

Working Paper No. 2016006



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Sticky dividends: A new explanation[☆]

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Abstract

This study proposes a generalized partial adjustment model of dividends in which managers set target dividends based on adaptively-formed earnings prospects. We show that firms adjust dividends to their target payouts much faster than previously documented. When managers form future earnings expectations based on a longer time-series of earnings, target dividends tend to become more stable. Thus, actual dividends tend to be more in line with the targets, driving up the speed of adjustment. Our model offers an insight that sticky dividends could be a consequence of managers' attempts to match dividend payouts with the smooth targets.

Keywords: Payout policy, Speed of adjustment, Dividend dynamics, Adaptive expectations

1. Introduction

Since Lintner (1956) studied corporate dividend policy and practice using a partial adjustment model, extensive prior research has documented a series of empirical findings and their plausible explanations.¹ Yet dividends remain one of

[☆]The authors thank the anonymous referee, Steve Bond, and Oren Sussman for their insightful comments. In particular, Hyun Joong Im acknowledges Steve Bond's valuable comments and lectures on Difference GMM and System GMM methods provided during his doctoral studies at the University of Oxford.

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¹See Allen and Michaely (1995) and DeAngelo et al. (2009) for excellent reviews of the related literature.

the most contested and thorniest puzzles in corporate finance (Allen et al., 2000). Research in more recent years, in particular, provides evidence that many of those empirical findings and underlying theories are to be revised or refuted. Among others, Brav et al. (2005), using survey and field interviews with financial executives, provide a new perspective on various aspects of corporate payout policy such as managers' beliefs and stances concerning dividend policy and its determinants. Of particular interest for this paper is their finding that more than four-fifths of executives target to remain consistent with historical dividend policy and take lagged dividends as a benchmark when choosing the current dividend policy. Also, the majority of firms are known to tie their dividends to the sustainable future earnings. While these managerial tendencies are in line with dividend conservatism, they also offer some clues on how firms and managers are likely to set the dividend targets.

Building on the documented managerial attention to past dividend history and future earnings prospects in setting today's dividend policy, this study aims to offer a novel insight into the mechanism through which firms' actual dividends remain sticky.² To that end, we propose a generalized partial adjustment model with adaptive expectations for future earnings.³ In our proposed model, the managerial attention to past dividends is reflected in the way managers form the future earnings prospects which has also been documented to be an important consideration for dividend payout decision. Hence, our model does capture the spirit of managers' tendency to consider both historical dividends and future earnings prospects in determining the current dividend policy. Our model is also consistent with managers' motive to maintain smooth dividends because of asymmetric response of the market to dividend increases and cuts. By allowing managers to set target dividends based on expected future earnings,⁴ our model can generate

²In Appendix A, we present the analysis of the time-series evolution of dividends for our cross-section of the firms following Lemmon et al. (2008). A preliminary examination reveals the presence of a permanent or long-run component that leads to highly persistent cross-sectional differences in dividend ratios. In addition, both nonparametric and parametric (ANCOVA) analyses of variance decomposition show that the time-invariant firm-specific components are the major source of total variation in dividends. That is, the majority of the total variation in dividends comes from cross-sectional differences as opposed to time-series variation. See Appendix A for further details.

³Chow (2011) provides a statistical reason and strong econometric evidence for supporting the adaptive expectations hypothesis in economics.

⁴Setting dividend targets in this manner is in line with the signaling hypothesis of dividends (Bhattacharya, 1979; Miller and Rock, 1985; John and Williams, 1985).

a smoother path of target dividends provided that managers form expectations adaptively when assessing future earnings prospects. Note that with adaptive expectation formation, future earnings prospects are formed as a weighted average of current and past earnings with geometrically declining weights.

Among the reported stylized facts lie the slow adjustments of dividends toward target payouts. For example, Fama and Babiak (1968) and Fama and French (2002) report quite low adjustment speeds of 0.37 and 0.33, respectively. Given the volatility in firms' earnings, it has remained a puzzle that actual dividends paid out do not reflect that volatility. Our model allows us to reexamine the adjustment speed of dividends to payout targets by explicitly modeling the dividend target formation process. Existing research often attributes smooth dividends to firms' reluctance to change dividends due to asymmetric information (i.e., signaling effect (Bhattacharya, 1979)) or agency conflicts (e.g., irrelevance of short-term profits to dividend decision (Easterbrook, 1984)).⁵ One important implication of those theories is that the manager's information set for dividend decision is likely to contain a longer series of past dividends as well as future earnings prospects. Incorporating this aspect of firms' dividend decisions, this study provides an alternative and richer explanation for this long-lived puzzle by showing that firms' target dividend payouts themselves are much "smoother" than previously documented. While volatile target payouts in conventional models result in fairly low speeds of adjustment, our estimation results suggest that firms tend to adjust their dividend payouts to the targets much faster.

2. Data and methodology

This study uses annual accounting data from the CRSP/Compustat Merged Database (CCM) for the years 1970–2015. Firms with standard industrial classification (SIC) codes between 6000 and 6999, between 4900 and 4999, or between 9000 and 9999 are excluded as these firms are in financial services, regulated utilities, or public administration. We require that each firm have at least 12 years of observations and there be no gaps in the middle of the sample period. We drop the observations if the dividend-to-total assets ratio (denoted $D_{i,t}$), earnings-to-total assets ratio (denoted $E_{i,t}$), or a proxy for Tobin's Q as measured by the sum of the book value of debt and market value of equity divided by the book value of total assets (denoted $Q_{i,t}$) is missing. All variables are winsorized at the 1st and 99th

⁵See Leary and Michaely (2011) for a comprehensive survey of the theoretical models.

percentiles to minimize the effects of outliers. There are a total of 24,926 firm-year observations, corresponding to 981 firms. Industry dummies are constructed according to Fama and French's (1997) 48 industry classification.

Waud (1966) shows that a conventional partial adjustment model and an adaptive expectations model yield indistinguishable empirical specifications as far as estimation is concerned. Hence, one cannot tell whether the estimated coefficient of the lagged dividend ratio is driven by the speed of dividend adjustment (γ) or the speed of expectations revision (ρ). See Appendix B for a detailed discussion of the identification problem. A novel feature of our model presented in this section is that it includes the ingredients of both the partial adjustment model and the adaptive expectations model. This feature allows us to sort out the respective effects of dividend adjustment speed (γ) and expectations revision speed (ρ) in the dynamics of corporate dividend policy. In addition, our model takes into account unobserved firm heterogeneity in setting dividend targets.

A generalized partial adjustment model of dividends with an adaptive expectations formation process in the panel data setting consists of the following three equations:

$$D_{i,t} - D_{i,t-1} = \gamma(D_{i,t}^* - D_{i,t-1}) + \pi_j + \kappa_t + v_{i,t}; \quad (1)$$

$$D_{i,t}^* = \alpha E_{i,t}^e + \beta Q_{i,t-1} + \mu_i; \quad (2)$$

$$E_{i,t}^e - E_{i,t-1}^e = \rho(E_{i,t} - E_{i,t-1}^e), \quad (3)$$

where $0 < \gamma \leq 1$ and $0 < \rho \leq 1$.⁶ Equation (1) describes the partial adjustment

⁶An alternative way to separately identify the dividend adjustment speed (γ) and the expectations revision speed (ρ) would be to estimate firm-specific time-series regressions and average firm-specific estimates for the two speeds. The firm-specific model can be written as follows:

$$D_t - D_{t-1} = \gamma(D_t^* - D_{t-1}) + v_t;$$

$$D_t^* = \alpha E_t^e + \beta Q_{t-1} + \mu;$$

$$E_t^e - E_{t-1}^e = \rho(E_t - E_{t-1}^e),$$

where $0 < \gamma \leq 1$ and $0 < \rho \leq 1$. D_t and D_t^* denote the actual and target dividends per share (or the actual and target dividend ratios) in year t . E_t denotes the earnings per share (or the earnings ratio) observed in period t , and E_{t-1}^e and E_t^e denote the earnings per share (or the earnings ratios) expected to prevail in periods $t-1$ and t , respectively. One can estimate the reduced-form firm-specific time-series regression model similar to Equation (7) firm by firm and aggregate the estimates of firm-specific parameters. However, this method is not feasible when annual data is used. In our sample, the median number of complete time-series observations for each firm is only 21. See Figure 1 for the histogram and kernel density curve for the distribution of the

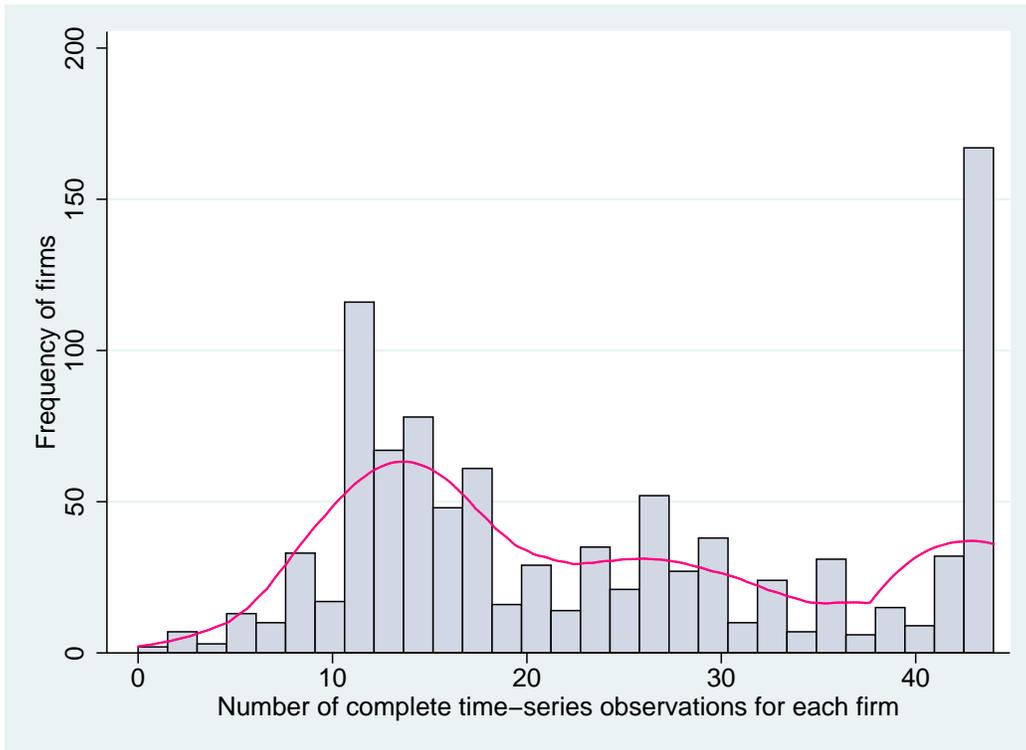
process of dividends. $D_{i,t}$ and $D_{i,t}^*$ denote the actual and target dividend ratios of firm i in year t . γ in Equation (1) denotes the speed of adjustment which measures how fast firms adjust to their target or optimal dividends. The error term in the partial adjustment equation consists of three parts. π_j and κ_t represent unobserved industry-specific and year-specific effects, and $v_{i,t}$ represents the idiosyncratic error with zero mean and no serial correlation. Note that the error components π_j and κ_t can be replaced by industry dummies and year dummies, respectively.

Equation (2) describes how the target dividend ratio is determined. We modify the conventional partial adjustment model described in Appendix B so that the target dividend ratio is determined by adaptively-formed earnings expectations rather than statically-formed earnings expectations. To make γ and ρ separately identifiable, we also include Tobin's Q measured at the beginning of year t ($Q_{i,t-1}$) as an additional observable determinant of the target payout ratio. In addition, we allow the target dividend ratio to be affected by unobserved firm-specific effects (μ_i). Lintner (1956), Fama and Babiak (1968), and Fama and French (2002) model the target dividend ratio as a function of observed current earnings, but do not include unobserved firm-specific effects. In the second equation, α and β capture target dividends–expected earnings sensitivity and target dividends–Tobin's Q sensitivity, respectively.

Most of classical literature directly related to the estimation of the partial adjustment model of dividends (e.g., Lintner (1956), Fama and Babiak (1968), Dewenter and Warther (1998), Skinner (2008), and Leary and Michaely (2011)) simply model the target payout ratio as a function of profitability (i.e., earnings) only. However, Fama and French (2002) who jointly study the dynamics of debt and dividends model the target dividend ratio as a function of several variables such as future growth opportunities (i.e., Tobin's Q), profitability (i.e., earnings), target leverage, R&D intensity, R&D dummy, and firm size. Given that most of the literature model the target dividend ratio as a function of earnings only,

number of complete time-series observations for each firm. Not all of the coefficient estimates are statistically significant in most of the firm-specific regressions so we cannot make reliable inferences on the dividend adjustment speed (γ) and the expectations revision speed (ρ) based on the firm-specific regressions. Thus, consistent with recent empirical corporate finance literature involving the estimation of a partial adjustment model of leverage (Flannery and Rangan, 2006; Lemmon et al., 2008; Faulkender et al., 2012; Ha et al., 2016), we use a panel data regression model with cross-sectionally comparable variables. While per-share variables such as dividends per share are not cross-sectionally comparable, standardized variables such as dividends-to-total assets ratio are cross-sectionally comparable.

Figure 1: Number of complete time-series observations for each firm



Note: This figure presents the histogram and the kernel density curve for the number of complete time-series observations for each firm. An observation is regarded as being incomplete if any of current dividend, first-lagged dividend, second-lagged dividend, first-lagged Tobin's Q, and second-lagged Tobin's Q is missing. The pink curve presents the Epanechnikov kernel density curve, while the light blue bar presents the frequency of firms.

we proceed to generalize the commonly used framework by modeling target dividends as a function of earnings prospects and unobserved firm-specific effects (i.e., $D_{i,t}^* = \alpha E_{i,t}^e + \mu_i$), and explicitly modeling the expectations formation process (i.e., $E_t^e - E_{t-1}^e = \rho(E_t - E_{t-1}^e)$). However, one cannot identify two speed parameters γ and ρ separately by estimating the resultant reduced-form dynamic panel data regression model.⁷ Therefore, we include Tobin's Q at the beginning of year t ($Q_{i,t-1}$) as an additional determinant of the target payout ratio to make γ and ρ separately identifiable. When more than one additional determinants are included in the target payout equation, algebra becomes very complicated. Therefore, we choose an approach of adding only one most important determinant. Among several candidates, a measure of future growth opportunities such as Tobin's Q seems to be most appropriate since prior studies have shown that firms' dividend payout policies are affected by the growth opportunities they have (e.g. Smith and Watts (1992)).

Equation (3) describes the adaptive expectations formation process. $E_{i,t}$ is the earnings ratio observed in period t , and $E_{i,t-1}^e$ and $E_{i,t}^e$ are the earnings ratios expected to prevail in periods $t-1$ and t , respectively. ρ represents the proportion of the expectation error taken to be permanent rather than transitory. For example, if $\rho = 1$, then all of the error is taken to be permanent and $E_{i,t}^e = E_{i,t}$.⁸

Substituting Equation (2) into Equation (1) gives the following equation:

$$\begin{aligned} D_{i,t} &= (1 - \gamma)D_{i,t-1} + \gamma D_{i,t}^* + \pi_j + \kappa_t + v_{i,t} \\ &= (1 - \gamma)D_{i,t-1} + \gamma\alpha E_{i,t}^e + \gamma\beta Q_{i,t-1} + \gamma\mu_i + \pi_j + \kappa_t + v_{i,t}. \end{aligned} \quad (4)$$

Evaluating Equation (4) one period back and rearranging the equation gives the following equation:

$$E_{i,t-1}^e = \frac{1}{\gamma\alpha} [D_{i,t-1} - (1 - \gamma)D_{i,t-2} - \gamma\beta Q_{i,t-2} - \gamma\mu_i - \pi_j - \kappa_{t-1} - v_{i,t-1}]. \quad (5)$$

⁷If the second equation is specified as $D_{i,t}^* = \alpha E_{i,t}^e + \mu_i$, one can obtain the following reduced-form regression model by employing the procedures used to obtain Equation (6):

$$D_{i,t} = [(1 - \gamma) + (1 - \rho)]D_{i,t-1} - (1 - \gamma)(1 - \rho)D_{i,t-2} + \gamma\rho\alpha E_{i,t} + \eta_i + \xi_{i,t},$$

where $\eta_i = \gamma\rho\mu_i$ and $\xi_{i,t} = \rho\pi_j + [(\kappa_t + v_{i,t}) - (1 - \rho)(\kappa_{t-1} + v_{i,t-1})]$. However, one cannot identify γ and ρ separately by estimating this reduced-form model.

⁸A firm's expected earnings can be expressed as a weighted average of its current and past observed earnings with geometrically declining weights if $0 < \rho < 1$. The weight for $E_{i,t-k}$ is $\rho(1 - \rho)^k$ for $k = 0, 1, 2, \dots$.

Substituting $\rho E_{i,t} + (1 - \rho)E_{i,t-1}^e$ for $E_{i,t}^e$ in Equation (4), substituting $\frac{1}{\gamma\alpha}[D_{i,t-1} - (1 - \gamma)D_{i,t-2} - \gamma\beta Q_{i,t-2} - \gamma\mu_i - \pi_j - \kappa_{t-1} - v_{i,t-1}]$ for $E_{i,t-1}^e$, and rearranging the equation gives the following reduced-form model:

$$\begin{aligned} D_{i,t} &= (1 - \gamma)D_{i,t-1} + \gamma\alpha\rho E_{i,t} + \gamma\alpha(1 - \rho)E_{i,t-1}^e + \gamma\beta Q_{i,t-1} + \gamma\mu_i + \pi_j + \kappa_t + v_{i,t} \\ &= [(1 - \gamma) + (1 - \rho)]D_{i,t-1} + \gamma\rho\alpha E_{i,t} - (1 - \gamma)(1 - \rho)D_{i,t-2} + \gamma\beta Q_{i,t-1} \\ &\quad - \gamma(1 - \rho)\beta Q_{i,t-2} + \gamma\rho\mu_i + \rho\pi_j + [(\kappa_t + v_{i,t}) - (1 - \rho)(\kappa_{t-1} + v_{i,t-1})]. \end{aligned} \quad (6)$$

This can be rewritten as the following standard dynamic panel regression model:

$$D_{i,t} = \delta_1 D_{i,t-1} + \delta_2 E_{i,t} + \delta_3 D_{i,t-2} + \delta_4 Q_{i,t-1} + \delta_5 Q_{i,t-2} + \eta_i + \xi_{i,t}, \quad (7)$$

where $\delta_1 = (1 - \gamma) + (1 - \rho)$, $\delta_2 = \gamma\rho\alpha$, $\delta_3 = -(1 - \gamma)(1 - \rho)$, $\delta_4 = \gamma\beta$, $\delta_5 = -\gamma(1 - \rho)\beta$, $\eta_i = \gamma\rho\mu_i$, and $\xi_{i,t} = \rho\pi_j + [(\kappa_t + v_{i,t}) - (1 - \rho)(\kappa_{t-1} + v_{i,t-1})]$. The error term $\xi_{i,t}$ is an MA(1) process if each of κ_t and $v_{i,t}$ is assumed to be white noise.⁹ A consistent estimator can be obtained using System GMM suggested by Arellano and Bover (1995) and Blundell and Bond (1998). The delta method is employed in order to estimate structural parameters $(\gamma, \rho, \alpha, \beta)$ as nonlinear combinations of regression coefficients.¹⁰

3. Results

Before we present our main results, we first estimate the conventional partial adjustment models that can be viewed as a special case of our generalized model

⁹This does not imply that the actual residuals always follow the process implied by the specification. However, in both Difference GMM and System GMM, a different error structure would result in a different set of valid instruments as suggested by the Sargan-Hansen test of overidentifying restrictions. A less restrictive assumption such as MA(1), compared with the case of MA(0), allows for a smaller number of valid instruments.

¹⁰We use the following nonlinear combinations of coefficients to obtain the structural parameters. First, dividing $-\delta_5$ by δ_4 gives an estimate of $1 - \rho$:

$$\frac{-\delta_5}{\delta_4} = \frac{\gamma(1 - \rho)\beta}{\gamma\beta} = (1 - \rho),$$

and therefore $\rho = 1 + \frac{\delta_5}{\delta_4}$. Second, we can get $(1 - \gamma)$ using the equation for δ_1 :

$$(1 - \gamma) = \delta_1 - (1 - \rho) = \delta_1 + \frac{\delta_5}{\delta_4},$$

and therefore $\gamma = 1 - \delta_1 - \frac{\delta_5}{\delta_4}$. Finally, $\alpha = \frac{\delta_2}{\gamma\rho}$ and $\beta = \frac{\delta_4}{\gamma}$.

in the sense that the speed of expectations revision (ρ) is set to 1. Thus, managers in this model form future earnings prospects based only on current earnings. Table 1 reports estimation results based on three different estimation methods, i.e., Pooled OLS, Within Groups, and System GMM estimators. Regardless of estimation methods, the parameter estimates, $\hat{\alpha}$ and $\hat{\beta}$, for target payout determinants are significantly positive at the 1% significance level. The estimated speed of adjustment ($\hat{\gamma}$) is comparable to the estimates reported in previous studies.¹¹ The Sargan-Hansen tests of overidentifying restrictions do not reject the specifications in Columns (3) and (4).¹² Note, however, that because the partial adjustment model and adaptive expectations model are observationally equivalent in their estimable forms, the parameter estimate ($\hat{\gamma}$) which we just interpreted as the speed of dividend adjustment may, in fact, represent the speed of expectations revision ($\hat{\rho}$).¹³

In Table 2, we report the main regression results for our generalized partial adjustment model. Although the estimation results are qualitatively similar across the estimation methods, our System GMM estimates reported in Columns (3) and (4) are considered better as they are known to be consistent and efficient. Moreover, our models as reported in those two columns are strongly supported by the Sargan-Hansen tests and Arellano-Bond second-order serial correlation tests. Several aspects of the estimates are of particular interest. First, the estimated speed of adjustment ($\hat{\gamma}$) is much higher than those reported in the existing literature. Note that, regardless of estimation methods, $\hat{\gamma}$ is also much higher than the adjustment speed estimated in Table 1. The results are qualitatively similar across the estimation methods, although $\hat{\gamma}$ is slightly higher with OLS estimates ($\hat{\gamma}^{OLS} = 0.994$;

¹¹Fama and French (2002) report an estimate of about 0.30. Dewenter and Warther (1998), on the other hand, obtain a much lower average estimate of 0.055 for 313 US firms studied. A somewhat higher speed from the Within Groups estimation in Table 1 may be driven by the short-panel bias (Nickell, 1981).

¹²In Columns (3) and (4), we report the set of instruments used in first-differenced equations and level equations. Arellano and Bond's (1991) second-order serial correlation tests suggest that the error term ξ_{it} is an MA(1) process. This reduces the number of lags available as instruments.

¹³The System GMM model reported in Column (4) is considered the best for the following reasons. First, the estimate for the lagged dependent variable based on System GMM lies between OLS and Within Groups estimates which tend to be biased upwards and downwards, respectively. Second, the goodness-of-fit score for System GMM model is slightly higher than that for Within Groups model and the same as that for OLS model. Third, p -value for the Sargan-Hansen test of overidentifying restrictions in Column (4) is much higher than that in Column (3). In any case, our main regression results are reported in Table 2.

Table 1: Estimation results for conventional partial adjustment models of dividends

ESTIMATION METHOD VARIABLES	(1) Pooled OLS $D_{i,t}$	(2) Within Groups $D_{i,t}$	(3) System GMM $D_{i,t}$	(4) System GMM $D_{i,t}$
First-lagged dividends ($D_{i,t-1}$)	0.825*** (0.011)	0.692*** (0.018)	0.831*** (0.020)	0.819*** (0.025)
Current earnings ($E_{i,t}$)	0.026*** (0.002)	0.024*** (0.002)	0.024*** (0.004)	0.028*** (0.006)
First-lagged Tobin's Q ($Q_{i,t-1}$)	0.001*** (0.000)	0.002*** (0.000)	0.001*** (0.000)	0.001** (0.000)
Constant	0.001 (0.001)	0.004*** (0.001)	-0.000 (0.001)	-0.000 (0.005)
Firm fixed effects	No	Yes	Yes	Yes
Industry fixed effects	Yes	No	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Number of observations	24,926	24,926	24,926	24,926
Number of firms	981	981	981	981
Goodness of fit— $(Corr(D_{i,t}, \widehat{D}_{i,t}))^2$	0.834	0.832	0.833	0.834
First-order serial correlation (p -value)			0.000	0.000
Second-order serial correlation (p -value)			0.000	0.000
Third-order serial correlation (p -value)			0.371	0.366
Sargan-Hansen test (p -value)			0.110	0.873
Dividend adjustment speed ($\widehat{\gamma}$) or expectations revision speed ($\widehat{\rho}$)	0.175*** (0.011)	0.308*** (0.018)	0.169*** (0.020)	0.181*** (0.025)
Target dividends–current earnings sensitivity ($\widehat{\alpha}$)	0.147*** (0.008)	0.079*** (0.006)	0.142*** (0.023)	0.156*** (0.031)
Target dividends–Tobin's Q sensitivity ($\widehat{\beta}$)	0.008*** (0.001)	0.006*** (0.001)	0.005** (0.002)	0.005** (0.002)
Instruments for first-differenced equations			$D_{i,t-4}, \dots, D_{i,t-8}$ $E_{i,t-4}, \dots, E_{i,t-8}$ $Q_{i,t-4}, \dots, Q_{i,t-8}$	$D_{i,t-4}, \dots, D_{i,t-10}$ $E_{i,t-4}, \dots, E_{i,t-10}$ $Q_{i,t-4}, \dots, Q_{i,t-10}$
Instruments for level equations			$\Delta D_{i,t-3}$ $\Delta E_{i,t-3}$ $\Delta Q_{i,t-3}$ Ind. dummies Year dummies	$\Delta D_{i,t-3}$ $\Delta E_{i,t-3}$ $\Delta Q_{i,t-3}$ Ind. dummies Year dummies

Note: In all four columns, we report standard errors that are asymptotically robust to both heteroskedasticity and serial correlation. In the last two columns, we report two-step GMM coefficients and standard errors which use the finite-sample correction proposed by Windmeijer (2005). ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

$\hat{\gamma}^{WG} = 0.933$; $\hat{\gamma}^{SGMM} = 0.930 \sim 0.946$). This finding corroborates our intuition that “sticky” dividends may not be evidence that firms do not actively reassess how much they should pay in dividends, but that they actively align their dividends with the “smooth” target payouts. Consequently, the actual dividends also tend to be smooth and the adjustment speeds are, in fact, higher than previously documented. Second, the speed of expectations revision ($\hat{\rho}$) is much lower than 1 ($\hat{\rho}^{OLS} = 0.384$; $\hat{\rho}^{WG} = 0.509$; $\hat{\rho}^{SGMM} = 0.449 \sim 0.459$). Note that the speed is implicitly assumed to be 1 in the conventional partial adjustment models.¹⁴ This result indicates that managers consider a longer history of performances rather than current earnings only in setting the target payouts, offering a plausible explanation for dividends’ tendency to lag behind earnings (Fama and Babiak, 1968).

Coefficients for all of the variables incorporated in Equation (6) are statistically significant at the 1% or 5% level. As evidenced by the significantly positive $\hat{\alpha}$ and $\hat{\beta}$ in Equation (2), future earnings prospects and growth opportunities have positive influences on target dividends. We implement the analysis of covariance (ANCOVA) to further examine the relative importance of various determinants in capturing the variation in target dividends. Table 3 shows, as predicted, that the total sum of squares in the generalized model (1.008) is only a small fraction (11.6%) of the conventional model counterpart (8.659), which confirms that target dividends remain far more stable over time in the generalized model. Similarly, Figure 2 shows that the volatility of target dividends in the generalized model is far below that in the conventional model.

The ANCOVA results reported in Panel B of Table 3 show that time-invariant firm-specific effects are the major source of the total variation. It is interesting to note that while the total variation explained by time-varying expected earnings on a stand-alone basis is 63.2% (Column (1)), its contribution (17.4% in column (5)) is smaller than that of time-invariant firm-specific effects (31.3% in Column (5)).¹⁵ Intuitively, this suggests that much of the explanatory power of existing (target) dividend determinants comes from the cross-sectional, as opposed to time-series, variation. Overall, our results provide some new evidence that firms’ target payout policies may not be as puzzling as previously thought. Rather, it may be

¹⁴Thus, conventional partial adjustment models impose a strong restriction on the way managers form future earnings prospects and set the target dividends.

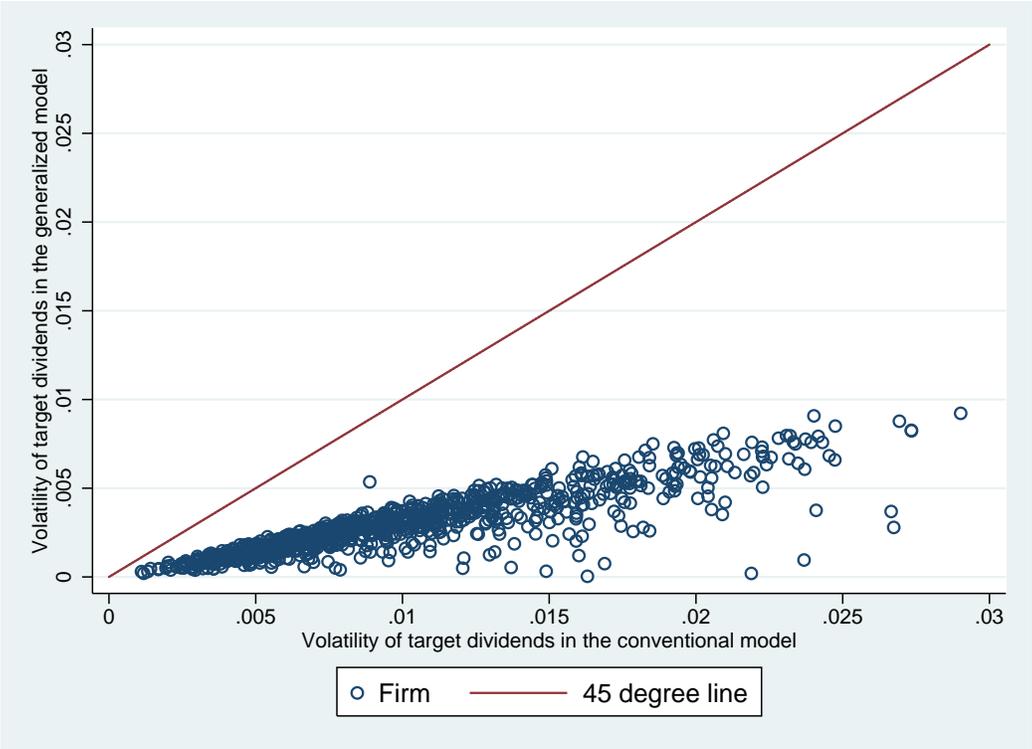
¹⁵The ANCOVA results reported in Panel A also show that the contribution of time-varying expected earnings (26.9% in Column (5)) is similar to that of time-invariant firm-specific effects (26.6% in Column (5)). This suggests that the contribution of time-invariant firm-specific effects is larger in the case of the generalized partial adjustment model (Panel B).

Table 2: Estimation results for generalized partial adjustment models of dividends

ESTIMATION METHOD VARIABLES	(1) Pooled OLS $D_{i,t}$	(2) Within Groups $D_{i,t}$	(3) System GMM $D_{i,t}$	(4) System GMM $D_{i,t}$
First-lagged dividends ($D_{i,t-1}$)	0.622*** (0.023)	0.558*** (0.025)	0.605*** (0.049)	0.611*** (0.043)
Current earnings ($E_{i,t}$)	0.026*** (0.002)	0.025*** (0.002)	0.027*** (0.004)	0.029*** (0.004)
Second-lagged dividends ($D_{i,t-2}$)	0.234*** (0.020)	0.183*** (0.019)	0.235*** (0.043)	0.222*** (0.038)
First-lagged Tobin's Q ($Q_{i,t-1}$)	0.003*** (0.000)	0.003*** (0.000)	0.002*** (0.001)	0.002*** (0.001)
Second-lagged Tobin's Q ($Q_{i,t-2}$)	-0.002*** (0.000)	-0.001*** (0.000)	-0.001** (0.000)	-0.001** (0.000)
Constant	0.001 (0.001)	0.003*** (0.001)	0.002* (0.001)	-0.001 (0.001)
Firm fixed effects	No	Yes	Yes	Yes
Industry fixed effects	Yes	No	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Number of observations	23,653	23,653	23,653	23,653
Number of firms	979	979	979	979
Goodness of fit— $(Corr(D_{i,t}, \hat{D}_{i,t}))^2$	0.840	0.838	0.840	0.840
First-order serial correlation (p -value)			0.000	0.000
Second-order serial correlation (p -value)			0.152	0.184
Sargan-Hansen test (p -value)			0.096	0.868
Dividend adjustment speed ($\hat{\gamma}$)	0.994*** (0.052)	0.933*** (0.064)	0.946*** (0.135)	0.930*** (0.125)
Expectations revision speed ($\hat{\rho}$)	0.384*** (0.053)	0.509*** (0.067)	0.449** (0.132)	0.459*** (0.123)
Target dividends—expected earnings sensitivity ($\hat{\alpha}$)	0.067*** (0.007)	0.053*** (0.005)	0.063** (0.014)	0.069*** (0.014)
Target dividends—Tobin's Q sensitivity ($\hat{\beta}$)	0.003*** (0.000)	0.003*** (0.000)	0.002** (0.001)	0.002*** (0.001)
Instruments for first-differenced equations			$D_{i,t-4}, \dots, D_{i,t-8}$ $E_{i,t-4}, \dots, E_{i,t-8}$ $Q_{i,t-4}, \dots, Q_{i,t-8}$	$D_{i,t-4}, \dots, D_{i,t-10}$ $E_{i,t-4}, \dots, E_{i,t-10}$ $Q_{i,t-4}, \dots, Q_{i,t-10}$
Instruments for level equations			$\Delta D_{i,t-3}$ $\Delta E_{i,t-3}$ $\Delta Q_{i,t-3}$ Ind. dummies Year dummies	$\Delta D_{i,t-3}$ $\Delta E_{i,t-3}$ $\Delta Q_{i,t-3}$ Ind. dummies Year dummies

Note: In all four columns, we report standard errors that are asymptotically robust to both heteroskedasticity and serial correlation. In the last two columns, we report two-step GMM coefficients and standard errors which use the finite-sample correction proposed by Windmeijer (2005). ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Figure 2: Comparison of volatilities of target dividends: conventional vs. generalized models



Note: This figure plots within-firm volatilities of target dividends in the generalized model against those in the conventional model. Each circle represents a firm among 969 firms.

the case that managers set target payouts cautiously by conditioning them on a longer stretch of available earnings data. The smooth dividend paths observed in the market, therefore, may be rational responses to target payouts determined in such a way, resulting in higher speeds of adjustment to the targets.

4. Conclusion

This study proposes a generalized partial adjustment model of dividends in which managers form future earnings prospects adaptively and set the target dividends based on the earnings prospects. The main contribution of this study is to present new evidence with respect to the dynamic behavior of firms' dividend policies. We show that the slow adjustments of dividends to target payouts reported using conventional models largely stem from a strong restriction imposed on the way firms determine their dividend targets. Given that firms' earnings are quite volatile, the target payouts themselves will be more volatile when managers set the targets solely based on the current earnings compared to when they use adaptive expectations. This will, in turn, lead to larger deviations of actual dividend payouts from the targets and hence slower speeds of dividend adjustments, *ceteris paribus*, making it more challenging to account for firms' dividend payout policies. If target dividends set by managers are smoother, on the other hand, actual dividends observed in the market will become more in line with the targets, driving up the speed of adjustment. Our model offers an insight that smooth dividend paths could be a consequence of managers' attempts to match dividend payouts with the targets. A variance decomposition analysis shows that firm-specific effects are predominant sources of variations in target payouts, suggesting that the majority of the total variation in target dividends is due to time-invariant factors.

Appendix

A. Empirical evidence for sticky dividends

We begin our analysis by studying the evolution of dividend ratios for our cross-section of firms in the spirit of Lemmon et al. (2008). Figure A.1 presents the average dividend-to-total assets ratios of three actual portfolios in "event time." The figure is constructed in the following manner. Each calendar year, we sort firms into three portfolios based on their dividend ratios, which we denote: Above

Table 3: Variance decompositions of target dividends

Panel A. Target dividends from the conventional partial adjustment model					
VARIABLES	(1) $D_{i,t}^*$	(2) $D_{i,t}^*$	(3) $D_{i,t}^*$	(4) $D_{i,t}^*$	(5) $D_{i,t}^*$
Current earnings ($E_{i,t}$)	0.669		0.420		0.269
Tobin's Q ($Q_{i,t-1}$)		0.314	0.065		0.020
Firm-specific effects (μ_i)				0.642	0.266
Number of Observations	24,926	24,926	24,926	24,926	24,926
Root MSE	0.011	0.015	0.010	0.011	0.000
Adjusted R-Squared	0.669	0.314	0.735	0.627	1.000
Total Sum of Squares	8.659				

Panel B. Target dividends from the generalized partial adjustment model					
VARIABLES	(1) $D_{i,t}^e$	(2) $D_{i,t}^*$	(3) $D_{i,t}^*$	(4) $D_{i,t}^*$	(5) $D_{i,t}^*$
Expected earnings ($E_{i,t}^e$)	0.632		0.345		0.174
Tobin's Q ($Q_{i,t-1}$)		0.342	0.056		0.018
Firm-specific effects (μ_i)				0.741	0.313
Number of observations	21,222	21,222	21,222	21,222	21,222
Root MSE	0.004	0.006	0.004	0.004	0.000
Adjusted R-Squared	0.632	0.342	0.688	0.728	1.000
Total Sum of Squares	1.008				

Note: We compute the partial sum of squares for each effect in the model and then normalize each estimate by the total sum of squares. For example, in Column (5) of Panel B, 31.3% of the total sum of squares can be attributed to unobserved firm-specific effects (μ_i). Expected earnings are computed as follows: $E_{i,t}^e = \sum_{k=0}^4 (1 - \hat{\rho})^k \hat{\rho} E_{i,t-k}$ where $\hat{\rho}$ is the estimated speed of expectation revision reported in Column (4), Table 2. To compute fixed effects in target dividends, we go through the following procedures. First, we compute within-firm average residuals in the dynamic regression model. Second, we add the mean of time effects to the within-firm average residuals to get firm-specific effects in dividends (η_i). Finally, we divide the firm-specific effects in dividends by $\hat{\gamma} (\hat{\gamma}\hat{\rho})$ to estimate firm-specific effects in target dividends (μ_i) in the conventional (generalized) model.

median, Below median, and Zero dividend.¹⁶ The portfolio formation year is denoted event year 0. We then compute the average dividend for each portfolio in each of the subsequent 20 years, holding the portfolio composition constant (but for firms that exit the sample). We repeat these two steps of sorting and averaging for every year in the sample period. This process generates 25 sets of event-time averages, one for each calendar year in our sample.¹⁷ We then calculate the averages of the average dividend-to-total assets ratios across the 25 sets within each event year, which are shown in bold lines. Surrounding dotted lines represent 95% confidence intervals.

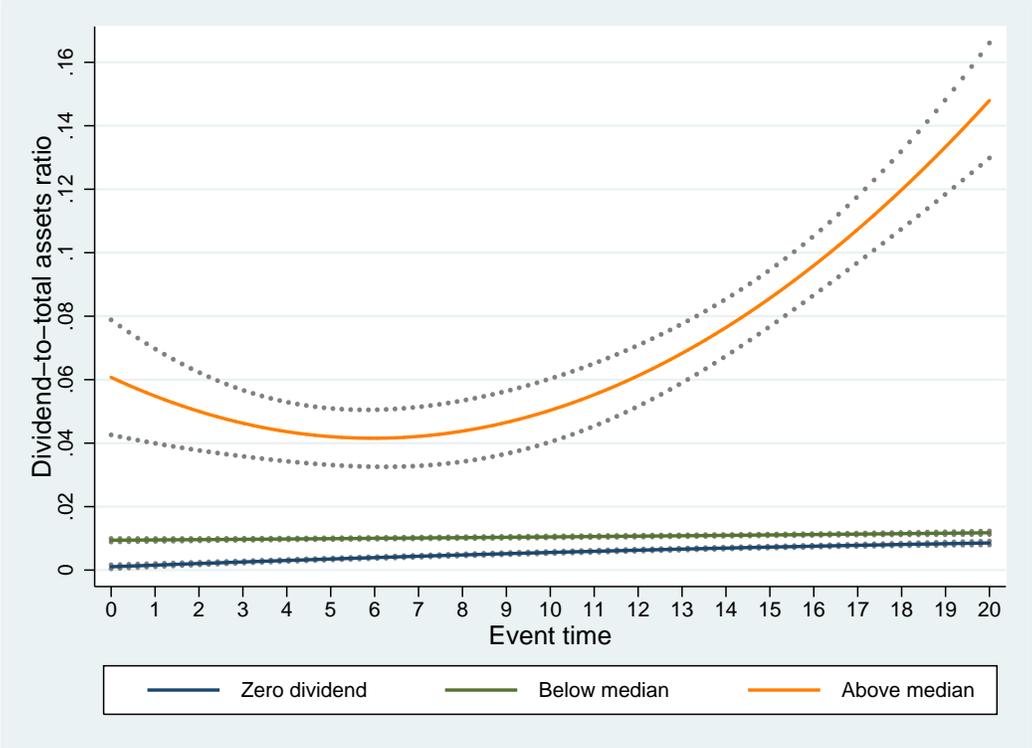
Several features of the figure are noteworthy. First, there exist a great deal of cross-sectional differences in the average dividend-to-total assets ratios in the initial portfolio formation period. Average dividend of the above-median-dividend portfolio is 5.3%, while average dividend of the below-median-dividend portfolio is only 0.9% and average dividend of the zero-dividend portfolio is exactly 0.0%. Second, there is significant divergence among all three portfolio averages over the event time. After 20 years, the above-median-dividend portfolio has increased to 15.7%, whereas the below-median-dividend portfolio (the zero-dividend portfolio) has increased to 1.2% (1.0%). Note that the average dividends across the portfolios 20 years later remain significantly different, both statistically and economically. When compared to the cross-sectional average of within-firm standard deviation of dividend-to-total assets ratios (1.3%), this differential is economically huge. Therefore, a preliminary examination of dividend ratios suggests the presence of a permanent or long-run component that leads to highly persistent cross-sectional differences in dividend ratios.

We then move on to a variance decomposition of dividend-to-total assets ratios. We begin with a nonparametric framework. Specifically, we compute the within- and between-firm variations of dividend ratios, finding that these estimates in terms of standard deviation are 1.23% and 1.59%, respectively. Thus, the between-firm variation is approximately 29% larger than the within-firm variation. Intuitively, this suggests that dividend varies significantly more across firms, as opposed to within firms over time, consistently with the patterns observed in

¹⁶The median is calculated using the sample consisting of firms with positive dividends in the portfolio formation year.

¹⁷As we require that firms exist for at least 20 years after the formation of portfolios, we perform the portfolio formation each year from 1971 to 1995 for our sample. We start from 1971 as we lose one observation due to the use of lagged total assets when we compute the dividend-to-total assets ratio.

Figure A.1: Average dividend-to-total assets ratios of actual dividend portfolios in event time



Note: This figure plots average dividend-to-total assets ratios of actual dividend portfolios. The sample consists of all firms (excluding financial firms, regulated utilities, or government entities) from the CCM database from 1970 to 2015. To obtain this figure, first, for each calendar year from 1971 to 1995, we sort the firms into three groups based on dividend-to-total assets ratios (denoted as Zero dividend, Below median, and Above median) and calculate the average ratios for each of the three portfolios in each of the subsequent 20 years, holding the portfolio composition constant. We use the median based on the sample consisting of firms with positive dividends in the portfolio formation year. We repeat this process for all the years from 1971 to 1995. This process generates 25 sets of event-time averages. Second, we compute the average of the average dividend-to-total assets ratios across the 25 sets within each event year to obtain the bold lines in the figure. Surrounding dotted lines represent 95% confidence intervals.

Table A.1: Variance decompositions of actual dividends

VARIABLES	(1) $D_{i,t}$	(2) $D_{i,t}$	(3) $D_{i,t}$	(4) $D_{i,t}$	(5) $D_{i,t}$
Current earnings ($E_{i,t}$)	0.229		0.100		0.022
Tobin's Q ($Q_{i,t-1}$)		0.225	0.095		0.012
Firm-specific effects (η_i)				0.637	0.360
Number of Observations	25,110	25,110	25,110	25,110	25,110
Root MSE	0.018	0.018	0.017	0.012	0.012
Adjusted R-Squared	0.229	0.225	0.324	0.623	0.671
Total Sum of Squares	10.392				

Note: We compute the partial sum of squares for each effect in the model and then normalize each estimate by the total sum of squares. For example, in Column (5), 36.0% of the total sum of squares can be attributed to unobserved firm-specific effects (η_i).

Figure A.1. We now turn to a parametric framework, analysis of covariance (ANCOVA), to decompose the variation in actual dividends attributable to different factors. Table A.1 shows that firm-specific effects (η_i) account for 36.0% of the total sum of squares (10.392) in the specification reported in Column (5). This also suggests that the time-invariant firm-specific components are the major source of total variation in dividends.

B. An identification problem

In this section we show that a conventional partial adjustment model and an adaptive expectations model yield indistinguishable empirical specifications for the dividend adjustment process.¹⁸ Nesting both models as special cases, our proposed model allows partial adjustment behavior and expectation updating to work together to characterize firms' dynamic dividend adjustment behavior. The conventional partial adjustment models of dividends found in the literature can be specified as the following three equations:

$$D_{i,t} - D_{i,t-1} = \gamma(D_{i,t}^* - D_{i,t-1}) + \pi_j + \kappa_t + v_{i,t}; \quad (\text{B.1})$$

$$D_{i,t}^* = \alpha E_{i,t}^e + \mu_i; \quad (\text{B.2})$$

$$E_{i,t}^e = E_{i,t}, \quad (\text{B.3})$$

¹⁸Although their proof is not done in the panel data setting, Waud (1966) first shows that a conventional partial adjustment model and an adaptive expectations model yield indistinguishable empirical specifications as far as estimation is concerned.

where $D_{i,t}$ and $D_{i,t}^*$ denote the actual and target dividends (scaled by assets) of firm i in year t .¹⁹ The target dividend ratio, $D_{i,t}^*$, is determined by statically-formed earnings expectations ($E_{i,t}^e$) and unobserved firm-specific effects (μ_i). Note that the conventional partial adjustment model implicitly assumes that earnings expectations are formed statically, i.e., $E_{i,t}^e = E_{i,t}$ (Waud, 1966).²⁰ Thus, the target dividend ratio is essentially determined by a fraction (α) of observed current earnings (scaled by assets) ($E_{i,t}$) and unobserved firm-specific effects (μ_i), where α denotes the target payout ratio to be applied to current earnings.²¹ γ represents the speed of adjustment which measures how fast firms adjust to their target or optimal dividends.

With some substitutions and re-parameterizations, we finally obtain the following standard dynamic panel regression model:

$$D_{i,t} = b_1 D_{i,t-1} + b_2 E_{i,t} + \eta_i + \xi_{i,t}, \quad (\text{B.4})$$

for $i = 1, \dots, N$ and $t = 2, \dots, T$ where $b_1 = (1 - \gamma)$ and $b_2 = \gamma\alpha$. Therefore, the speed of adjustment can be estimated as $\hat{\gamma} = 1 - \hat{b}_1$. Similarly, the sensitivity of target dividends to earnings can be estimated as $\hat{\alpha} = \hat{b}_2 / (1 - \hat{b}_1)$.

We now consider an adaptive expectations model of dividends to highlight a major potential cause of the reported slow dividend adjustment speeds. It may arise from the fact that the dynamic panel regression models used to estimate the adjustment speed can also be derived by assuming that firms adaptively form expectations of their earnings to determine their actual dividend policies. The expectation formation process is specified as follows:

$$E_{i,t}^e - E_{i,t-1}^e = \rho(E_{i,t} - E_{i,t-1}^e), \quad (\text{B.5})$$

where $0 < \rho \leq 1$. $E_{i,t}$ is the earnings ratio observed in period t , and $E_{i,t-1}^e$ and $E_{i,t}^e$ are the earnings ratios expected to prevail in periods $t - 1$ and t , respectively. ρ

¹⁹The error term in the partial adjustment equation consists of three parts. π_j and κ_i represent unobserved industry-specific and year-specific effects, and $v_{i,t}$ represents the idiosyncratic error with zero mean and no serial correlation. Note that the error components π_j and κ_i can be replaced by industry dummies and year dummies, respectively.

²⁰The static expectations formation is essentially a special case of the adaptive expectations formation in that the static expectations formation process is equivalent to the adaptive expectations formation process with $\rho = 1$.

²¹Lintner (1956), Fama and Babiak (1968), and Fama and French (2002) also model the target dividend ratio as a function of observed current earnings, but do not include unobserved firm-specific effects.

represents the proportion of the expectation error $(E_{i,t} - E_{i,t-1}^e)$ taken to be permanent rather than transitory. For example, if $\rho = 1$, then all of the error is taken to be permanent and $E_{i,t}^e = E_{i,t}$. Note that a firm's expected earnings can be expressed as a weighted average of its current and past observed earnings with geometrically declining weights if $0 < \rho < 1$. The weight for $E_{i,t-k}$ is $\rho(1 - \rho)^k$ for $k = 0, 1, 2, \dots$.

Assume now that the expected earnings ratio ($E_{i,t}^e$) determines the actual dividend ratio $D_{i,t}$:

$$D_{i,t} = \alpha E_{i,t}^e + \mu_i + \pi_j + \kappa_t + v_{i,t}. \quad (\text{B.6})$$

Substituting $\rho E_{i,t} + (1 - \rho)E_{i,t-1}^e$ for $E_{i,t}^e$, substituting $\frac{1}{\alpha}(D_{i,t-1} - \mu_i - \pi_j - \kappa_{t-1} - v_{i,t-1})$ for $E_{i,t-1}^e$, and rearranging the equation gives the following standard dynamic panel regression model:

$$D_{i,t} = b_1 D_{i,t-1} + b_2 E_{i,t} + \eta_i + \xi_{i,t}, \quad (\text{B.7})$$

for $i = 1, \dots, N$ and $t = 1, \dots, T$ where $b_1 = (1 - \rho)$ and $b_2 = \rho\alpha$. Therefore, the speed of expectations revision can be estimated as $\widehat{\rho} = 1 - \widehat{b}_1$.

It can clearly be seen that the reduced-form equations for the partial adjustment model and the adaptive expectations model are indistinguishable. Hence, one cannot tell whether the estimated coefficient of the lagged dividend ratio (\widehat{b}_1) is driven by the speed of dividend adjustment (γ) or the speed of expectations revision (ρ). That is, one cannot separately identify γ and ρ using the dynamic panel data regression model described above. Therefore, we use a generalized partial adjustment model with an adaptive expectations formation process which renders both parameters identifiable. The model is described in Section 2.

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