mu}^{-1} \delta_{\mu} + X^{\prime} \Sigma_{y}^{-1} y^t]
$$

(A.25)

A.3.2  $J | \mu, \xi, \beta, h, D^T$

It is easy to show that for any given $t \in [1, T]$

$$
\text{Pr} \left( J_t = 1 | \mu_t, \xi_t, \beta, \lambda, X_t, X_t^j, h_t, D^T \right) \propto p(y_t | \mu_t, \xi_t, J_t = 1, \beta, X_t, h_t) \\
\times \text{Pr} (J_t = 1 | X_t^j, \lambda)
$$

(A.26)

where

$$
p(y_t | \mu_t, \xi_t, J_t = 1, \beta, X_t, h_t) \sim \mathcal{N} (y_t | \mu_t + \xi_t + \beta^t X_t, e^{h_t})
$$

(A.27)

and $\text{Pr} (J_t = 1 | X_t^j, \lambda) = \Phi (\lambda^t X_t^j)$ while

$$
\text{Pr} \left( J_t = 0 | \mu_t, \xi_t, \beta, \lambda, X_t, X_t^j, h_t, D^T \right) \propto p(y_t | \mu_t, \xi_t, J_t = 0, \beta, X_t, h_t) \\
\times \text{Pr} (J_t = 0 | X_t^j, \lambda)
$$

(A.28)

where

$$
p(y_t | \mu_t, \xi_t, J_t = 0, \beta, X_t, h_t) \sim \mathcal{N} (y_t | \mu_t + \beta^t X_t, e^{h_t})
$$

(A.29)

and $\text{Pr} (J_t = 0 | X_t^j, \lambda) = 1 - \Phi (\lambda^t X_t^j)$.

A.3.3  $\xi | \mu, J, \beta, h, \sigma_\xi^2, D^T$

Start by noting that when $J_t = 0$, $\xi_t | J_t = 0, D^T \sim \mathcal{N}(0, \sigma_\xi^2)$. In other words, when $J_t = 0$ we rely on $\xi_t$ prior distribution in (A.5). In constrast, when $J_t = 1$, it is possible to rewrite
the observation equation of the model in (A.1) as
\[ y_t - \mu_t - \beta'X_t = \xi_t + \epsilon_t, \quad \epsilon_t \sim \mathcal{N}(0, e^{h_t}). \]  

(A.30)

Combining (A.30) with (A.5) leads to:
\[ \xi_t | \mu_t, J_t = 1, \beta, h_t, \sigma^2, D^T \sim \mathcal{N}(\tilde{\mu}_t, \tilde{\sigma}^2_t) \]  

(A.31)

where
\[ \tilde{\sigma}^2_t = (\sigma^{-2} + e^{-h_t})^{-1} \]
\[ \tilde{\mu}_t = \tilde{\sigma}^2_t (e^{-h_t} (y_t - \mu_t - \beta'X_t)) . \]  

(A.32)

### A.3.4 \( h | \mu, \xi, J, \mu_h, \phi_h, \sigma^2_h, \beta, D^T \)

Start by combining the state equation for \( h_t \) in (A.3) with the initial condition for \( h_1 \) in (A.7) into:
\[ H_h h = \tilde{\delta}_h + \epsilon_h, \quad \epsilon_h \sim \mathcal{N}(0, \Sigma_h) \]  

(A.33)

where
\[ H_h = \begin{bmatrix} 1 & 0 & \ldots & \ldots & \ldots & 0 \\ -\phi_h & 1 & 0 & \ldots & \ldots & 0 \\ \vdots & \vdots & \ddots & \ddots & \vdots & \vdots \\ 0 & \ldots & \ldots & 0 & -\phi_h & 1 \end{bmatrix}, \quad \tilde{\delta}_h = \begin{bmatrix} \mu_h + \frac{\beta'X_1}{(1-\phi_h)} \\ (1-\phi_h)\mu_h + \beta'X_2 \\ \vdots \\ (1-\phi_h)\mu_h + \beta'X_T \end{bmatrix} \]  

(A.34)

and
\[ \Sigma_h = \begin{bmatrix} \sigma^2_h(1-\phi_h) \\ \sigma^2_h \\ \vdots \\ \sigma^2_h \end{bmatrix} \]  

(A.35)
This leads to

\[ h \sim N \left( \delta_h, (H'_h \Sigma_h^{-1} H_h)^{-1} \right) \]  

(A.36)

where \( \delta_h = H_h^{-1} \tilde{\delta}_h \). Note next that the observation equation is a non-linear function in \( h \), so we follow Chan and Grant (2016b) and first log-linearize it. Recall from (A.14) that

\[ y^* | \mu, h, J, \xi, \beta \sim N(\mu, \Sigma_y). \]  

(A.37)

A second-order Taylor expansion of (A.37) around \( \tilde{h} \) leads to the following approximation:

\[
\ln p(y^* | \mu, h, J, \xi, \beta) \approx \ln p(y^* | \mu, \tilde{h}, J, \xi, \beta) + (h - \tilde{h})' f - \frac{1}{2} (h - \tilde{h})' G (h - \tilde{h})
\]  

(A.38)

where \( f \) is \( T \times 1 \) vector of gradients and \( G \) is \( T \times T \) matrix containing the elements of the negative Hessian, while \( \tilde{h} \) denotes the mode of \( \ln p(y^* | \mu, h, J, \xi, \beta) \). In particular,

\[
f = \begin{bmatrix} f_1 \\ \vdots \\ f_T \end{bmatrix}, \quad G = \begin{bmatrix} G_{11} & \cdots \\ \vdots & \ddots \\ G_{TT} \end{bmatrix}
\]  

(A.39)

with

\[
f_t = \frac{\partial \ln p(y^*_t | \mu_t, h_t, J_t, \xi_t, \beta)}{\partial h_t} \bigg|_{h_t = \tilde{h}_t}
\]  

(A.40)

and

\[
G_{tt} = -\frac{\partial^2 \ln p(y^*_t | \mu_t, h_t, J_t, \xi_t, \beta)}{\partial h_t^2} \bigg|_{h_t = \tilde{h}_t}
\]  

(A.41)

with

\[
f_t = -\frac{1}{2} + \frac{1}{2} e^{-h_t} (y^*_t - \mu_t)^2
\]

\[
G_{tt} = -\frac{1}{2} e^{-h_t} (y^*_t - \mu_t)^2
\]  

(A.42)
Some additional algebra leads to

$$\ln p(y^* | \mu, h, J, \xi, \beta) \propto h' f - \frac{1}{2} h' G h + h' G \tilde{h}$$

$$\propto -\frac{1}{2} \left( h' G h - 2 h' \left( f - G \tilde{h} \right) \right)$$

(A.43)

Combining (A.43) with (A.36) leads to the following posterior for $h$:

$$h|\mu, \xi, J, \mu_h, \phi_h, \sigma^2_h, \beta, D_T \sim \mathcal{N}\left( K_h^{-1} k_h, \Sigma_h^{-1} \right)$$

(A.44)

where

$$K_h = H_h' \Sigma_h^{-1} H_h + G$$

(A.45)

$$k_h = H_h' \Sigma_h^{-1} H_h \delta_h + f + G \tilde{h}$$

(A.46)

The choice of $\tilde{h}$ is crucial, and we follow Chan and Grant (2016b).

A.3.5 $\mu_y, \phi, \sigma^2, \mu_h, \psi_h, \sigma^2_h, \lambda, \sigma^2_\xi, \beta, \beta_h | \mu, h, \xi, J, D_T$

We break the posterior into 10 separate blocks:

- $\mu_y | \mu, \phi, \sigma^2, D_T$:

  Start by combining (A.2) and (A.6) and rewriting them as:

  $$Z_\mu = X_\mu \mu_y + \epsilon_\mu \sim \mathcal{N}(0, \Sigma_\mu)$$

  (A.47)

  where

  $$Z_\mu = \begin{bmatrix} \mu_1 \\ \mu_2 - \phi_\mu \mu_1 \\ \vdots \\ \mu_T - \phi_\mu \mu_T \end{bmatrix}, \quad X_\mu = \begin{bmatrix} 1 \\ (1 - \phi_\mu) \\ \vdots \\ (1 - \phi_\mu) \end{bmatrix}.$$ 

  (A.48)
Combining (A.47) with the prior for $\mu_y$ in (A.8) leads to

$$
\mu_y | \mu, \phi, \sigma^2, D^T \sim \mathcal{N} (\overline{\mu}_y, \nabla_{\mu_y})
$$

(A.49)

where

$$
\nabla_{\mu_y} = \left[ V^{-1}_{\mu_y} + X'_{\mu} \Sigma^{-1}_{\mu} X_{\mu} \right]^{-1}
$$

(A.50)

and

$$
\overline{\mu}_y = \nabla_{\mu_y} \left[ V_{\mu_y\mu_y} \mu_0 + X'_{\mu} \Sigma^{-1}_{\mu} Z_{\mu} \right]
$$

(A.51)

- $\phi_{\mu} | \mu, \mu_y, \sigma^2_{\mu}, D^T$:

Following Kim et al. (1998), we start by obtaining a candidate draw from the following distribution:

$$
\phi^*_\mu \sim \mathcal{N} (\overline{\phi}_{\mu}, \nabla_{\mu}) \times I (|\phi_{\mu}| < 1)
$$

(A.52)

where

$$
\nabla_{\phi_{\mu}} = \left( V^{-1}_{\phi_{\mu}} + \frac{X'_{\phi_{\mu}} X_{\phi_{\mu}}}{\sigma^2_{\mu}} \right)^{-1}
$$

(A.53)

and where

$$
\overline{\phi}_{\mu} = \nabla_{\phi_{\mu}} \left( V^{-1}_{\phi_{\mu}} \phi_{\mu} + \frac{X'_{\phi_{\mu}} Z_{\phi_{\mu}}}{\sigma^2_{\mu}} \right)
$$

(A.54)

$$
Z_{\phi_{\mu}} = \begin{bmatrix}
\mu_2 - \mu_y \\
\vdots \\
\mu_T - \mu_y
\end{bmatrix}, \quad X_{\phi_{\mu}} = \begin{bmatrix}
\mu_1 - \mu_y \\
\vdots \\
\mu_{T-1} - \mu_y
\end{bmatrix}
$$

(A.55)
Next, if the draw is retained (i.e., satisfy the stationarity restriction), we accept \( \phi^*_\mu \) with probability \\
\( e^{g(\phi^*_\mu) - g(\phi^{old}_\mu)} \) where \( \phi^{old}_\mu \) is the retained draw from the previous iteration of the Gibbs sampler, and \\

\[
g(\phi_\mu) = \ln p(\phi_\mu) - \frac{1}{2} \ln \left( \frac{\sigma^2_\mu}{1 - \phi^2_\mu} \right) - \frac{(1 - \phi^2_\mu)}{2\sigma^2_\mu} (\mu_1 - \mu_y)^2 \tag{A.56}
\]

with \( p(\phi_\mu) \) denoting the prior of \( \phi_\mu \) from (A.8).

- \( \sigma^2_\mu \mid \mu, \mu_y, \phi_\mu, D^T \):

The posterior for \( \sigma^2_\mu \) is readily available, and is given by:

\[
\sigma^2_\mu \mid \mu, \mu_y, \phi_\mu, D^T \sim IG \left( V_\mu + \frac{T}{2}, S_\mu \right) \tag{A.57}
\]

where

\[
S_\mu = S_\mu + \frac{1}{2} \left[ (1 - \phi^2_\mu)(\mu_1 - \mu_y)^2 + \sum_{t=1}^{T-1} (\mu_{t+1} - \mu_y - \phi_\mu(\mu_t - \mu_y))^2 \right] \tag{A.58}
\]

- \( \mu_h \mid h, \phi_h, \sigma^2_h, \beta_h D^T \):

Start by combining (A.3) and (A.7) into:

\[
Z_h = X_h \mu_h + \epsilon_h \quad \epsilon_h \sim \mathcal{N}(0, \Sigma_h) \tag{A.59}
\]

where

\[
X_h = \begin{bmatrix} 1 \\ 1 - \phi_h \\ \vdots \\ 1 - \phi_h \end{bmatrix}, \quad Z_h = \begin{bmatrix} h_1 - \frac{\beta'_h X^h_1}{1 - \phi_h} \\ h_2 - \phi_h h_1 - \beta'_h X^h_2 \\ \vdots \\ h_T - \phi_h h_{T-1} - \beta'_h X^h_T \end{bmatrix}. \tag{A.60}
\]

Next, combine (A.59) with the prior for \( \mu_h \) in (A.9) to get

\[
\mu_h \mid h, \phi_h, \sigma^2_h, \beta_h, D^T \sim \mathcal{N}(\mu_h, \Sigma_h) \tag{A.61}
\]
where
\[ \nabla_{\mu_h} = \left[ V_{\mu_h}^{-1} + X_h' \Sigma_h^{-1} X_h \right]^{-1} \] (A.62)
and
\[ \mu_h = \nabla_{\mu_h} \left[ V_{\mu_h}^{-1} \mu_h + X_h' \Sigma_h^{-1} Z_h \right] \] (A.63)

• \( \phi_h | h, \mu_h, \sigma^2_h, \beta_h, D^T \):

As with \( \phi_\mu \), we follow Kim et al. (1998) and first obtain a candidate draw from the following distribution:
\[ \phi^*_h \sim N(\bar{\phi}_h, \nabla_h) \times I(\phi_h < 1) \] (A.64)
where
\[ \nabla_{\phi_h} = \left( V_{\phi_h}^{-1} + \frac{X_{\phi_h} X_{\phi_h}}{\sigma^2_h} \right)^{-1}, \] (A.65)
\[ \bar{\phi}_h = \nabla_{\phi_h} \left( V_{\phi_h}^{-1} \phi_{h_0} + \frac{X_{\phi_h} Z_{\phi_h}}{\sigma^2_h} \right) \] (A.66)
and where
\[ Z_{\phi_h} = \begin{bmatrix} h_2 - \mu_h - \beta_h' X_h^2 \\ \vdots \\ h_T - \mu_h - \beta_h' X_h^T \end{bmatrix}, \quad X_{\phi_h} = \begin{bmatrix} h_1 - \mu_h \\ \vdots \\ h_{T-1} - \mu_h \end{bmatrix} \] (A.67)

Next, if the draw is retained (i.e., satisfy the stationarity restriction), we accept \( \phi^*_h \) with probability \( e^{g(\phi^*_h) - g(\phi^{old}_h)} \) where \( \phi^{old}_h \) is the retained draw from the previous iteration of the Gibbs sampler, and
\[ g (\phi_h) = \ln p (\phi_h) - \frac{1}{2} \ln \left( \frac{\sigma^2_h}{1 - \phi^2_h} \right) - \frac{(1 - \phi^2_h)}{2\sigma^2_h} \left( h_1 - \mu_h - \frac{\beta_h' X_h^T}{1 - \phi_h} \right)^2 \] (A.68)
with \( p(\phi_h) \) denoting the prior of \( \phi_h \).

- \( \sigma^2_h|\mathbf{h}, \mu_h, \phi_h, \beta_h, \mathcal{D}^T \):

The posterior for \( \sigma^2_h \) is readily available, and is given by:

\[
\sigma^2_h|\mathbf{h}, \mu_h, \phi_h, \beta_h, \mathcal{D}^T \sim IG \left( \frac{V_h + \frac{T}{2}}{2}, S_h \right) \tag{A.69}
\]

where

\[
S_h = S_h + \frac{1}{2} \left[ (1 - \phi_h^2) \left( h_1 - \mu_h - \frac{\beta_h' \mathbf{X}_1}{1 - \phi_h} \right)^2 + \sum_{t=1}^{T-1} \left( h_{t+1} - \mu_h - \phi_h (h_t - \mu_h) - \beta_h' \mathbf{X}_{t+1} \right)^2 \right] \tag{A.70}
\]

- \( \beta_h|\mathbf{h}, \mu_h, \phi_h, \sigma^2_h, \mathcal{D}^T \):

Start by rewriting (A.3) as follows

\[
\mathbf{Z}_{\beta_h} = \mathbf{X}_{\beta_h} \beta_h + \epsilon_h \quad \epsilon_h \sim \mathcal{N}(0, \Sigma_h) \tag{A.71}
\]

where

\[
\mathbf{Z}_{\beta_h} = \begin{bmatrix} h_1 - \mu_h \\ h_2 - \mu_h - \phi_h(h_1 - \mu_h) \\ \vdots \\ h_T - \mu_h - \phi_h(h_{T-1} - \mu_h) \end{bmatrix}, \quad \mathbf{X}_{\beta_h} = \begin{bmatrix} (1 - \phi_h)^{-1} \mathbf{X}_1^{h'} \\ \mathbf{X}_2^{h'} \\ \vdots \\ \mathbf{X}_T^{h'} \end{bmatrix}. \tag{A.72}
\]

Combing (A.71) with the prior for \( \beta_h \) in (A.13) leads to the following posterior distribution:

\[
\beta_h|\mathbf{h}, \mu_h, \phi_h, \sigma^2_h, \mathcal{D}^T \sim \mathcal{N}(\overline{\beta}_h, \mathbf{V}_{\beta_h}) \tag{A.73}
\]
where

$$
\overline{V}_\beta^h = \left( V_{\beta h}^{-1} + X'_{\beta h} \Sigma_h^{-1} X_{\beta h} \right)^{-1} \tag{A.74}
$$

and

$$
\overline{\beta}_h = \overline{V}_\beta^h \left( V_{\beta h}^{-1} \overline{\beta}_h + X'_{\beta h} \Sigma_h^{-1} Z_{\beta h} \right). \tag{A.75}
$$

- $\lambda|W, D^T$ and $W|\lambda, J, D^T$:

We follow Albert and Chib (1993) and to simplify the computations introduce the auxiliary latent state variable $W_t$, $t = 1, ..., T$. We proceed by first rewriting the stochastic process of the jump intensity in (A.4) as

$$
J_{t+1} = \begin{cases} 
1 & \text{if } W_{t+1} > 0 \\
0 & \text{if } W_{t+1} \leq 0 
\end{cases} \tag{A.76}
$$

where

$$
W_{t+1} = \lambda' X^J_{t+1} + \epsilon_{W_{t+1}}, \quad \epsilon_{W_{t+1}} \sim N(0, 1) \tag{A.77}
$$

or, more compactly,

$$
W = X^J \lambda + \epsilon_W, \quad \epsilon_W \sim N(0, I_T) \tag{A.78}
$$

where

$$
X^J = \begin{bmatrix} X^J_1 \\ \vdots \\ X^J_T \end{bmatrix}, \quad W = \begin{bmatrix} W_1 \\ \vdots \\ W_T \end{bmatrix}. \tag{A.79}
$$

The posterior of $\lambda$ is readily available, and given by

$$
\lambda|W, D^T \sim N(\mu_\lambda, V_\lambda) \tag{A.80}
$$
where
\[
\bar{V}_{\lambda} = \left[ V_{\lambda}^{-1} + X' J' X \right]^{-1}
\]  
(A.81)

and
\[
\mu_{\lambda} = \bar{V}_{\lambda} \left[ V_{\lambda}^{-1} \mu_{\lambda} + X' J \right].
\]  
(A.82)

As for the sequence of latent variables \( \{W_t\}_{t=1}^T \), we have that
\[
W_t| \lambda, J_t, D \sim \begin{cases} 
TN(\lambda' X_{t+1}, 1, 0, \infty) & \text{if } J_t = 1 \\
TN(\lambda' X_{t+1}, 1, -\infty, 0) & \text{if } J_t = 0
\end{cases}
\]  
(A.83)

where \( TN(\mu, \sigma^2, lb, ub) \) denotes a truncated normal distribution with mean \( \mu \), variance \( \sigma^2 \), and lower and upper bound \( lb, ub \).

- \( \sigma_\xi^2 | \xi, D^T \):

The posterior distribution for \( \sigma_\xi^2 \) is readily available, and given by
\[
\sigma_\xi^2 | \xi, D^T \sim IG \left( V_{\xi} + \frac{T}{2}, S_{\xi} \right)
\]  
(A.84)

where
\[
S_{\xi} = S_{\xi} + \frac{1}{2} \sum_{t=1}^{T} \xi_t^2.
\]  
(A.85)

- \( \beta | \mu, h, J, \xi, D^T \):

Start by rewriting (A.1) as follows:
\[
y^{**} = X \beta + \epsilon \quad \epsilon \sim \mathcal{N}(0, \Sigma_y)
\]  
(A.86)

75
where

\[
y^{**} = \begin{bmatrix}
y_1 - \mu_1 - J_1 \xi_1 \\
\vdots \\
y_T - \mu_T - J_T \xi_T
\end{bmatrix}, \quad X' = \begin{bmatrix}
X'_1 \\
\vdots \\
X'_{\gamma}
\end{bmatrix}.
\] (A.87)

Next, combine (A.86) with the prior distribution for \( \beta \) in (A.12) to obtain:

\[
\beta | \mu, h, J, \xi, D^T \sim \mathcal{N}(\beta, V_\beta) \] (A.88)

where

\[
V_\beta = \left[ V_\beta^{-1} + X' \Sigma_y^{-1} X \right]^{-1}
\] (A.89)

and

\[
\beta = V_\beta \left[ V_\beta^{-1} \beta_0 + X' \Sigma_y^{-1} y^{**} \right]
\] (A.90)
Internet Appendix B  MCMC  Convergence and Efficiency

In this Appendix, we discuss the convergence properties of our MCMC algorithm for both the mean-reverting, stochastic volatility model with jumps described in Section 3.1 and the joint return-cash flow model described in Section 5.1. All results are based on samples of 2,000 retained draws, obtained by sampling a total of 101,000 draws, discarding the first 1,000 draws, and retaining every 20th draw of the post-burn samples.

Table B.1 and Table B.2 report summary statistics of inefficiency factors (IF) for the posterior estimates of all key parameters of the cash flow and return-cash flow models, respectively. Generally speaking, values of the IFs below 20 are taken as indication that the chain has satisfactory mixing properties. As is clear from the entries in both tables, our algorithm shows excellent mixing properties.
### PANEL A: DIVIDENDS

<table>
<thead>
<tr>
<th></th>
<th>IF 4%</th>
<th>IF 8%</th>
<th>IF 15%</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu_d$</td>
<td>0.888</td>
<td>0.747</td>
<td>0.714</td>
</tr>
<tr>
<td>$\phi_\mu$</td>
<td>3.681</td>
<td>3.488</td>
<td>3.413</td>
</tr>
<tr>
<td>$\sigma^2_\mu$</td>
<td>7.054</td>
<td>6.337</td>
<td>6.454</td>
</tr>
<tr>
<td>$\mu_h$</td>
<td>0.766</td>
<td>0.554</td>
<td>0.369</td>
</tr>
<tr>
<td>$\phi_h$</td>
<td>0.650</td>
<td>0.439</td>
<td>0.333</td>
</tr>
<tr>
<td>$\sigma^2_h$</td>
<td>0.741</td>
<td>0.645</td>
<td>0.521</td>
</tr>
<tr>
<td>$\sigma^2_\xi$</td>
<td>3.218</td>
<td>3.222</td>
<td>3.797</td>
</tr>
</tbody>
</table>

### PANEL B: DIVIDENDS (from 1927)

<table>
<thead>
<tr>
<th></th>
<th>IF 4%</th>
<th>IF 8%</th>
<th>IF 15%</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu_d$</td>
<td>1.447</td>
<td>1.614</td>
<td>1.921</td>
</tr>
<tr>
<td>$\phi_\mu$</td>
<td>3.041</td>
<td>3.270</td>
<td>3.174</td>
</tr>
<tr>
<td>$\sigma^2_\mu$</td>
<td>6.944</td>
<td>7.504</td>
<td>9.093</td>
</tr>
<tr>
<td>$\mu_h$</td>
<td>0.840</td>
<td>0.797</td>
<td>0.853</td>
</tr>
<tr>
<td>$\phi_h$</td>
<td>0.741</td>
<td>0.612</td>
<td>0.409</td>
</tr>
<tr>
<td>$\sigma^2_h$</td>
<td>0.616</td>
<td>0.474</td>
<td>0.336</td>
</tr>
<tr>
<td>$\sigma^2_\xi$</td>
<td>1.918</td>
<td>1.913</td>
<td>1.770</td>
</tr>
</tbody>
</table>

**Table B.1: Inefficiency factors of the model.** This table reports the inefficiency factors for the key parameters of the mean-reverting, stochastic volatility model with jumps described in Section 3.1. Panel A reports results for the model using the daily dividend growth series starting in 1973, while Panel B shows estimates using the daily dividend growth series and starting in 1927. For each individual parameter, the inefficiency factor is estimated as $1 + 2 \sum_{k=1}^{\infty} \rho_k$ where $\rho_k$ is the $k$th-order autocorrelation of the chain of retained draws. The estimates use the Newey-West kernel and a bandwidth of 4%, 8%, or 15% of the sample of retained draws. All results are based on a sample of 2,000 retained draws, obtained by sampling a total of 101,000 draws, discarding the first 1,000 and retaining every 20th draw of the post-burn sample.
### Joint returns-cash flow model

<table>
<thead>
<tr>
<th></th>
<th>IF 4%</th>
<th>IF 8%</th>
<th>IF 15%</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_1$</td>
<td>0.748</td>
<td>0.490</td>
<td>0.404</td>
</tr>
<tr>
<td>$\beta_2$</td>
<td>1.321</td>
<td>1.289</td>
<td>1.340</td>
</tr>
<tr>
<td>$\beta_3$</td>
<td>0.985</td>
<td>1.075</td>
<td>1.076</td>
</tr>
<tr>
<td>$\beta_4$</td>
<td>0.741</td>
<td>0.580</td>
<td>0.485</td>
</tr>
<tr>
<td>$\mu_r$</td>
<td>0.985</td>
<td>0.849</td>
<td>0.660</td>
</tr>
<tr>
<td>$\phi_{\mu r}$</td>
<td>1.285</td>
<td>0.969</td>
<td>0.730</td>
</tr>
<tr>
<td>$\mu_{hr}$</td>
<td>4.367</td>
<td>4.195</td>
<td>2.582</td>
</tr>
<tr>
<td>$\phi_{hr}$</td>
<td>1.162</td>
<td>1.242</td>
<td>1.217</td>
</tr>
<tr>
<td>$\gamma_1$</td>
<td>1.603</td>
<td>1.353</td>
<td>0.473</td>
</tr>
<tr>
<td>$\gamma_2$</td>
<td>3.454</td>
<td>3.215</td>
<td>2.010</td>
</tr>
<tr>
<td>$\gamma_3$</td>
<td>14.260</td>
<td>13.886</td>
<td>11.485</td>
</tr>
<tr>
<td>$\lambda_1^r$</td>
<td>3.628</td>
<td>3.329</td>
<td>2.172</td>
</tr>
<tr>
<td>$\lambda_2^r$</td>
<td>1.291</td>
<td>1.191</td>
<td>1.291</td>
</tr>
<tr>
<td>$\lambda_3^r$</td>
<td>1.482</td>
<td>1.341</td>
<td>1.358</td>
</tr>
<tr>
<td>$\sigma_{\mu r}$</td>
<td>7.653</td>
<td>8.299</td>
<td>8.975</td>
</tr>
<tr>
<td>$\sigma_{hr}$</td>
<td>1.092</td>
<td>1.076</td>
<td>0.840</td>
</tr>
<tr>
<td>$\sigma_{\xi r}$</td>
<td>5.288</td>
<td>5.189</td>
<td>3.823</td>
</tr>
</tbody>
</table>

Table B.2: Inefficiency factors of the joint return-cash flow model. This table reports the inefficiency factors for the key parameters of the joint return-cash flow model in Section 5.1. For each individual parameter, the inefficiency factor is estimated as $1 + 2 \sum_{k=1}^{\infty} \rho_k$ where $\rho_k$ is the $k$th-order autocorrelation of the chain of retained draws. The estimates use the Newey-West kernel and a bandwidth of 4%, 8%, or 15% of the sample of retained draws. All results are based on a sample of 2,000 retained draws, obtained by sampling a total of 101,000 draws, discarding the first 1,000 and retaining every 20th draw of the post-burn sample. Data: 1973-2016.