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Heterogeneity in the Speed of Adjustment to Target Leverage: A UK Study

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Abstract

Responding to the need to address heterogeneity in the speed of adjustment (SOA) to target leverage in a manner that reflects the fractional nature of leverage, we estimate SOAs across sub-samples of UK firms using the Dynamic Panel Fractional estimator (DPF). Using firm risk as a categorising variable, we show that riskier firms tend to adjust to target leverage at a faster rate, suggesting opportunity costs of being away from target leverage are higher for riskier firms. We also demonstrate the bias in SOAs as estimated using a model that does not account for the fractional nature of leverage, and show that this bias can result in spurious inferences being made when comparing SOAs across sub-samples. Our results cast doubt on existing evidence relating to heterogeneity in SOAs of UK firms.

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I. Introduction

Since Modigliani and Miller postulated their capital structure irrelevancy theorem in 1958, extensive research has been conducted on the relevance of capital structure to firm value. Principal among the competing theories that have emerged are the trade-off theory, pecking order theory and market timing theory, and research in the area of capital structure has focused on assessing the validity of these theories. One testing method commonly adopted is to employ a dynamic partial adjustment model to test for the existence of a target leverage ratio which firms actively adjust towards, and to estimate the speed at which adjustment takes place. Evidence indicating speedy adjustment to target leverage would provide support for the trade-off theory over its leading competitor, as its core hypothesis states that each firm has a unique optimal capital structure at which its cost of capital is minimised and firm value is maximised. Results of studies adopting this approach almost unanimously conclude that firms make financing decisions with adjustment towards a target capital structure in mind, suggesting the trade-off theory plays a significant role in explaining capital structure decisions.

However, there are two reasons why the manner in which this approach is commonly adopted may be problematic. First, there is a growing consensus that the factors motivating firms' financing decisions are not homogenous across firms (Beattie *et al*., 2006; Frank and Goyal, 2009; Graham and Leary, 2011), and so any speed of adjustment estimated using a large aggregated sample of firm-year observations fails to take this heterogeneity into account. Thus, although a comparison of results across these studies suggests firms actively adjust to target leverage ratios, the speeds of adjustment estimated only indicate the importance to the "average" firm of achieving target leverage. Second, the dynamic partial adjustment model involves regressing current actual leverage ratios on lagged actual leverage ratios, with the coefficient on lagged actual leverage implying the speed of adjustment (SOA) to target leverage. However, the methods commonly employed to estimate this model ignore or do not fully account for the censored nature of the leverage ratio. Leverage ratios can only take values from 0 to 1, and thus methodologies that don't take the fractional nature of leverage ratios into account will produce biased estimates of the speed of adjustment (Elsas and Florysiak, 2011).

Following on from the work of Elsas and Florysiak (2011) and Drobetz et al (2015), this study responds to these issues by estimating the Dynamic Panel Fractional (DPF) estimator on sub-samples of UK firm-year observations across which theory and empirical evidence suggest speeds of adjustment are likely to vary. Our results show that the DPF estimator implies a faster average SOA (27.9%) as compared to that implied by the Blundell-Bond (2008) estimator (20.9%), a finding consistent with that of Drobetz et al (2015). This indicates that prior reported UK average adjustment speeds estimated using the Blundell-Bond (BB) estimator may not represent the true leverage targeting behaviour of the "average" UK firm. Furthermore, when we split our sample into sub-samples based on risk, the results produced by the DPF estimator indicate that riskier firms exhibit faster SOAs, suggesting opportunity costs of being away from target leverage are higher for riskier firms. These findings are consistent with those of Elsas and Florysiak (2011, 2015). However, these differences in the SOAs across the risk sub-samples are smaller in magnitude than those implied by the BB estimator, and thus question the heterogeneity in the SOAs of UK firms as reported by prior studies employing the BB estimator.

This study makes two key contributions to the capital structure literature. First, to the best of our knowledge we are the first study to examine heterogeneity in the SOAs of UK firms using the DPF estimator. Although Drobetz et al (2015) estimate the SOA of the average UK firm using the DPF estimator, any results presented in relation to sub-samples are based on sub-samples of firms across the G7 countries, and thus heterogeneity of SOAs specifically within the UK is not addressed. Second, by comparing the heterogeneity in SOAs across the DPF and BB estimators using three different sub-sampling methods, we extend the work of Elsas and Florysiak (2015) who compare heterogeneity in SOAs across DPF and BB estimators using sub-samples of US firms based on credit ratings alone.

The remainder of this paper is structured as follows: Section II reviews the extant literature relating to dynamic partial adjustment models. Section III outlines the salient features of our data and methodology. Section IV discusses the results of the DPF and BB estimators and section V concludes.

II. Literature Review

Over the last half century, the capital structure literature has focused on forming theories that can explain observed variation in firms' capital structures, and subsequently assessing the validity of these theories via econometric tests of their empirical predictions. Many different methodological approaches have been adopted to test these predictions, resulting in evidence being found in favour of and against each theory. One approach that has come to dominate recent empirical studies is the dynamic partial adjustment model. This model assesses whether or not firms financing decisions are motivated by a desire to achieve a target leverage ratio, and estimates the speed at which adjustment to this target occurs. Evidence indicating such behaviour would provide support for the explanatory power of the trade-off theory, as it hypothesises that each firm has an optimal capital structure, that if achieved, will minimise cost of capital and maximise firm value. Moreover, such evidence would also raise doubt as to the validity of the pecking order theory and market timing theory, as both theories imply a firm's capital structure is the accumulation of a series of historical financing decisions that have not been aimed at achieving a target leverage ratio. Thus, the dynamic partial adjustment model is often employed as a test of the trade-off theory versus competing theories, with results invariably indicating firms actively adjust to a target leverage ratio. However, two issues with the manner in which this approach is commonly employed have been identified, suggesting a more nuanced approach is required if it is to be fit for purpose.

Conditionality of Factors

There is a growing consensus that the factors affecting firms' capital structures are not homogenous across firms, but are conditional on firm characteristics (Frank and Goyal, 2009), economic circumstances (Drobetz and Wanzenried, 2006) and market setting (Antoniou et al, 2008). This conditionality implies that dynamic partial adjustment models estimated using large aggregated samples of firm-year observations may result in spurious inferences being made as to the relative explanatory powers of capital structure theories. The "average" firm may be seen to adjust to target leverage ratios, but the speed of adjustment (SOA) to target leverage might vary significantly across sub-samples of firms. Thus, it may be the case that for some firms, closing the gap between actual and target leverage may be of second order importance to considerations consistent with the pecking order theory or market timing theory, but this would be unidentified or understated if large aggregated samples are employed.

In an attempt to account for this potential heterogeneity in leverage targeting behaviour, a number of studies estimate SOAs for sub-samples of firms across which the benefits and costs of achieving target leverage, or the ability to do so, are likely to differ. Oztekin (2015) conducts a cross country comparison of SOAs, where countries are characterised by the quality of their legal and financial institutions. The study finds that in countries with high quality institutions firms exhibit faster adjustment speeds, as the costs of adjustment are lower and firms have better access to capital markets. Using US data, Liao et al (2015) assess the role of corporate governance on firms' SOAs. The results show that firms with better corporate governance practices have higher target leverage ratios and adjust faster to these targets, whilst firms with entrenched management tend to have lower target leverage ratios and exhibit slower adjustment speeds. Estimating the cost of deviation from target leverage via its effect on the cost of equity, Zhou et al (2016) investigate SOAs across sub-samples that differ in terms of the sensitivity of the cost of equity to deviation from target leverage. Their findings indicate that firms whose cost of equity is highly sensitive to deviations from target tend to have higher SOAs, with the effect being more pronounce when firms are above their target leverage rather than below.

Fractional Nature of Leverage

The dynamic partial adjustment model involves regressing firms' current leverage ratios on lagged leverage ratios and an estimate of the target leverage ratio. A statistically significant coefficient for the lagged leverage ratio indicates firms' actively adjust to target leverage, whilst the magnitude of the coefficient implies the SOA. A number of econometric methods have been employed to estimate such a model, where issues relating to unobserved firm fixed-effects, the inclusion of the lagged dependent variable as an explanatory variable, and the unbalanced nature of panels can be adequately addressed (Drobetz et al, 2015). However, one issue that continuously fails to be addressed is the fractional nature of leverage.

By definition, a firm's leverage ratio is bounded between 0 and 1. However, standard estimators used to measure SOA fail to take this into account, resulting in SOA estimates that may be severely biased due to mechanical mean reversion (Chang and Disgupta, 2009). Furthermore, easy work-arounds often used to reduce this bias, such as dropping all observations with zero leverage, or observations with values of leverage below 0.1 and above 0.9, fail to adequately account for the impact of the bounded leverage ratio (Elsas and Florysiak, 2015). To address this issue of mechanical mean reversion, Elsas and Florysiak (2011) develop a doubly censored Tobit estimator, referred to as the Dynamic Panel Fractional (DPF) estimator, which can be applied to unbalanced panel data where the lagged dependent variable is included as an explanatory variable and unobserved firm fixed effects are present. They demonstrate that not only is the estimator robust to mechanical mean reversion, it can identify zero SOAs when changes in leverage are random, and is the only estimator that should be employed when comparing SOAs across sub-samples.

III. Data and Methodology

Building on the work of Elsas and Florysiak (2011) and Drobetz et al (2015), this study investigates heterogeneity in the SOAs of UK firms by applying the DPF estimator to sub-samples of firms across which the opportunity cost of deviation from target leverage is expected to differ.

Data

Our sample is sourced from DataStream, and is comprised of UK listed firms for which relevant data is available between 1/7/1995 and 30/06/2016. Following almost all studies on capital structure, financial institutions are excluded, and to minimise the effect of outliers, all variables are winsorised at the 1% level at both ends of their distributions. Observations with negative values of book value of equity are dropped, whilst firms must have a minimum of three consecutive observations to be included in the sample. The final dataset is an unbalanced panel of 18,337 firm-year observations, 3,531 of which have zero debt.

Variables

We employ 7 independent variables which collectively proxy for a firm's target leverage ratio. These variables are firm size, asset tangibility, profitability, market-to-book, capital expenditure, research and development, and a dummy variable indicating whether or not research and development costs are reported in the income statement. We measure our leverage ratios in book values only, prompted by Beattie *et al*. (2006) who find that 83% of UK Finance directors who measure financial gearing do so using book values. Table 1 provides definitions of the dependent and independent variables employed, table 2 presents descriptive statistics for all variables and table 3 presents univariate correlation coefficients between each pair of variables.

Table 1: Variable Definitions

Variable	Definition and Notes
Leverage *tdta*	The ratio of total debt to total assets.
Firm Size *lnta*	The natural log of total assets.
Asset Tangibility *tang*	The ratio of net property, plant and equipment to total assets.
Profitability *roa*	The ratio of EBIT to total assets
Market-to-Book *mtb*	The ratio of market value ordinary shares + total debt + book value preference shares to total assets
Capital Expenditure *capexta*	The ratio of capital expenditure to total assets
Research and Development *resdev*	The ratio of research and development expenditure to total assets
R&D Dummy *resdevdum*	A dummy variable that takes a value of 1 when a firm reports research and development expenditure and 0 otherwise

Table 2: Descriptive Statistics

	Minimum	Maximum	Median	Mean	Standard Deviation
tdta	0	0.6300	0.1118	0.1511	0.1550
lnta	6.4409	16.1885	10.6067	10.7696	2.0166
tang	0	0.9296	0.1595	0.2485	0.2510
roa	-1.5770	0.3524	0.0556	-0.0258	0.2901
mtb	0.2269	12.6277	1.0704	1.6749	1.8954
capexta	0	0.3224	0.0285	0.0477	0.0580
resdev	0	0.4677	0	0.0272	0.0760
resdevdum	0	1	0	0.3153	0.4647
Statistics are calculated having winsorised all variables at the 1% level at both ends of their distributions					

Table 3: Univariate Correlation Coefficients

	tdta	*lnta*	*tang*	*roa*	*mtb*	*capexta*	*resdev*	*resdevdum*
tdta	1.00							
lnta	0.34***	1.00						
tang	0.38***	0.28***	1.00					
roa	0.10***	0.39***	0.17***	1.00				
mtb	-0.17***	-0.26***	-0.16***	-0.26***	1.00			
capexta	0.13***	0.08***	0.533***	0.06***	0.05***	1.00		
resdev	-0.19***	-0.20***	-0.18***	-0.38***	0.33***	-0.07***	1.00	
resdevdum	-0.10***	-0.005	-0.14***	-0.12***	0.16***	-0.07***	0.53***	1.00
Coefficients estimated are Pearson correlation coefficients. *, ** and *** denote coefficient significance levels of $p \leq .01$, $p \leq .05$ and $p \leq .1$, respectively. Statistics are calculated having winsorised all variables at the 1% level at both ends of their distributions								

Formulation of Dynamic Partial Adjustment Model

Assume that each firm has its own endogenously determined target leverage ratio, which is a function of a set of observable lagged firm characteristics, as well as unobservable firm-specific time-invariant effects. This can be expressed as:

$$D*_{it} = \sum_{k=1}^{k} \beta_k x_{kit-1} + \alpha_i + u_{it} \qquad (1)$$

where $D*_{it}$ is the target leverage ratio of firm *i* at time *t*, $\sum_{k=1}^{k} \beta_k x_{kit-1}$ is a set of *k* firm characteristics for firm *i* at time *t-1*, α_i represents unobserved firm-specific time-invariant effects, and u_{it} is an error term. If firms are assumed to adjust their leverage ratios each period such that the actual leverage ratio is as close as possible to the target leverage ratio for that period, the change in the actual leverage ratio in a given time period can be expressed as:

$$D_{it} - D_{it-1} = \lambda(D*_{it} - D_{it-1}) \qquad (2)$$

where D_{it} is the actual leverage ratio in time *t*, $D_{it} - D_{it-1}$ is the change in actual leverage ratio from time *t-1* to *t*, $D*_{it} - D_{it-1}$ is the required change in leverage ratio from time *t-1* to *t* to achieve the target leverage ratio, and λ represents the fraction of the required change in the leverage ratio actually achieved.

In the traditional static model the firm is assumed to always be at its optimum leverage ratio, and thus the change in the leverage ratio in any period exactly equals the required change, and hence $\lambda = 1$. If, however, firms are indifferent to their capital structures, no target exists and any change in the leverage ratio is randomly associated with the perceived required change, hence $\lambda = 0$. Finally, if firms do attempt to achieve an optimum capital structure but are hindered by adjustment costs, the actual change will be a fraction of the required change, and λ will lie between 0 and 1. λ therefore represents the speed at which the firm adjusts to its target. Combining equations 1 and 2 above results in:

$$D_{it} - D_{it-1} = \lambda\left[\left(\sum_{k=1}^{k} \beta_k x_{kit-1} + \alpha_i + + u_{it}\right) - D_{it-1}\right] \qquad (3)$$

Bringing all D_{it-1} over to the RHS, multiplying out the terms in brackets, and factoring out D_{it-1} results in:

$$D_{it} = (1-\lambda)D_{it-1} + \lambda\sum_{k=1}^{k}\beta_k x_{kit-1} + \lambda\alpha_i + \lambda u_{it} \tag{4}$$

Thus, the model to be tested states that the leverage ratio of firm *i* in time *t* is a function of the leverage ratio in time *t-1*, and a set of firm characteristics hypothesised to represent a firm's target leverage ratio in time *t*. In order to account for the fractional nature of the dependent variable, we estimate equation 4 using the DPF estimator developed by Elsas and Floysiak (2011). We also estimate the model using the System Generalised Methods of Moments estimator as developed by Blundell and Bond (1998), as this is the most commonly employed estimator when implementing a dynamic partial adjustment model, particularly when SOAs are compared across sub-samples. Estimating both models allows us to demonstrate the scale of the bias in the estimate of the SOA when estimators that do not address the fractional nature of the dependent variable are employed to compare SOAs across sub-samples. For both models we include time dummies to capture the effect of unobserved time-specific firm-invariant fixed effects.

Sub-Sampling Method

In order to investigate heterogeneity in the SOAs of UK firms, we follow the approach of Elsas and Florysiak (2011, 2015) and divide firms into sub-samples based on risk. Elsas and Florysiak (2011) suggest that whilst riskier firms may exhibit slower speeds of adjustment due to higher adjustment costs, they may also exhibit faster adjustment speeds due to higher opportunity costs of being away from target leverage. Thus, estimating SOAs across sub-samples that differ in terms of risk provides an opportunity to not only investigate heterogeneity in SOAs, but also generate evidence in favour of one of two hypotheses that are in direct contradiction.

To distinguish between high and low risk firms, we use three variables as categorising mechanisms. First, as the cash flows of larger firms are likely to be less volatile due to greater diversification of lines of business, we classify large firms as low risk and small firms as high risk. Second, as the liquidation values of firms are likely to be directly related to the degree to which their assets are tangible in nature, we classify firms with high proportions of tangible assets as low risk and firms with low proportions of tangible assets as high risk. Finally, given that firm size and asset tangibility may proxy firm characteristics other than risk, we conduct exploratory factor analysis on all of our explanatory variables. We find that the factor loadings of the first factor generated, and the only factor with an eigenvalue greater than one, are positive in firm size, asset tangibility, profitability and capital expenditure, and negative in market-to-book, research and development, and research and development dummy. We assume this factor to represent risk i.e. firms that are larger, more profitable, have higher levels of new and existing tangible assets, have fewer growth opportunities and invest less in research and development pose lower risk to investors. We therefore estimate a factor score for each observation, and classify firms with a high factor score as low risk and firms with a low factor score as high risk.

IV. Results

Table 4 presents the results of the dynamic partial adjustment model using the full sample of firm-year observations. The Wald χ^2 statistic for each model rejects the null hypothesis that the coefficients of the explanatory variables are equal to zero, whilst the AR(2) and Hansen χ^2 statistics relating to the BB model indicate, respectively, that second order serial correlation is not present and that the set of instruments employed can be considered exogenous.

The coefficients of the lagged dependent variables as generated by the DPF and BB estimators imply SOAs of 27.9% and 20.9%, respectively, suggesting the average UK firm does indeed adjust to a target leverage ratio. However, qualitatively speaking, the bias associated with the BB estimator appears to be quite significant, as the DPF estimator is approximately 33% faster in relative terms. This is consistent with the findings of Drobetz et al (2015) who observe an SOA of 25% for the average firm in the G7 countries when employing the DPF estimator, and a corresponding SOA of 18.2% when employing the BB estimator. Furthermore, dropping firm-year observations with 0 leverage ratios appears to have little or no impact in terms of reducing the bias associated with the BB estimator, as the implied SOA using the sub-sample with positive leverage ratios is 20.2%. These results suggest that SOAs estimated for UK firms in prior studies using the BB estimator may be drawing spurious conclusions as to the true SOA of the average UK firm.

In relation to the determinants of target leverage, the coefficients for l.lnta, l.mtb and l.capexta are consistent across the three models and with the existing literature, indicating that larger firms with fewer growth opportunities and higher spending on fixed assets have higher target leverage ratios as they pose less risk to lenders. The results relating to l.tang, l.roa, l.resdev and l.resdevdum appear model dependent, with coefficient signs and significance levels varying by estimator and sample. Why the coefficients for these variables should differ across the models is not immediately apparent. Of particular interest are the positive coefficients for l.roa and l.resdev as generated by the DPF estimator, as most studies find negative coefficients for these variables. Perhaps more profitable firms have greater access to debt markets due to increased ability to repay debt, whilst firms with significant investment in R&D favour debt financing due to potential adverse selection costs associated with equity issues.

Table 4: Results of the Dynamic Partial Adjustment Model – Full Sample

	DPF	BB	BB tdta>0
l.tdta	0.721*** (0.009)	0.791*** (0.024)	0.798*** (0.026)
l.lnta	0.010*** (0.002)	0.008*** (0.002)	0.006** (0.002)
l.tang	-0.003 (0.010)	0.036** (0.016)	0.018 (0.018)
l.roa	0.009** (0.004)	0.008 (0.007)	0.008 (0.009)
l.mtb	-0.002*** (0.0006)	-0.002*** (0.0008)	-0.003** (0.001)
l.capexta	0.132*** (0.020)	0.102*** (0.030)	0.153*** (0.035)
l.resdev	0.049** (0.024)	0.051* (0.030)	-0.019 (0.050)
l.resdevdum	-0.004 (0.004)	-0.007 (0.006)	0.001 (0.008)
N	15,752	15,752	12,187
Wald $\chi^2(35)$	13961***		
Wald $\chi^2(29)$		3245***	36342***
AR(1)		-15.36***	-14.92***
AR(2)		-0.07	0.49
Hansen $\chi^2(303)$		314	288
Standard errors are in parentheses. . *, ** and *** denote coefficient significance levels of $p \leq .01$, $p \leq .05$ and $p \leq .1$, respectively.			

To investigate the heterogeneity in SOAs across UK firms, table 5 presents SOAs generated using sub-samples of firm-year observations. For the sake of brevity, only the coefficients and standard errors (in parentheses) of the lagged dependent variable are presented, along with the implied SOAs, the difference in SOAs across sub-samples, and a z-test statistic that indicates the extent to which SOAs can be considered significantly different across sub-samples.[4] All lagged coefficients are significant at the 1% level. The sub-samples are generated using firm size, asset tangibility and a factor assumed to represent risk as categorising variables. Panel A presents results for sub-samples with observations below and above the sample median value of the relevant categorising variable. Panel B presents results for sub-samples with observations below and above the sample 25th and 75th percentile values of the relevant categorising variable, respectively.

A comparison of the SOAs across the three pairs of sub-samples in panel A show that riskier firms adjust to target leverage ratios faster than less risky firms. These results are consistent with those of Elsas and Florysiak (2011, 2015) and suggest that riskier firms face higher opportunity costs of deviating from target leverage, and thus have a greater incentive to adjust to target leverage. In addition, the larger disparities across the sub-sample SOAs as generated by the BB estimator demonstrate support for Elsas and Florysiak's (2015) assertion, that when assessing heterogeneity of SOAs, a biased estimator may lead to spurious inferences being made. Indeed, panel B demonstrates that this bias can lead to increasingly unreliable results being generated as ever more extreme sub-samples are compared. The disparities between the sub-sample SOAs as generated by the BB model become larger and statistically more significant in panel B, whilst those relating to the DPF model become smaller and statistically less significant across the asset tangibility sub-samples and risk factor sub-samples. As such, the SOAs generated by the DPF model in panels A and B suggest the relationship between SOA and firm size may be monotonic, whilst those between SOA and asset tangibility, and SOA and risk factor, may be non-monotonic. On the other hand, the SOAs generated by the BB model suggest all three relationships are monotonic. These results are again comparable to those presented by Elsas

[1] The z test statistic is calculated as follows: $z = \frac{\beta_1 - \beta_2}{\sqrt{se\beta_1^2 + se\beta_2^2}}$, where β_1 and β_2 are the coefficients of the lagged dependent variable within each sub-sample pairing, and $se\beta_1$ and $se\beta_2$ are the associated standard errors.

and Florysiak (2015), where the patterns of SOAs generated by the DPF and BB models across sub-samples based on credit ratings differ significantly.

Table 5: SOAs across Risk Sub-Samples

		DPF			BB		
Categorising Variable	Sub-Sample	*l.tdta*	SOA	Diff *z-test*	*l.tdta*	SOA	Diff *z-test*
Panel A							
Firm Size	Small	0.712 (0.016)	0.288	0.051 *2.40***	0.765 (0.035)	0.235	0.084 *1.85**
	Large	0.763 (0.014)	0.237		0.849 (0.029)	0.151	
Asset Tangibility	Low Tangibility	0.704 (0.015)	0.296	0.041 *2.07***	0.726 (0.034)	0.274	0.083 *1.83**
	High Tangibility	0.745 (0.013)	0.255		0.809 (0.030)	0.191	
Risk Factor	High Risk	0.714 (0.016)	0.286	0.050 *2.43***	0.735 (0.029)	0.265	0.090 *2.27***
	Low Risk	0.764 (0.013)	0.236		0.825 (0.027)	0.175	
Panel B							
Firm Size	Very Small	0.678 (0.026)	0.322	0.092 *2.96****	0.664 (0.046)	0.336	0.126 *2.27***
	Very Large	0.770 (0.017)	0.230		0.790 (0.031)	0.210	
Asset Tangibility	Very Low Tangibility	0.732 (0.025)	0.268	0.015 *0.48*	0.599 (0.051)	0.401	0.255 *4.24****
	Very High Tangibility	0.747 (0.019)	0.253		0.854 (0.032)	0.146	
Risk Factor	Very High Risk	0.712 (0.028)	0.288	0.046 *1.36*	0.654 (0.054)	0.346	0.193 *3.15****
	Very Low Risk	0.758 (0.019)	0.242		0.847 (0.029)	0.153	

V. Conclusion

This study investigates heterogeneity in the speed of adjustment (SOA) to target leverage in UK firms. Using the Dynamic Panel Fractional estimator which accounts for the censored nature of leverage, we find that a firm's SOA to target leverage is dependent on the level of risk it poses to investors. High risk firms are observed to adjust to target leverage at a faster rate than low risk firms, suggesting that the opportunity cost of deviation from target leverage is higher for riskier firms. We also demonstrate that SOAs estimated using the Blundell-Bond (BB) estimator, which does not account for the censored nature of leverage, produces markedly different SOAs, both when the full sample of observations is employed, and when SOAs are estimated across sub-samples of observations. These findings suggest that SOAs reported by studies using the BB estimator are likely biased, particularly in relation to SOAs generated using sub-samples. Our results are consistent with those of Elsas and Florysiak (2011, 2015) and Drobetz et al (2015), and demonstrate the need to address both heterogeneity in SOAs and the fractional nature of leverage when estimating SOAs in a dynamic partial adjustment setting.

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