# Reconciling Divergent Findings on the Speed of Leverage Adjustment*


**Abstract**

Estimates of firms' speeds of leverage adjustment ($SOA$s) vary wildly. Studies producing these estimates impose a strong constraint: An average $SOA$ is estimated for *all firms* in a sample. Using finite mixture models ($FMM$) we uncover four distinct types of behaviors characterizing $SOA$s. The four behaviors in this regard can be classified as: *Nearly stable* ($SOA$ = 2%); *slower adjusters* ($SOA$ = 28%); *faster adjusters* ($SOA$ = 62%) and *drifters* ($SOA$ = -3%) who slowly move away from estimated leverage targets.



*Keywords:* Speed of leverage adjustment, finite mixture models.

*JEL:* G30, G32


**Highlights**

- We demonstrate the usefulness of finite mixture models in corporate finance in general.
- The approach implemented here uncovers four distinct patterns of firms' speeds of leverage adjustment.
- The four $SOA$ behaviors are *nearly stable*, *slower adjusters*, *faster adjusters* and *drifters*.
- The four $SOA$ behaviors have systematic associations with firm characteristics.

## 1. Introduction and Background

The concept of target leverage has attracted considerable attention in studies of capital structure. Numerous papers have documented firms adjusting their leverage to a target (behavior consistent with the trade-off theory).[1] Estimates of the speed of adjustment (SOA) vary widely. Table 1 summarizes the estimated $SOA$s for leverage. Leary and Roberts (2005) provide an alternative view of capital adjustment that potentially has different assumptions to many of the papers summarized in Table 1.[2] These estimates range from 8.8% per annum to over 39% per annum, suggesting half-lives of between 1.40 and 7.52 years.[3] Table 1 also documents the breadth of estimation methods used to estimate these differing figures. While the methods and estimates vary, the studies present considerable agreement in imposing a potentially strong constraint on the data: An average $SOA$ is estimated for *all* firms.

Insert Table 1 here

The variation in the estimates of $SOA$ is both perplexing and challenging. We depart from papers imposing the constraint that the $SOA$ is the same for *all* firms. We use finite mixture models ($FMM$) to test the assumption that an average SOA for all firms is an appropriate way of estimating SOAs (and, by construction, testing the trade-off theory). $FMM$ involves probabilistically splitting the sample (all firm-year observations) into a finite number of homogeneous classes, or groups. It is important to note that using $FMM$ it is the data, not the researcher that determines group membership. A result of using $FMM$ is that the same explanatory variables (firm-specific characteristics) can have differing effects across the groups or classes (Bago d'Uva and Jones 2009). In other words, we can use $FMM$ to make inferences about each subpopulation and classify individual firm-year observations into classes.[4]

We demonstrate that, for our sample, the assumption that there is an average $SOA$ for all firms does not hold. Indeed, we find evidence that there are four distinct groups or classes of firms with respect to leverage levels. Importantly, these differ significantly with respect not only to expected leverage levels within each group or class, but also to the different behaviors firms adopt when adjusting leverage.

[1]Static trade-off theory argues that firms set their capital structure in a single period (Kraus and Litzenberger 1973; Jensen and Meckling 1976; Myers 1977; Bradley et al. 1984). The dynamic trade-off model introduces time and frictions and suggests that adjustment occurs over a number of years (Dang et al. 2012; Faulkender et al. 2012).

[2]They argue that "...most empirical tests, however, implicitly assume that this rebalancing is cost-less: in the absence of adjustment costs, firms can continuously rebalance their capital structures toward an optimal level of leverage. However, in the presence of such costs, it may be suboptimal to respond immediately to capital structure shocks" on page 2576. FMM might be usefully applied to the survival analysis presented in their paper although its implementation is more complex than the methodology we explore here. Despite their issue with the literature, Leary and Roberts' findings are consistent with dynamic trade-off (see footnote 1)

[3]Half-life is the time the adjustment needs to close the gap by 50% between the observed leverage ratio and the target leverage. Half-life is calculated as $\ln(0.5)/\ln(1\text{-}SOA)$.

[4]For example, Hui et al. (2015), find that the new observed likelihood criterion, $\mathrm{AIC}_{\mathrm{mix}}$ and the BIC, perform strongly regardless of the level of classification uncertainty.

We find that over half of the sample adjusts leverage to targets, and of these, around 35% have an estimated average $SOA$ of around 28% (the *slower adjusters*; group 2); whilst group 3, comprising about 15% of the sample, are *faster adjusters*, with an estimated $SOA$ of 62%. An estimated quarter of the sample (the *nearly stable* group; group 1) has an estimated $SOA$ of 2%; whilst the remaining firm-year observations (the *drifters*; group 4) appear to slowly move away from the estimated leverage targets. Note that the $SOA$s for *slower* and *faster adjusters* (groups 2 and 3, respectively) are at the higher end of the estimates summarized in Table 8.

Our paper makes two major contributions to the existing literature. First, we use the $FMM$ to classify firm-year observations into subpopulations based on all observed firm-specific characteristics used in the literature. An advantage of utilizing $FMM$, rather than specifying firm characteristics, is that it discovers, rather than imposes, the underlying structure of the data. Imposing a structure may have the potential advantage of testing a particular theory (though not necessarily competing theories) and may simply beg the question that is supposedly being examined.

*Ex post* the $FMM$ technique has the advantage of facilitating the consideration of uncovering joint correlations of observed firm heterogeneity and class membership. Here, we demonstrate how fractional multinomial logit models can address this question following an initial classification generated by the $FMM$. We find a pattern generally consistent with firms being 'more keen' to move towards targets if they are firms with low growth opportunities, lower profitability or smaller size. These appear to undertake *faster* leverage adjustment than those with opposite characteristics, that is, firms with higher growth opportunities, greater profitability or larger size. Further, firms with more tangible assets are keen to be *slower adjusters*.

Secondly, the methodology employed highlights the importance of considering the robustness of analyses in corporate finance to the 'one-model-fits-all' approach. We analyze the panel of firm-year data using the $FMM$ approach. The approach is tractable and our discussion is pitched to assist corporate finance researchers who wish to consider the robustness of their results in other domains. We present an overview of the methodology in section 2 before presenting our data selection and results in section 3. Section 4 concludes the paper.

## 2. Methods

The key starting point for us was the seminal work by Flannery and Hankins (2013) and the following derives heavily from their set-up. In the first instance, assume, as is common, that the leverage ratio ($Lev$) of firm $i$ ($i = 1, \ldots, N$) in time period $t$ ($t = 1, \ldots, T$) is determined in the following manner

$$Lev_{i,t+1} - Lev_{it} = \lambda \left( Lev^*_{i,t+1} - Lev_{it} \right) + u_{i,t+1}, \tag{1}$$

where $Lev^*$ represents the firm's target leverage ratio ($target\ lev$) and $u_{it+1}$ an error term. That is, the firm simply adjusts to their $target\ lev$ at the speed given by the key (unknown) parameter in the model, $\lambda$.

Equation (1) is made operational by assuming that target leverage is a function of a $(k \times 1)$ vector of observed firm heterogeneity $x_{it}$, as well as a scalar unobserved firm effect, $\alpha_i$, such that

$$Lev_i^* = x_{it}'\beta + \alpha_i \tag{2}$$

Substituting equation (2) into equation (1) yields an estimable model of the form

$$\begin{aligned} Lev_{i,t+1} &= \lambda \left(x_{it}'\beta + \alpha_i\right) + (1-\lambda)\, Lev_{it} + u_{i,t+1} \\ &= x_{it}'\left(\beta\lambda\right) + \lambda\alpha_i + (1-\lambda)\, Lev_{it} + u_{i,t+1}. \end{aligned} \tag{3}$$

Essentially, equation (3) is a simple re-parametrization of the standard dynamic (linear) panel data ($DPD$) model of the generic form

$$y_{it} = \delta y_{i,t-1} + x_{it}'\beta + \alpha_i + \epsilon_{it}. \tag{4}$$

Flannery and Hankins (2013) note that estimating equation (4) can be achieved by traditional methods, such as ordinary least squares ($OLS$), least squares dummy variables ($LSDV$) (or equivalently, the usual *within* estimator (Mátyás and Sevestre 2006)) or a random effects ($GLS$) approach (Mátyás and Sevestre 2006). All yield-biased and inconsistent parameters are estimates with finite $T$ (Nickell 1981; Sevestre and Trognon 1985). The nature of this inconsistency essentially stems from the fact that, regardless of the particular (preceding) estimation technique used, the lagged dependent variable $y_{i,t-1}$, or transformations of it, will be correlated with the equation's error term (or transformations of it).

Consistent estimation of such a $DPD$ model has spawned a small industry of research papers focussed on how one may consistently estimate the parameters of interest in a model such as equation (4); see, for example, Anderson and Hsiao (1982), Arellano (1989), Arellano and Bond (1991), Blundell and Bond (1998) and, for a useful summary, Harris et al. (2008). The majority of the proposed estimators are based on instrument variable ($IV$) estimation, or more generally on the (linear and nonlinear) generalized method of moments ($GMM$) approach (Harris et al. 2008).

Applying these estimators in practice is not straightforward, with the researcher often having to make decisions regarding the assumed exogeneity/endogeneity of covariates, their relationship with unobserved effects, the length of the lag structure in defining valid instrument sets, and so on. Moreover, any tests available to aid the applied researcher in these respects, often have poor properties (Harris et al. 2009).

Empirically, there is also evidence that a range of differing consistent estimators can yield vastly different parameters of interest (Lee et al. 1998). A consistent finding in the vast simulation literature on $DPD$ models is that the performance of consistent estimators can be extremely poor, variable, and vary greatly across different simulation scenarios; for example, Harris and Mátyás (2004).

Combined, the facts that the bias of the *within* estimator is decreasing in $T$ and its empirically stable performance (Kiviet 1995; Harris and Mátyás 2004) have led many authors to recommend it in $DPD$ models where $T$ is large (Judson and Owen 1999; Flannery and Hankins 2013). Indeed, $T$ is larger than 30 as seen in the empirical analyses that follow. For these reasons, the *within* estimator will form the basis of our analysis. Moreover, a wide range of consistent estimators, as well as bias-corrected ones (Kiviet 1995), were experimented with before proceeding to the $FMM$ approach (below). All approaches yielded very similar results suggesting that very little, if any, fixed $T$ bias is present in the *within* results.

The *within* panel data estimator is obtained by running $OLS$ on the transformed model

$$\begin{aligned} (y_{it} - \bar{y}_{i.}) &= \delta \left(y_{i,t-1} - \bar{y}_{i,-1}\right) + \left(x_{it} - \bar{x}_{i.}\right)' \beta \\ WY &= \delta WY_{-1} + WX\beta. \end{aligned} \tag{5}$$

where $W$ is the usual *within* transformation matrix (Mátyás and Sevestre 2006), and where the second line of equation (5) is a matrix stacked version of the first line. It is important to note that only the data have been transformed (*cf.* equations (4) and (5)) but not the parameters of interest.

### 2.1. Allowing for differential SOAs

There is evidence supporting heterogeneity in $SOA$ which considers the firm-specific effects. Studies point to a tendency to adjust toward the target leverage is higher for firms that are overleveraged than underleveraged firms (for example, Drobetz and Wanzenried 2006; Byoun 2008; Elsas and Florysiak 2011; Warr et al. 2012). Fama and French (2002) found that dividend payers tend to adjust their leverage more slowly than those not paying dividends (see Faulkender et al. (2012)). Faulkender et al. (2012) and Flannery and Rangan (2006) both provided evidence that larger firms adjust excess leverage more slowly. Drobetz and Wanzenried (2006) also found that firms with higher growth opportunities appear to adjust more quickly. Dang et al. (2012) suggest that firms with large financing deficits, large investments or low earnings volatility tend to adjust more quickly than those with the opposite characteristics. Dudley (2012) finds that large investment projects provide firms with opportunities to adjust at a low marginal cost, hence they appear to move toward their target leverages during periods of large project investments.

As noted above, one of the puzzling conclusions from a review of the extensive empirical literature on $SOA$s is the broad range of findings. In part, this can be clearly attributed to differing techniques; countries; sample periods; firm selections; and so on. However, even after taking these caveats into account, the sheer scale of this range is staggering (Table 1). It can be hypothesized that it is possible to reconcile these differences by allowing the $SOA$ to (endogenously) differ across particular groups (or classes) of firm-year observations. Moreover, which particular 'group' of firm or one particular firm belongs to may evolve over time. For example, the same firm may be a slower adjuster in some years and a faster adjuster in other years. The different groups of firms will be broadly defined by relative homogeneity *within* each class with respect to $SOA$ and leverage levels. Additionally, we expect heterogeneity *across* the classes.

Clearly, *a priori* such a group or class will be unknown (unobserved by) to the researcher. However, there is a large stand of literature that addresses exactly this problem, utilizing what are usually referred to as $FMM$. A useful summary of $FMM$ (also sometimes known as *latent class models*) can be found in McLachlan and Peel (2000). In general, the $FMM$ approach involves probabilistically splitting the population into a finite number of homogeneous classes or groups. Within each of these, typically, the same statistical model applies, although these are characterized by differing parameters of that particular model. In this way, the same explanatory variables can have differing effects across the groups or classes (Bago d'Uva and Jones 2009); indeed, this is exactly what is required in the current context, as we wish $\lambda$ in equation (3), in particular, to vary across firm-groups.

$\tilde{x}_{it}$ as $(y_{i,t-1}, x_{it})$ and $\theta$ as all of the parameters in the model, then in such a set up the overall density for a firm $i$ at time $t$ (an $it$ observation), $f(y_{it}|\tilde{x}_{it}, \theta)$, can be written as an additive mixture density of $Q$ distinct sub-densities, weighted by their mixing probabilities $\pi_q$, such that the overall density is

$$f(y_{it}|\tilde{x}_{it}) = \sum_{q=1}^{Q} \pi_q \times (y_{it}|\tilde{x}_{it}, \theta_q). \tag{6}$$

Importantly, equation (6) makes it clear that all *within*-class model parameters, $\lambda$, are free to vary by class $q, \theta_q$. Note that for the arguments made above, each *within*-class density will be given by a fixed effects specification; that is a linear regression density on the *within* transformed data corresponding to equation (5). Once equation (6) has been fully specified, it can be estimated by standard maximum likelihood techniques, or the $EM$ algorithm (McLachlan and Peel 2000).

An issue with the specification of such $FMM$s is how to choose $Q$. That is, how many classes should one consider? On the one hand, it would be good to introduce as much heterogeneity into the model as feasibly possible; whereas on the other hand, it would be ideal to have as parsimonious specification as possible. As it is not straightforward to base hypotheses tests on the number of classes (which would essentially involve testing for zero probabilities), practitioners invariably choose on the basis of information criteria ($IC$). There are several such $IC$ metrics available to the applied researcher. Common ones are: $BIC/SC$ (Schwarz 1978), $AIC$ (Akaike 1987) and corrected $AIC$, $CAIC$ (Bozdogan 1987). The $BIC$ can be shown to be consistent in the sense that $\Pr\left(\widehat{Q} = Q^*\right) \to 1$ as $N \to \infty$, such that this will be our preferred metric.

Although the prior or marginal probabilities (which would be akin to population proportions in each class), will be constant, and given by $\hat{\pi}_q$, it is possible to also calculate the so-called posterior probabilities which will vary by observation. The posterior probabilities essentially answer the question: *given the full model results and all of the data on the observational unit, what is the probability that they belong in class $q$?* Posterior probabilities are typically used to predict the class of a particular observation unit. *Ex post* it is also possible to look at correlations and associations of these predicted posterior probabilities with observed covariates.

## 3. Data and Analyses

Using the Compustat and Centre for Research in Security Prices (CRSP) database from Wharton Research Data Services (WRDS), we collected data for the period 1972 to 2016. The sample selection procedure is summarized in Table 2. First, firms operating in the financial sector (banks, insurance and life assurance firms and investment trusts) and firms in the utility sector (electricity, water and gas) are excluded from the sample because their leverage ratios differ from the leverage of other firms in the sample and are determined by other features of the market. We omit firm-year observations with a negative book value of equity or missing data for long-term debt, debt in current liabilities or any of the leverage determinants.

Insert Table 2 here

Flannery and Hankins (2013) presented a recent influential study on the methodology of estimating $SOA$s. Their paper therefore represents a natural starting point for our analysis and we attempted to collect a data set as similar to theirs as possible. In particular, we obtained data from Compustat for firms with 30 years' or more of continuous data for the period beginning in 1972 and ending in 2016. Similarly, all variables are winsorized at the 1st and 99th percentiles to minimize the potential impact of outliers. We obtain a final unbalanced panel of 17,474 firm-year observations from 475 firms.[5]

We also follow Flannery and Hankins (2013) in model specification with respect to covariate specification and present these, and definitions, in Table 3 and summary statistics in Table 4. The explanatory variables are well-known in $SOA$ literature and we will postpone the discussion of their interpretation and theoretical import until later on.

Insert Table 3 here

Insert Table 4 here

The time over which we conducted our analyses, and the number of firm-year observations we used, differ slightly from that of Flannery and Hankins (2013). Nonetheless, Table 5 demonstrates that the dataset yields very similar results when replicating their specification(s). For

[5] The sample in Flannery and Hankins (2013) consists of 19,140 firm-year observations from 638 firms, each with 30 years of data.

example, we found a $SOA$ of 25% when we did not include year indicator variables and 26% when did. Flannery and Hankins (2013) found a $SOA$ of 25% when year-indicator variables are included in the regression.[6] Additionally, estimated coefficients of the explanatory variables are all 'in the ballpark' save for median leverage in the industry (*ind median*) and research and development ($RD$).

Insert Table 5 here

Table 5 confirms that we can replicate key results from Flannery and Hankins (2013). The results presented in Table 5 reflect the strong constraint on the data that we would like to criticize: One SOA is estimated for all firms. We now depart from this constraint and consider if the 'one size fits all' approach is appropriate for analyses of SOA. It might be the case that one size does indeed, fit all. If a 1-class model were found to be optimal, a single SOA estimate would be appropriate. The following analysis shows that this is not the case. Turning to the $FMM$ results (running equation 6), Table 6 and Figure 1 present the $BIC$ values for up to 7 possible classes. The $BIC$ is lowest for 4 classes (4 groups in this class).[7]

Insert Table 6 about here

Insert Figure 1 about here

Before turning to our key findings, we first present some summary evidence as to the appropriateness of the $FMM$ approach employed here. In Figure 2, we plot three-kernel density estimates ($KDE$s): The (*within*-transformed) observed-leverage levels; predicted-leverage levels from a standard fixed effects model[8]; and finally, the (prior probabilities weighted) predicted density from the 4-class $FMM$ model. In particular, the former is a standard $KDE$ of (transformed) leverage levels. The 4-class $KDE$ is obtained by taking a random draw from the four implied normal distributions (with means and variances corresponding to those estimated by class, $X'\beta_q$ and $\sigma_q^2$) for each class and observation. These are then weighted by the estimated prior class probabilities and summed and the $KDE$ calculated on the values of this weighted density. The same is undertaken for the simple fixed-effects model. The $FMM$ clearly does a very good job of explaining actual leverage levels, and is clearly much improved in comparison to the standard fixed effects approach.

Insert Figure 2 here

Insert Table 7 here

[6] The $SOA$ of 25% is presented in Table 1 of Flannery and Hankins (2013).
[7] We conduct a robustness test, tobit regression and find consistent results.
[8] All variables enter in their *within*-transformed form.

The $FMM$ procedure simultaneously endogenously (probabilistically) allocates firm-year observations into particular classes; optimally determines the number of such classes (via the $IC$ approach described above); and produces separate fixed effects regression functions for each *within*-class behavioral equation. The results of this exercise are presented in Table 7. This presents the four *within*-class model results as chosen by the optimal $BIC$ value reported in Table 6. It differs simply, and primarily, by splitting the usual single equation result, into multiple ones corresponding to the different estimated classes. Coefficients, and their associated $p$-values, are interpreted in the standard way (as one would discuss standard results such as those presented in Table 5).

The estimated $SOA$s for the four groups reported in Table 7 help facilitate labels which can be used to describe them. That is, the procedure estimates different values of $(1-\lambda)$, and consequently similarly differing $SOA$s, for each of the identified classes. Given the focus of the paper, we choose to label the classes according to the different implied or estimated $SOA$s across them. Thus group 1 represents the *nearly stable* group with the average $SOA$ is 2% for firms in this group. Group 2 are *slower adjusters*, the average $SOA$ for this group is 28%, while group 3 are *faster adjusters* with an estimated $SOA$ of 62%. The remaining observations correspond to firms that are slowly moving away from their target (at a rate of -3%); this is group 4, the *drifters*.

As we have noted above, $FMM$ produces class-specific regression results where the coefficients, and associated $p$-values, allow us to determine the sensitivity of leverage levels to variation in the independent covariates across the different classes. We are mindful of the current $p$-hacking debate in finance and note that the searching process utilized in $FMM$ is reminiscent of the process criticized by Harvey (2017). Therefore, we follow Johnson (2013) and Kim and Ji (2015) and discuss coefficients only at 5% confidence level or less.[9]

In Table 7, size ($fsize$) has a positive association with debt for *slower adjusters*, *faster adjusters* and *drifters* (groups 2, 3 and 4, respectively), although the effect for the *faster adjusters* is larger (the coefficient is 0.0062 for group 2, 0.0184 for group 3 and 0.0060 for group 4). These results are consistent with the trade-off theory which suggests that large firms have easier access to debt markets (Titman and Wessels 1988). The positive association of tangible assets ($PPE$) with increasing debt (the coefficient is 0.0344 for group 2, 0.0721 for group 3 and 0.0678 for group 4) is consistent with our expectation, derived from the literature, that firms with higher levels of tangible assets may use these as collateral to take on more debt (Rajan and Zingales 1995). The market-to-book ratio ($MB$), a proxy for a firm's growth opportunities (Kayhan and Titman 2007), is positive and statistically significant for *slower adjusters* (group 2) but negative for *faster adjusters* (group 3). The negative coefficient (-0.0087 for group 3) is consistent with Wu and Wang (2005), that asymmetric information caused by growth

[9] We do not discuss coefficients associated with lagged leverage ($lev$) as these are the source of $SOA$s discussed in the previous paragraph.

opportunities can facilitate new equity issuance. On the other hand, the finding of a positive relationship between $MB$ and leverage for *slower adjusters* (0.0039 for group 2) suggests that these firms issue debt (increase leverage) to fund projects.

The positive coefficient for industry median leverage (*ind median*) for *faster adjusters* (group 3) reflects the sensitivity of the leverage of this group to industry norms (Bradley et al. 1984). The negative relationship of leverage to profitability (statistically significant for *faster adjusters* or group 3) is consistent with the theoretical predictions of the pecking order theory which argues that higher profitability ($profit$) should result in less leverage (Frank and Goyal 2009; Rajan and Zingales 1995). However, it is inconsistent with the notion that debt is more advantageous due to its tax benefits when profits are high (Jensen and Meckling 1976; DeAngelo and Masulis 1980). The analyses presented in Table 7 do not support DeAngelo and Masulis (1980) who argue that depreciation proxies for the tax benefits of debt. Depreciation (*dep*) is found to have a negative association with leverage for *slower adjusters* (group 2), *faster adjusters* (group 3) and *drifters* (group 4).

In addition to the class regression results, Table 7 presents not only the class-specific $SOA$ results but also the *prior probabilities* for each group (Greene 2012). These are estimates of the population proportions in each group. We can see that 20% are in group 1, around 25% in each of groups 3 and 4, and the final 30% in group 2.

It is of interest to predict group membership for each firm-year observation. By definition, the prior probabilities of Table 7 cannot be used as they are firm-year constant. On the other hand, for predicting class membership, it is usual to use what are known as *posterior*, or conditional on the data, probabilities (Greene 2012) given by

$$Prob(class_{it} = q|\tilde{x}_{it}, y_{it}) = \frac{f(y_{it}|class = q, \tilde{x}_{it})Prob(class_{it} = q|\tilde{x}_{it})}{\sum_{q=1}^{Q} f(y_{it}|class = q, \tilde{x}_{it})Prob(class_{it} = q|\tilde{x}_{it})}. \tag{7}$$

With these firm-year varying probabilities in hand, observations are allocated to each group according to the maximum probability rule.

In addition to the varying $SOA$ estimates by group, they can also be classified by the expected leverage levels within each group as shown in Table 8. The expected leverage of groups 2 and 3, the *slower* and *faster adjusters* are trivially close, yet the $SOA$ for these two groups (28% and 62% respectively) differs markedly. We also report the posterior probability and the percentage of the firm-year sample (based on the maximum (posterior) probability rule) for each group in Table 8. We find 27.80% of the total firm-year observations in group 1, the *nearly stable*. About 35% is in group 2, the *slower adjusters* (35.88% of the sample), 15% is in group 3, the *faster adjusters* (15.33% of the sample) and 20% in group 4, the *drifters* (which comprise 20.99% of the firm-year sample).

Insert Table 8 here

The analyses presented in Table 7, and discussed above, focus on the determinants of the level of leverage for each of the four groups. $FMM$ allows us to move beyond this somewhat typical analysis. It generates data that allow us to consider the reasons for an observation to be in a particular group. For example, why are some observations moving away from the target while others are moving either quickly or slowly towards the target?

A simple way of beginning to classify observations by group could be to consider summary statistics. We present summary statistics for each group in Table 9. We find that *faster adjusters* hold higher leverage (*lev*) than others, which is consistent with the trade-off theory that such firms make a quicker adjustment to avoid potentially financial distress costs. The firm size (*fsize* and *PPE*) of *slower adjusters* and *drifters* are relatively bigger than others and such phenomenon is consistent with the findings of Flannery and Rangan (2006). Summary statistics allow us to make some simple comments on univariate effects. We would wish however, to consider the effects of firm specific characteristics in a more robust multivariate setting.

Therefore, we proceed by examining the multivariate correlations between group membership and observed firm characteristics. To do this, we model the firm-year posterior probabilities using a fractional multinomial logit regression (Khang et al. 2015), using the same set of covariates as above. In essence, this is a straightforward application of the usual multinomial logit model, but the usual mutually exclusive observed $q = 1, \ldots, Q$ outcomes are replaced by proportions or probabilities which sum to one. Thus the results of this can be interpreted as the factors that affect the share of firm-year observations in each class. In particular, a partial effect of magnitude $a$ of variable $x$ in class 1, would imply that a 1-unit increase in $x$ would increase the share of observations in class 1 by the amount $a$.

These results are reported in Table 10.[10] Panel A of Table 10 presents the estimated coefficients for groups 2, 3 and 4 (the *slower adjusters*, *faster adjusters* and *drifters*, respectively) using group 1, the *near stable* group as the base case. We present the results in Panel A for completeness but focus on the marginal effects presented in Panel B.

Insert Table 9 here

Insert Table 10 here

Panel B of Table 10 reports the average marginal effects of the fractional multinomial logit regression. Recent studies by D'Mello and Gruskin (2014) and Strebulaev and Yang (2013) present evidence that many firms follow a low leverage policy and such behavior is a persistent phenomenon. DeAngelo and Roll (2015) argue that leverage stability is mostly found in firms with lower leverage. Therefore, we will not discuss group 1, the *nearly stable* group, which exhibits low average leverage (average leverage is 0.087 presented in Table 9).

We start by comparing the marginal effects between *slower adjusters* (group 2), *faster adjusters* (group 3) and *drifters* (group 4). The size of the firm (*fsize*) is found to have a

[10]Similar quantitative results are found using a standard multinomial logistics regression where groups are predicted based on the maximum (posterior) probability rule.

negative and statistically significant marginal effect for the *faster adjusters* (group 3) while there is a positive marginal effect for both *slower adjusters* (group 2) and *drifters* (group 4). A positive marginal effect (0.0084 for group 2; 0.0066 for group 4) suggests that the size of the firm is positively associated with the likelihood of a firm being a *slower adjuster* or *drifter*. The negative marginal effect (-0.0063 for group 3) implies that the bigger the firm size, the less likely to be a *faster adjuster*. Our findings support Flannery and Rangan (2006) and Dang et al. (2012) who argue that larger firms tend to use public debt and it is costly to adjust leverage (for example, brokerage fees). They face less cash flow volatility, lower financial distress costs and fewer debt covenants. Hence, such firms have less incentive to adjust their leverage, implying a slower adjustment speed for larger firms and *vice versa*.

Tangible assets (*PPE*) can be used as collateral to take on more debt (Rajan and Zingales 1995). We observe a positive and statistically significant marginal effect of *PPE* for both *slower adjusters* (group 2) and *drifters* (group 4). This is consistent with the findings reported for the variable, firm size (*fsize*). Larger firms are usually mature and have more tangible assets. Leverage adjustment generally incurs substantial transaction costs (for example, brokerage fees), so large firms with more collateral have less incentive and external pressure to adjust leverage, implying a slower $SOA$.

Firms might be expected to raise equity funding when their growth opportunities, proxied by their market-to-book ratios (*MB*), are relatively high (Hovakimian et al. 2004). Given that the marginal effect for *drifters* (group 4) is negligible (the marginal effect is considerably minor compared to *slower adjusters* and *faster adjusters*), we again concentrate on the marginal effect of *MB* for *slower adjusters* and *faster adjusters*. A positive and statistically significant marginal effect (0.0271) is observed for *slower adjusters* (group 2) but it is negative (-0.0603) for *faster adjusters* (group 3). This reflects the fact that high-growth firms are more likely to undertake slower leverage adjustment and/or low-growth firms are more likely to undertake faster adjustment.

High-growth firms are generally younger, carry less leverage and rely heavily on equity funding to support their growth opportunities. As a result, they can adjust their leverage more easily via external capital markets, implying a slower leverage adjustment for such firms. On the other hand, low-growth firms are generally highly profitable and cash-rich. Hence, they may maintain a high-leverage policy to mitigate the free cash flow problem (Jensen 1986) and find it more beneficial to adjust at a faster pace towards the target leverage to avoid financial distress and potential bankruptcy costs.

For the measurement of firm's research and development (*RD* and *RD dummy*), we observe a negative and statistically significant marginal effect (*RD* is -0.3132) for *faster adjusters* (group 3) but a positive marginal effect (*RD dummy* is 0.0259 for group 2 and 0.0225 for group 4) for both *slower adjusters* (group 2) and *drifters* (group 4). Our findings suggest that firms with large discretionary expenditures, such as research and development expenses, may have less scope for leverage adjustment, implying a slower adjustment pace for such firms.

Highly profitable firms are less likely to face financial constraints. The trade-off theory suggests that more profitable firms have more incentive to take advantage of the debt interest shield benefits. Hence, more profitable firms should have more debt in their capital structure. On the other hand, the pecking order theory predicts that more profitable firms will use their retained earnings to support their operations and investments. Therefore higher profitability should result in less leverage (Frank and Goyal 2009; Rajan and Zingales 1995). We observe a positive (0.1216) and statistically significant marginal effect of *profit* for *slower adjusters* (group 2) but a negative marginal effect (-0.2830) for *faster adjusters* (group 3). These results support the pecking order theory (Myers and Majluf 1984; Titman and Wessels 1988) which predicts that less profitable firms are generally highly levered. Given that highly levered firms often face a substantial financial distress burden compared to low levered firms, less profitable firms should have more incentive to adjust their leverage, implying a *faster* adjustment speed for less profitable firms. The negative marginal effect of *profit* (-0.1050) for *drifters* (group 4) suggests that less profitable firms may have limited internal funds or financial instability (due to being highly levered), which prevent them from making leverage adjustments towards the target leverage (moving away from their target leverage).

The results for depreciation (*dep*) are mixed. Its marginal effects for both *slower adjusters* (group 2) and *faster adjusters* (group 3) are positive and statistically significant, although the marginal effect is double the rate for *faster adjusters* in relation to *slower adjusters* (0.2918 for group 2; 0.6037 for group 3). Such findings suggest that firms with higher depreciation expenses (non-debt tax shield) are likely to adjust their leverage towards the target leverage (which can be at a slow or fast pace). Our results are consistent with our findings for *MB*: Firms which invest heavily in tangible assets and generate high levels of depreciation and tax credits tend to hold a higher level of leverage (Bradley et al. 1984). As a result, the motivation to achieve the target leverage is stronger for such firms.

## 4. Conclusion

The wide dispersion of estimates of firms' $SOA$s is well known. $SOA$ estimates vary but studies agree on imposing a strong, and we argue, a potentially wrong constraint on the data: An average $SOA$ estimated for all firms.

The $FMM$ used in this paper demonstrates that restricting all firms to have the same $SOA$ is not optimal. We present evidence that there are four different behaviors as revealed by $FMM$. Around a quarter of the sample is in the *nearly stable* group (group 1) with 2% as the average $SOA$. 35% of the sample contains *slower adjusters* (group 2), with an average $SOA$ of 28%. 15% of the sample is *faster adjusters* and their estimated $SOA$ is 62%. 20% is *drifters* (group 4) and they are slowly moving away from their target (at a rate of -3%).

$FMM$ has the advantage of facilitating consideration of why observations fall within a particular group. We utilize fractional multinomial logit regression to analyze the marginal effects associated with group membership and find evidence that the firms' observed characteristics can be associated with group membership in ways which are often consistent with expectations generated from the literature on capital structure.

We find that the behavior characterized by the four classes discovered by $FMM$ has significant associations with firm characteristics. For example, firms with low growth opportunities, low profitability or smaller size appear to undertake *faster* leverage adjustment than those with opposite characteristics. Further, firms with more tangible assets are keen to be *slower adjusters*.

In addition to contributing to our understanding of $SOA$ and leverage, we believe that the methodology we demonstrated should be a standard element of the financial economist's toolkit. The technique is tractable. It is potentially relevant to many issues analyzed in finance generally and in corporate finance in particular.

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Table 1: Estimated SOA's in Empirical Studies of Capital Structure in US firms

| **Article** | **Estimator** | **Estimated SOA (per year)** | |
|---|---|---|---|
| | | Book leverage | Market leverage |
| Taggart (1977) | GLS | $13\%^{a}$ | |
| Jalilvand and Harris (1984) | GLS | $37.36\%^{a}$ | |
| Fama and French (2002) | FM | $10\%^{b,c}$ ;$18\%^{b,d}$ | $7\%^{e,c}$; $15\%^{e,d}$ |
| Flannery and Rangan (2006) | FM | | $13.3\%^{e}$ |
| | Fixed effects | | $38\%^{e}$ |
| | IV | | 34.4%;$36.4\%^{f}$ |
| Kayhan and Titman (2007) | OLS | 41% in 5 years$^{b}$ | 35% in 5 years$^{e}$ |
| Titman and Tsyplakov (2007) | OLS | | $7.1\%^{g}$ |
| Lemmon et al. (2008) | OLS | $13\%^{a}$; $17\%^{a}$ | |
| | Fixed effects | $36\%^{a}$; $39\%^{a}$ | |
| | System GMM | $22\%^{a}$; $25\%^{a}$ | |
| Byoun (2008) | OLS | $22.17\%^{a}$; $22.58\%^{b}$ | $21.47\%^{h}$; $21.57\%^{e}$ |
| | Mixed effects | $23.96\%^{a}$; $39.47\%^{b}$ | $21.75\%^{h}$; $32.27\%^{e}$ |
| Huang and Ritter (2009) | LD | $17\%^{b}$ | $23.2\%^{e}$ |
| Harford et al. (2009) | Evolution of leverage deviations | | between 15.3% and 24.5% $^{e}$ |
| Hovakimian and Li (2011) | OLS; Fixed effects | $9.7\%^{b}$;$8.8\%^{b}$ | |
| Elsas and Florysiak (2011) | Fixed effects;DPF | | 39.10%;26.30% |
| Faulkender et al. (2012) | System GMM | 21.90% | 22.30% |
| Warr et al. (2012) | FM | $33.25\%^{b}$ | $35.36\%^{e}$ |
| | System GMM | $27.70\%^{b}$ | $29.25\%^{e}$ |
| McMillan and Camara (2012) | FE IV | | $53\%^{e,i}$; $58\%^{e,j}$ |
| | Difference GMM | | $48\%^{e,i}$; $54\%^{e,j}$ |
| | LSDVC | | $34\%^{e,i}$; $41\%^{e,j}$ |
| Flannery and Hankins (2013) | OLS;Fixed effects; System GMM | | $13\%^{k}$;$25\%^{k}$;$15\%^{k}$ |
| Lockhart (2014) | System GMM | | 23.6% |
| Dang et al. (2014) | IV | $31\%^{l}$;$33\%^{m}$ | |
| | System GMM | $29\%^{l}$;$31\%^{m}$ | |
| Chang et al. (2014) | Fixed effects | | $58.1\%^{m,n}$;$28.5\%^{m,o}$;$51.7\%^{l,n}$;$20.9\%^{l,o}$ |
| Elsas and Florysiak (2015) | DPF | 27% | 26% |
| Drobetz et al. (2015) | DPF | 26.1% | 33.6% |
| Chang et al. (2015) | Fixed effects | | $17.6\%^{q}$;$44.2\%^{p}$;$58.8\%^{r}$;$44.8\%^{s}$ |
| Liao et al. (2015) | System GMM | | 36.8% |
| Zhou et al. (2016) | Fixed effects | | $24.57\%^{e}$ |

[a] Long-term debt scaled by book assets; [b] Book debt scaled by book assets; [c] Dividend payer; [d] Non-dividend payer; [e] Book debt scaled by the market value of assets; [f] Only for firms with the middle 50% of leverage ratio; [g] Face value of debt scaled by the market value of equity plus the face value of debt; [h] Long-term debt scaled by the market value of assets; [i] Domestic corporations; [j] Multinational corporations; [k] Firms surviving at least 30 years; [l] One-stage partial adjustment model; [m] Two-stage partial adjustment model; [n] Firms with strong governance; [o] Firms with weak governance; [p] Firms with strong governance structures in the industries with low competition; [q] Firms with weak governance structures in the industries with low competition; [r] Firms with strong governance structures in the highly-competitive industries; [s] Firms with weak governance structures in the highly-competitive industries.

DPF: Dynamic panel data with a fractional dependent variable; FM: Fama and Macbeth; GLS: Generalized linear square; GMM: Generalized method of moments; IV: Instrument variables; LD: Long differencing; LSDVC: Bias-corrected least squares dumnmy variable approach; OLS: Ordinary least square.

Table 2: Sample selection[+]

| | Sample | | |
|---|---|---|---|
| | **Initial** | **Excluded** | **Remaining** |
| Number of firm-year observations | 291,525 | | |
| Less: | | | |
| Financial (SIC codes 6000 - 6900) and utilities (SIC codes 4900 - 4999) firms | | 75,941 | |
| Firm-year observations with negative book value of equity | | 15,961 | |
| Firm-year observations with missing long-term debt | | 438 | |
| Firm-year observations with missing debt in current liabilities | | 342 | |
| Firm-year observations with missing value in the leverage determinants | | 104,036 | |
| Firm-year observations without 30 years of continous data | | 77,333 | |
| Firm-year observations available for the study | | | 17,474 |

[+]The breakdown of the total sample firm-year observations. The sample is an unbalanced panel which consists of 475 firms (17,474 firm-year observations) over the period of 1972 - 2016.

Table 3: Variables definitions[+]

| **Variables** | **Definitions** |
|---|---|
| Leverage (*lev*) | The sum of debt in current liabilities (item DLC) and total long-term debt (item DLTT), scaled by total assets (item AT) |
| Firm size (*fsize*) | The natural logarithm of total assets (item AT) |
| Tangible assets (*PPE*) | Net property, plant and equipment (item PPENT) scaled by total assets (item AT) |
| Market-to-book ratio (*MB*) | The market value of the firm scaled by the book value of the total assets (item AT) |
| Research and development (*RD*) | Research and development expense (item XRD) scaled by sales (item SALE) |
| Research and development dummy (*RD dummy*) | The dummy variable takes a value of unity if the firm has incurred research and development expense, and zero otherwise |
| Industry median leverage (*ind median*) | The median leverage ratio of the relevant industry |
| Profitability (*profit*) | Operating income before depreciation (item OIBDP) scaled by total assets (item AT) |
| Depreciation (*dep*) | Depreciation and amortisation (item DP) scaled by total assets (item AT) |

[+]The variables construction for analysis. Firm-level accounting data between 1972 and 2016 were collected from the Compustat and the Centre for Research in Security Prices database from Wharton Research Data Services.

Table 4: Summary statistics for the estimation sample+

| Variables | Mean | Std. Dev. | Minimum | Maximum |
|---|---|---|---|---|
| *lev* | 0.1929 | 0.1824 | 0 | 0.9173 |
| *fsize* | 6.2601 | 2.3650 | 0.5531 | 11.1575 |
| *PPE* | 0.2742 | 0.1608 | 0 | 0.9191 |
| *MB* | 1.7848 | 1.2484 | 0.5403 | 10.9059 |
| *RD* | 0.0468 | 0.0608 | 0 | 0.7690 |
| *ind median* | 0.1402 | 0.1181 | -1.006 | 0.4174 |
| *profit* | 0.0443 | 0.0224 | 0 | 0.2387 |
| *dep* | 0.1749 | 0.1141 | 0 | 0.6785 |

+The sample is an unbalanced panel which consists of 475 firms of which 17, 474 firm-year observations, over the period of 1972 - 2016.

Table 5: Speed of leverage adjustment+

| | **Panel A:** *All firm-year observations* | | **Panel B:** *Flannery and Hankins (2013)* |
|---|---|---|---|
| *fsize* | 0.0024** | 0.0128** | 0.0170** |
| | *0.001* | *0.000* | *0.000* |
| *PPE* | 0.0697** | 0.0469** | 0.0590** |
| | *0.000* | *0.000* | *0.000* |
| *MB* | -0.0001 | -0.0019* | -0.0020* |
| | *0.947* | *0.011* | *0.036* |
| *RD* | -0.0454* | -0.0240 | 0.0040 |
| | *0.038* | *0.253* | *0.932* |
| *RD dummy* | -0.0161 | -0.0246* | -0.0010 |
| | *0.119* | *0.013* | *0.797* |
| *ind median* | 0.0588** | 0.0488** | -0.0040 |
| | *0.000* | *0.001* | *0.737* |
| *profit* | -0.0236** | -0.0427** | -0.0420** |
| | *0.006* | *0.000* | *0.000* |
| *dep* | -0.3997** | -0.3236** | -0.5010** |
| | *0.000* | *0.000* | *0.000* |
| *lev* | 0.7456** | 0.7412** | 0.7520** |
| | *0.000* | *0.000* | *0.000* |
| *Constant* | 0.0421** | -0.0264 | -0.2720** |
| | *0.000* | *0.091* | *0.000* |
| Year dummies | *No* | *Yes* | *Yes* |
| Adjusted SOA (1-*lev*) | 25% | 26% | 25% |
| Observation | 17,474 | 17,474 | 19,140 |
| Firms | 475 | 475 | 638 |

+Estimated coefficients and p-values (in italics) using fixed-effects (FE) regressions. Panel A presents the results using the sample firm-years' observations in this paper. Panel B presents the results obtained from Table 1 in Flannery and Hankins (2013), F&H. * and ** denote significance at 5% and 1% confidence levels, respectively.

Table 6: $BIC$ from finite mixture models

| **Classes** | **Bayesian Information Criterion (BIC)** |
|---|---|
| 1 | - 36,333.93 |
| 2 | - 43,032.49 |
| 3 | - 44,360.90 |
| 4 | - 44,654.92 |
| 5 | - 44,200.95 |
| 6 | - 44,150.73 |
| 7 | - 44,170.69 |
| Lowest IC | - 44,654.92 |
| Class with lowest IC | 4 |

Table 7: Finite mixture the preferred 4-class model+

| | **Group 1** | **Group 2** | **Group 3** | **Group 4** |
|---|---|---|---|---|
| | *Nearly stable* | *Slower adjusters* | *Faster adjusters* | *Drifters* |
| *fsize* | 0.0003 | 0.0062** | 0.0184** | 0.0060** |
| | *0.193* | *0.000* | *0.000* | *0.002* |
| *PPE* | -0.0006 | 0.0344* | 0.0721* | 0.0678** |
| | *0.858* | *0.010* | *0.026* | *0.000* |
| *MB* | 0.0001 | 0.0039** | -0.0087* | 0.0021 |
| | *0.323* | *0.000* | *0.016* | *0.123* |
| *RD* | 0.0005 | -0.0068 | -0.1707* | -0.0142 |
| | *0.897* | *0.818* | *0.038* | *0.720* |
| *RD dummy* | -0.0102* | -0.0121 | -0.0522 | 0.0554* |
| | *0.016* | *0.388* | *0.061* | *0.012* |
| *ind median* | -0.0025 | 0.0320 | 0.1774** | 0.0423 |
| | *0.525* | *0.081* | *0.001* | *0.143* |
| *profit* | -0.0012 | 0.0199 | -0.1696** | -0.0127 |
| | *0.527* | *0.065* | *0.000* | *0.382* |
| *dep* | -0.0049 | -0.1720** | -0.5071** | -0.3005** |
| | *0.717* | *0.008* | *0.003* | *0.002* |
| *lev* | 0.9832** | 0.7230** | 0.3775** | 1.0336** |
| | *0.000* | *0.000* | *0.000* | *0.000* |
| *Constant* | 0.0006 | -0.0157 | -0.0030 | -0.0046 |
| | *0.793* | *0.176* | *0.937* | *0.744* |
| Prior Probability | 0.1893 | 0.3066 | 0.2384 | 0.2657 |
| S.E. of prior probability | 0.007 | 0.013 | 0.010 | 0.014 |
| Year dummies | *Yes* | *Yes* | *Yes* | *Yes* |
| Adj SOA (1-lev) | 2% | 28% | 62% | -3% |

+The estimated coefficients and p-values (in italics) of each group in the 4-class model using the *within* transformed model. * and ** denote significance at the 5% and 1% confidence levels, respectively.

Table 8: Faster and slower leverage adjustment+

| | **SOAs** | **Expected leverage ratio** | **Marginal probabilities, $\hat{\pi}_q$** | **% of sample** | **N** |
|---|---|---|---|---|---|
| **Group 3** (*Faster adjusters*) | 62% | 0.1206 | 23.84% | 15.33% | 2,678 |
| **Group 2** (*Slower adjusters*) | 28% | 0.1844 | 30.66% | 35.88% | 6,270 |
| **Group 1** (*Nearly stable*) | 2% | 0.1821 | 18.93% | 27.80% | 4,858 |
| **Group 4** (*Drifters*) | -3% | 0.3008 | 26.57% | 20.99% | 3,668 |

+The speed of leverage adjustment ($SOA$s), expected value of leverage and posterior probability.

Table 9: Descriptive statistics of 4-class model

| **Variables** | **Mean** | **Std. Dev.** | **Min** | **Max** |
|---|---|---|---|---|
| | | *Panel A:* **Group 1** *(Nearly stable)* | | |
| *lev* | 0.0870 | 0.1403 | 0 | 0.9173 |
| *fsize* | 5.9722 | 2.3912 | 0.5134 | 11.2037 |
| *PPE* | 0.2413 | 0.1563 | 0 | 0.9191 |
| *MB* | 2.2906 | 1.7256 | 0.5403 | 10.9059 |
| *RD* | 0.0584 | 0.0708 | 0 | 0.7690 |
| *ind median* | 0.1477 | 0.1108 | 0 | 0.6785 |
| *profit* | 0.1527 | 0.1444 | -1.0056 | 0.4174 |
| *dep* | 0.0418 | 0.0226 | 0.0001 | 0.2034 |
| | | *Panel B:* **Group 2** *(Slower adjusters)* | | |
| *lev* | 0.1770 | 0.1440 | 0 | 0.8599 |
| *fsize* | 6.5860 | 2.3194 | 0.5134 | 11.2037 |
| *PPE* | 0.2868 | 0.1594 | 0 | 0.9191 |
| *MB* | 1.7859 | 1.0815 | 0.5403 | 10.9059 |
| *RD* | 0.0430 | 0.0564 | 0 | 0.7690 |
| *ind median* | 0.1776 | 0.1089 | 0 | 0.5825 |
| *profit* | 0.1488 | 0.1055 | -1.0056 | 0.4174 |
| *dep* | 0.0454 | 0.0215 | 0.0001 | 0.2387 |
| | | *Panel C:* **Group 3** *(Faster adjusters)* | | |
| *lev* | 0.3109 | 0.1882 | 0 | 0.9173 |
| *fsize* | 5.7935 | 2.2994 | 0.5134 | 11.2037 |
| *PPE* | 0.2702 | 0.1607 | 0 | 0.9191 |
| *MB* | 1.3206 | 0.6042 | 0.5403 | 10.7604 |
| *RD* | 0.0403 | 0.0526 | 0 | 0.7690 |
| *ind median* | 0.1888 | 0.1180 | 0.0025 | 0.6761 |
| *profit* | 0.1128 | 0.1078 | -1.0056 | 0.4174 |
| *dep* | 0.0442 | 0.0238 | 0.0001 | 0.2387 |
| | | *Panel D:* **Group 4** *(Drifters)* | | |
| *lev* | 0.2741 | 0.1978 | 0 | 0.9173 |
| *fsize* | 6.3816 | 2.4256 | 0.5134 | 11.2037 |
| *PPE* | 0.2993 | 0.1618 | 0 | 0.9191 |
| *MB* | 1.4512 | 0.7788 | 0.5403 | 10.9059 |
| *RD* | 0.0425 | 0.0571 | 0 | 0.7690 |
| *ind median* | 0.1964 | 0.1173 | 0.0025 | 0.6428 |
| *profit* | 0.1288 | 0.1015 | -1.0056 | 0.4174 |
| *dep* | 0.0460 | 0.0224 | 0.0001 | 0.2387 |

Table 10: Fractional multinomial logit regression

**Panel A:** *Estimated coefficients (coeff.)*

| **Variables** | **Coeff.** | $p$**-value** | **Coeff.** | $p$**-value** | **Coeff.** | $p$**-value** |
|---|---|---|---|---|---|---|
| | **Group 2** | *(Slower adjusters)* | **Group 3** | *(Faster adjusters)* | **Group 4** | *(Drifters)* |
| *fsize* | 0.0747** | *0.000* | 0.0207 | *0.198* | 0.0724** | *0.000* |
| *PPE* | 0.8279** | *0.000* | 0.4459 | *0.126* | 0.9888** | *0.000* |
| *MB* | -0.1221** | *0.000* | -0.4777** | *0.000* | -0.2314** | *0.000* |
| *RD* | -2.1944** | *0.001* | -3.3834** | *0.000* | -1.9384** | *0.003* |
| *RD dummy* | 0.3790** | *0.003* | 0.3203* | *0.03* | 0.3828** | *0.003* |
| *ind median* | 1.0332** | *0.000* | 1.3361** | *0.000* | 1.3922** | *0.000* |
| *profit* | -1.1038** | *0.000* | -2.7669** | *0.000* | -1.9285** | *0.000* |
| *dep* | 5.26748** | *0.000* | 7.0120** | *0.000* | 3.9277** | *0.005* |

**Panel B:** *Average marginal effects (AME)*

| **Variables** | **AME** | $p$**-value** | **AME** | $p$**-value** | **AME** | $p$**-value** | **AME** | $p$**-value** |
|---|---|---|---|---|---|---|---|---|
| | **Group 1** | (*Nearly stable*) | **Group 2** | (*Slower adjusters*) | **Group 3** | (*Faster adjusters*) | **Group 4** | (*Drifters*) |
| *fsize* | -0.0086** | *0.000* | 0.0084** | *0.000* | -0.0063** | *0.000* | 0.0066** | *0.000* |
| *PPE* | -0.1129** | *0.002* | 0.0621** | *0.002* | -0.0443 | *0.087* | 0.0951** | *0.000* |
| *MB* | 0.0372** | *0.000* | 0.0271** | *0.000* | -0.0603** | *0.000* | -0.0040* | *0.011* |
| *RD* | 0.3549** | *0.000* | -0.0640 | *0.306* | -0.3132** | *0.000* | 0.0222 | *0.641* |
| *RD dummy* | -0.0530** | *0.006* | 0.0259** | *0.006* | 0.0046 | *0.698* | 0.0225** | *0.005* |
| *ind median* | -0.1796** | *0.000* | 0.0091 | *0.708* | 0.0714* | *0.042* | 0.0991** | *0.000* |
| *profit* | 0.2664** | *0.000* | 0.1216** | *0.000* | -0.2830** | *0.000* | -0.1050** | *0.000* |
| *dep* | -0.7731** | *0.000* | 0.2918* | *0.040* | 0.6037** | *0.001* | -0.1224 | *0.233* |

$^{+}$The estimated coefficients and p-values (in italics) of each group in the 4-class is presented in Panel A. Panel B reports the average marginal effects of each group in 4-class. * and ** denote significance at the 5% and 1% confidence levels, respectively.

Figure 1: Values of $BIC$ for various class $FMM$ models

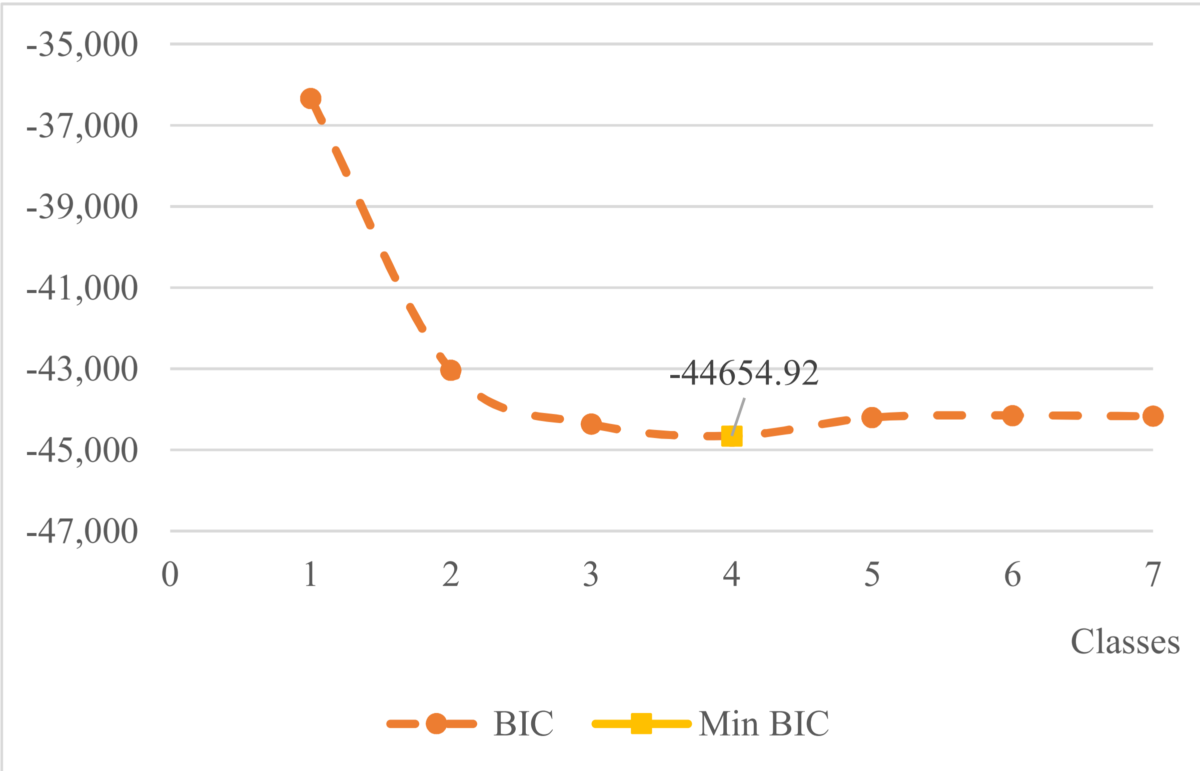

Figure 2: Kernel density for observed, expected values and fixed-effects regression