



Bias correction in the estimation of dynamic panel models in corporate finance



Qing Zhou^{a,c}, Robert Faff^{a,b,*}, Karen Alpert^a

^a UQ Business School, The University of Queensland, Australia

^b Department of Accounting and Finance, University of Strathclyde, Glasgow, Scotland, United Kingdom

^c School of Management, Xi'an Jiaotong University, China

ARTICLE INFO

Article history:

Received 21 August 2013

Received in revised form 26 January 2014

Accepted 27 January 2014

Available online 9 February 2014

JEL classification:

G30

C23

Keywords:

Dynamic panels

Corporate finance

Bias-correction

ABSTRACT

Dynamic panel models play an increasingly important role in numerous areas of corporate finance research, and a variety of (biased) estimation methods have been proposed in the literature. The biases inherent in these estimation methods have a material impact on inferences about corporate behavior, especially when the empirical model is misspecified. We propose a bias-corrected global minimum variance (GMV) combined estimation procedure to mitigate this estimation problem. We choose the capital structure speed of adjustment (SOA) setting to illustrate the proposed method using both simulated and actual empirical corporate finance data. The GMV estimator non-trivially reduces bias and hence meaningfully increases the reliability of inferences based on parameter estimates. This method can be readily applied to many other corporate finance contexts.

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1. Introduction

A number of techniques have become increasingly popular in corporate finance research (e.g., dynamic structure modeling and quasi-experimentation). While each of these major new approaches has been shown to provide novel insights, inevitably they all have some form of limitation. Dynamic panel bias,¹ endogeneity issues, empirical model misspecification, and other potential corporate data issues (both separately and in combination) can introduce severe biases into existing baseline estimations, which cast serious doubt over the credibility of the inferences drawn regarding corporate decision making. Despite such issues, inference in corporate finance research is likely to continue to rely heavily on cross-sectional regressions, with dynamic panel models playing an increasingly prominent role (Flannery and Hankins, 2013; Wintoki et al., 2012).

To address the well-known difficulties relating to the identification of parameters in corporate dynamic panel models (e.g., Flannery and Hankins, 2013; Huang and Ritter, 2009), we propose a bias-corrected minimum variance combined estimation procedure. Moreover, we use various statistical specifications to evaluate the performance of this method in an empirically meaningful manner for corporate finance research. Following the lead of several recent studies of corporate finance methodology (e.g., Flannery and Hankins, 2013; Strebulaev and Whited, 2012), we choose capital structure as the research context in which to illustrate our approach. We make this choice, not only because of the prominence and familiarity of capital structure within corporate finance research, but also because of the longstanding and widespread recognition of the challenge of reliably estimating the speed of adjustment (SOA) for leverage in dynamic panel models.² Indeed, capital structure represents a mature research area that can substantially benefit from the bias correction methods that we advocate.

* Corresponding author at: UQ Business School, The University of Queensland, Brisbane, QLD 4072, Australia. Tel.: +61 7 3346 8055; fax: +61 7 3346 8166.

E-mail addresses: q.zhou@business.uq.edu.au (Q. Zhou), r.faff@business.uq.edu.au (R. Faff), k.alpert@business.uq.edu.au (K. Alpert).

¹ This type of bias is also known as “short panel bias”.

² See Huang and Ritter (2009) and Flannery and Hankins (2013) for comprehensive comparisons of the most widely used SOA estimators.

While we ground our study in the specific area of SOA estimation, we aim to establish a generally applicable framework and thereby contribute to a broad range of corporate finance studies which share in common inherently dynamic questions, featuring endogenous variables, and that are subject to non-trivial model misspecification. Furthermore, we extend our study to compute a consensus SOA estimate derived from a diverse set of popular extant estimators.

SOA-related research is controversial. The partial adjustment model itself could be misspecified (Chang and Dasgupta, 2009; Hovakimian and Li, 2011; Iliev and Welch, 2010) and thus can spuriously favor the adjustment hypothesis. However, there are also studies supporting the partial adjustment model (e.g., Liu, 2009). Therefore, whether and to what extent firms actually adjust leverage to a target is still an open question, and thus, uncovering the underlying economic force is of primary importance to capital structure researchers (Graham and Leary, 2011).

But, there is no logical reason to dismiss any given research stream, since it is very likely that each and every method can provide some incremental insight despite their respective limitations (Hennessy, 2013). Undeniably, recent advances in corporate finance research, such as dynamic structure modeling and natural experiments, can mitigate endogeneity and causal inference problems. Nevertheless, the existing dynamic modeling literature is primarily theoretical, and the related models have not yet been thoroughly tested (Welch, 2013). Moreover, high-quality, credible natural experiments are extremely difficult to identify in corporate finance (Strebulaev and Whited, 2013). As a consequence, the reduced-form dynamic panel model remains a critically important tool for testing and drawing inferences in corporate finance research.

We contribute to the broader literature by providing a readily implementable alternative method for solving the bias estimation problem in realistic corporate settings. In these contexts, endogenous regressors, unbalanced panels, and the potential misspecification of empirical models collectively are formidable obstacles to many interesting question-driven investigations. Our study is the first to examine the performance of bias-correction methods under various conditions typically encountered in corporate datasets. Our objective is to provide new insights from a different perspective, backed up by meaningful analyses aimed at enhancing the toolkit available to corporate empiricists.

Our paper proceeds as follows. Section 2 briefly reviews SOA estimation in a partial adjustment framework. Section 3 addresses the materiality of bias in the estimated SOA, formulating and applying a general, simulation-based bias correction method as a solution. Section 4 further investigates the proposed method using an actual empirical sample of corporate finance data. Section 5 provides a broader discussion, while Section 6 concludes the paper.

2. Biased estimations in capital structure research: theory and models

2.1. Brief literature overview

The question of how leverage ratios are determined remains elusive three decades after Myers' (1984) AFA presidential address. It is still the most important outstanding question in capital structure literature (Welch, 2013). The three preeminent theories of capital structure are the static trade-off model, the pecking order model, and the more recently popularized market timing model (see Baker and Martin, 2011, for an overview of these theories). Empirical tests of the implications of these theories have spawned numerous papers in the extant literature. While each of these theories has successfully explained several patterns observed in capital structure, they have generally failed to explain much of the observed heterogeneity.

Recent studies have utilized several approaches to address the shortcomings of these traditional models. As Graham and Leary (2011) discuss in their review, different perspectives regarding the nature of these shortcomings have been adopted in these recent empirical studies. In particular, one of the most documented problematic issues in capital structure research relates to SOA inferences. Huang and Ritter (2009) view the estimation of the speed with which firms adjust toward their target leverage levels as the most important issue in capital structure research. Iliev and Welch (2010, p. 2) in recognizing the importance of SOA estimation, state the following regarding the perspective expressed by Huang and Ritter (2009):

The literature is now settled with these starkly different estimates. Even if Huang and Ritter are too optimistic in their assessment of its importance, the SOA is still a readily empirically observable and interpretable statistic that characterizes aggregate corporate capital structure behavior. Its magnitude is of interest not only to many academics, but also to many practitioners and students.

However, no consensus has been reached. Indeed, the literature sends a confused message regarding how best to estimate SOA and the model specification of leverage adjustment behavior. At best, empirical models can only serve as approximations of the underlying "truth"; therefore, all such models can be falsified (Strebulaev and Whited, 2013). Partial adjustment models that account for dynamics represent overly simplified approximations of reality but remain among the most widely accepted reduced-form empirical models in leverage studies. Thus, we purposefully select SOA estimation in a partial adjustment model to illustrate the bias correction method in scenarios involving correctly specified as well as misspecified models.

2.2. Estimation and specification of leverage dynamics

2.2.1. Biased estimation: dynamic panel bias

The partial adjustment model states that corporate financial leverage adjusts towards long-run target leverage, but due to adjustment costs, actual leverage is only partially adjusted toward optimal leverage during each period (Fischer et al., 1989). A

basic partial adjustment model must include a lagged dependent variable to control for prior leverage and fixed effects to control for individual unobservable firm characteristics. The partial adjustment framework can be specified as follows:

$$L_{it+1} - L_{it} = \lambda(TL_{it+1} - L_{it}) + \delta_{it+1} \quad (1)$$

and

$$TL_{it+1} = \beta X_{it} + F_i \quad (2)$$

where L is a firm's leverage ratio, which is the ratio of interest-bearing debt to the sum of interest-bearing debt and the market value of equity; TL is the target leverage ratio; λ is the adjustment speed toward the target (i.e., the SOA); δ is an error term; X_i is a vector of observable firm-specific determinants of the target leverage; and F_i is a firm fixed effect. The subscripts indicate the firm and year dimensions.

A two-stage procedure is a natural and intuitive approach for the estimation of these regression models, but this type of procedure is likely to suffer from the errors-in-variables problem. Therefore, recent studies have adopted a one-stage estimation approach in which Eq. (2) is substituted into Eq. (1) to produce the following model:

$$L_{it+1} = (1 - \lambda)L_{it} + (\lambda\beta)X_{it} + \lambda F_i + \delta_{it+1}. \quad (3)$$

The basic model specification for the leverage partial adjustment model given by Eq. (3) is therefore a standard, linear, first-order dynamic panel model with fixed effects that has the following general econometric form:

$$y_{it} = \gamma y_{it-1} + \beta X_{it} + F_i + \varepsilon_{it}. \quad (4)$$

The SOA (λ), which is the primary variable of interest, can be estimated as $1 - \gamma$. However, the estimation of Eq. (4) is problematic. In essence, the major issue in the estimation process relates to the fact that the equation's disturbance term is correlated with the lagged dependent variable (see Nickell, 1981; Sevestre and Trognon, 1985). This correlation causes the pooled ordinary least squares (OLS) and fixed effect (FE) estimators, which are conventional panel estimation approaches, to be biased and inconsistent under the typical conditions of a large N and a fixed T . Given that, as documented in the extant literature, Compustat firms have a median life of 10 to 14 years, there is a limited time span for sample data, which is not sufficient to render these biases negligible. In particular, the aforementioned methods produce significant finite-sample biases in estimations of the speed of adjustment (Baltagi, 2008; Nickell, 1981), thereby providing misleading evidence for the trade-off theory.

The instrumental variable (IV) (e.g., Flannery and Rangan, 2006) and generalized method of moments (GMM) estimation methods (e.g., Antoniou et al., 2008; Lemmon et al., 2008; Miguel and Pindado, 2001) have been proposed and applied in empirical corporate finance studies to mitigate the dynamic panel bias and endogeneity problem. However, empirical researchers in corporate finance are typically restricted to the use of a firm's own history (lags of a firm's variables) for identification due to the scarcity of purely exogenous instruments in many interesting corporate research contexts. The large number of available instruments and a lack of clear guidance regarding the choice of instruments lead to severe identification problems for GMM estimations (Huang and Ritter, 2009). The weakness of the specification tests³ and the sensitivity of GMM estimation to instrument choice mean that GMM estimations are difficult to justify in many corporate settings. Moreover, the persistence of particular corporate variables (e.g., financial leverage) raises concerns regarding the weak instrument problem (e.g., Hausman et al., 2005; Stock et al., 2002). The recently adopted estimation methods of long differencing (LD) and least squares dummy variable correction (LSDVC) have produced some promising results but can still generate biased estimates if endogenous variables and persistent dependent variables are evident in the data (see Flannery and Hankins, 2013).

These documented estimators rely on various assumptions regarding heterogeneity, serial correlation, panel balance, or endogeneity. Thus, the features of an examined dataset must be carefully scrutinized prior to the use of any of these estimator approaches. It is desirable for an estimate to display low variability and minimal biases across samples. However, recent studies by Flannery and Hankins (2013) and Dang et al. (2013) that have compared estimation methods demonstrate that all of the available estimators are biased if applied to realistic corporate finance data.

2.2.2. The misspecification of leverage dynamics

Biases can be created not only by issues relating to estimation uncertainty in a partial adjustment framework but also by potential misspecifications in empirical models (e.g., the mismeasurement and/or omission of variables). These misspecifications are a major concern addressed by numerous recent empirical corporate investigations.⁴ In combination with dynamic panel bias, misspecification substantially exacerbates the extent to which estimates are biased and can even induce a spurious reversal in the sign of parameters of interest (Lee, 2012). Simulation studies by Chang and Dasgupta (2009) and Elsas and Florysiak (2011) illustrate how the bounded variable feature of leverage produces a spurious “mean-reverting” process; these studies raise concerns regarding the potential misspecification of leverage dynamics. However, this type of bias has only attracted limited attention in existing SOA empirical studies.

³ Wintoki et al. (2012) examine power of tests of the second-order serial correlation (AR(2)) and over-identification (the Hansen J statistic) in corporate settings and show that tests of instrument validity cannot completely eliminate the possibility of biased GMM estimates.

⁴ See Graham and Leary (2011) for a discussion of the issue of empirical model misspecification in capital structure studies.

The deeper lags of leverage are among the most obvious omissions of capital structure models. Because leverage is path dependent, lags of leverage beyond the first lag can impact a firm's current leverage; in other words, capital structure decisions made over the prior 2 or 3 years can be correlated with capital structure decisions during the current period. Thus, the partial adjustment model specification (e.g., [Flannery and Rangan, 2006](#)) might not completely describe corporate leverage dynamics. In addition, a lack of characteristic variables for a firm during current and prior periods might represent a critical source of potential model under-specification. These sources of misspecification of corporate leverage dynamics produce serial correlations in the residuals ε_{it} ; thus, $E(\varepsilon_{it}\varepsilon_{it-s}) \neq 0$ for $s > 0$. Such serial correlation causes problems in the estimation of Eq. (4) and has even greater influence on the dynamic panel GMM estimator, which relies on the assumption that longer lags are exogenous to current residuals. Moreover, in the dynamic panel GMM estimator, these longer lags are used as instruments ([Wintoki et al., 2012](#)).

Notably, the length of the time series T is short in empirical corporate finance studies, and a first-order autoregressive structure is unavoidable in these types of investigations. While corporate empiricists are hampered by data limitations, serious attention must be devoted to investigating whether misspecifications can significantly influence inferences regarding model parameters. In particular, the combination of model misspecification and short panel biases can produce far greater estimation distortions than might be expected from simply summing their individual effects ([Lee, 2012](#)). Therefore, estimation biases that often are materially detrimental to the ultimate conclusions of a research question need to be corrected, and these corrections must be robust to misspecifications in leverage dynamics.

Notwithstanding our focus on SOA estimation, the following general empirical specification illustrates the broader potential for our approach:

$$y_{it} = \alpha + \sum_{s=1}^S \gamma_s y_{it-s} + \beta X_{it} + F_i + \varepsilon_{it}. \quad (5)$$

where y_{it} represents a broad variety of factors, such as corporate performance, leverage, cash holdings, or corporate investment, and X_{it} represents characteristic variables, which might include endogenous variables (e.g., board structure, as discussed by [Wintoki et al. \(2012\)](#)).

3. Bias correction and a consensus SOA estimate

3.1. How can we correct the bias for SOA estimates?

To simplify our illustrative example for bias correction, we focus on the estimation of γ ($\lambda(\text{SOA}) = 1 - \gamma$) in Eq. (4).⁵ SOA estimation is a major point of interest in most investigations that test the trade-off theory of capital structure. For an initial estimator $\hat{\gamma}_i$, assuming $E(\hat{\gamma}_i)$ exists, we can always write the following expression:

$$\hat{\gamma}_i = \gamma_0 + b_i(\gamma_0, n) + v_i(\gamma_0, n). \quad (6)$$

In the above equation, γ_0 denotes the true γ value, and $b_i(\gamma_0, n) \equiv E(\hat{\gamma}_i) - \gamma_0$, representing the bias function, which is a function of $\hat{\gamma}_i$ and the sample size n . $v_i(\gamma_0, n)$ is the random error. Because n is typically fixed in empirical corporate work, any bias is generally dependent on the true underlying values of parameters. The bias $b_i(\gamma_0, n)$ of a given SOA estimator derives from three sources: estimation issues, model misspecification, and induced bias produced by the interaction between these two. This concept can be expressed as follows:

$$b_i(\gamma_0, n) = b_i^e(\gamma_0, n) + b_i^m(\gamma_0, n) + b_i^c(\gamma_0, n) \quad (7)$$

where $b_i^e(\gamma_0, n)$, $b_i^m(\gamma_0, n)$, and $b_i^c(\gamma_0, n)$ represent the biases generated by estimation issues, model misspecification, and the interaction between the two, respectively. Therefore, the analytical bias-correction formula approach (e.g., LSDVC) to correct the bias coming from estimation issues (e.g., dynamic panel bias) might actually lead to an increase in the total bias $b_i(\gamma_0, n)$. This perverse result can occur because while LSDVC reduces $b_i^e(\gamma_0, n)$ as intended, it might at the same time, inflate the other two types of biases, $b_i^m(\gamma_0, n)$ and $b_i^c(\gamma_0, n)$. That is, the latter two effects might outweigh the beneficial reduction in the first.

The bootstrap bias correction proposed in the literature (e.g., [Everaert and Pozzi, 2007](#)) usually assumes a flat bias function that satisfies $b(\gamma, n) = b(n)$ for all γ and adopts a constant bias correction (CBC) procedure. However, estimation biases are unlikely to be constant. Indeed, as observed in estimates of dynamic capital structure models, biases in estimates of γ tend to become larger as the true value of γ approaches unity. Accordingly, a more realistic bias function is a linear (or perhaps even a non-linear) transformation of the true γ value.

We use a simple linear bias correction (LBC) as our single-estimator bias correction method.⁶ Following [MacKinnon and Smith \(1998\)](#), we summarize the implementation of both the CBC and LBC methods in [Appendix A](#). Two unknown parameters in the

⁵ The estimation of long-run relationships between the target and its determinants shown in regression (2) is also important. In our unreported results, the estimated coefficients on firm characteristic variables are subject to biases that can switch the signs of these coefficients.

⁶ Although non-linear bias correction (NBC) is also potentially relevant to our scenarios, this method requires more computational time to fit the bias function than the LBC or CBC approaches and may severely inflate estimation variances. The differences between LBC and NBC are not overly concerning because the LBC and NBC methods are actually identical through $O_p(n^{-1})$ (see [MacKinnon and Smith, 1998](#)). Moreover, the LBC and NBC approaches perform similarly in practice.

linear bias function, the intercept C and the slope S , can be solved empirically by utilizing two points (e.g., initial estimate $\hat{\gamma}$ and the CBC estimate $\tilde{\gamma}$). The LBC estimator $\tilde{\gamma}$ will be unbiased whenever the bias function is linear, and, as shown in [Appendix A](#), the overall estimation accuracy will increase if the bias function is upward sloping ($S > 0$) or if the variance of γ is relatively small compared to the bias component. Another advantage of this method is its generality. The method is applicable in a broad range of model specifications and can be used in conjunction with a variety of baseline estimators.

We investigate the bias-correction performance for six of the most popular baseline estimators in existing studies of capital structure: (1) OLS; (2) fixed effects (FE); (3) [Arellano and Bond's \(1991\)](#) difference GMM (AB); (4) [Blundell and Bond's \(1998\)](#) system GMM (BB); (5) [Huang and Ritter's \(2009\)](#) 4-period long difference estimation (LD4); and (6) LSDVC ([Bruno, 2005](#); [Kiviet, 1995](#)). We summarize the estimation procedure in [Appendix B](#). Prior to implementing the bias-correction analysis, we first examine the bias features of these single estimators and how their inherent biases affect economic inferences in the context of corporate finance. Few existing studies provide such a detailed discussion in this regard.

We then perform two sets of simulations. The first simulation analysis assumes that the estimation model is correctly specified and that the firm characteristic variables are generated independently and identically following normal distributions. The second set of simulations involves model misspecification generated by incorporating second-order serial correlation into the residuals. In addition, other problematic data issues (e.g., endogeneity, missing data, and unbalanced panel) are embedded in the second set of simulated datasets to illustrate in an empirically meaningful way, the bias-correction in such a highly problematic scenario. We generate our data for these two scenarios in a similar way to [Flannery and Hankins \(2013\)](#), but rather than solely focusing on

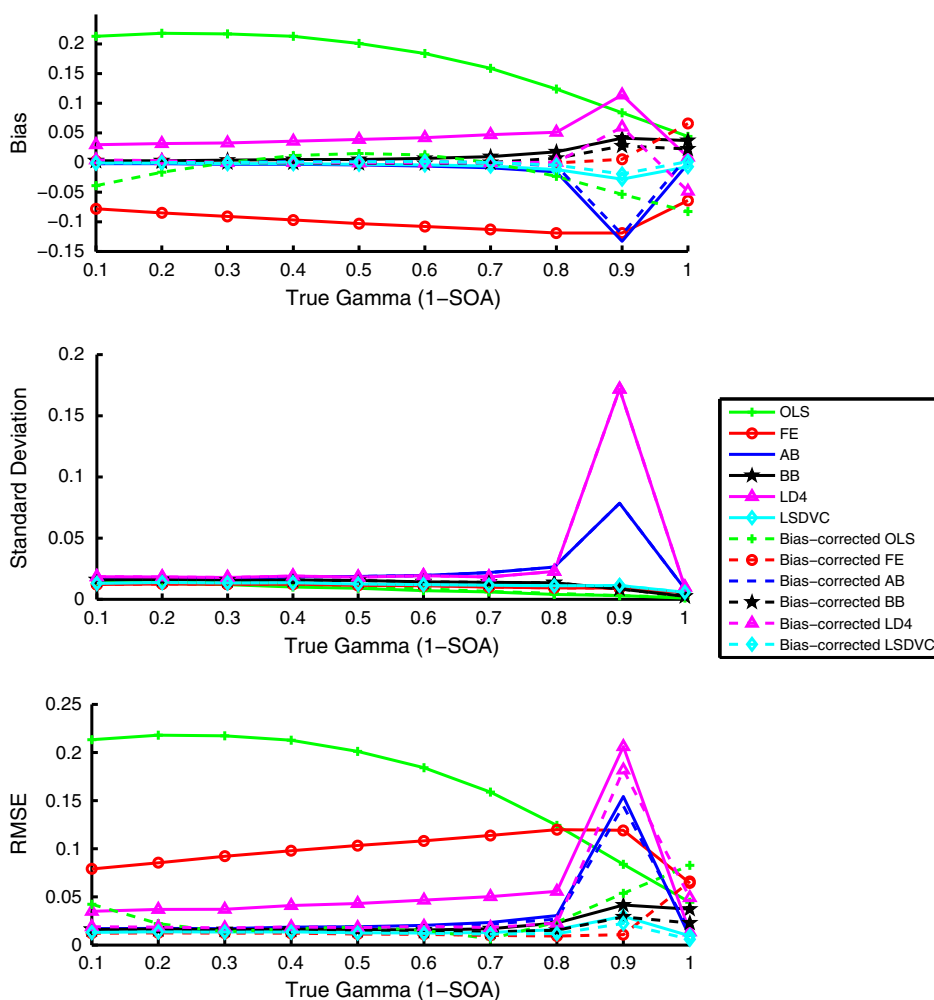


Fig. 1. Simulated performance of bias-corrected vs. baseline single estimators of the partial adjustment model absent model misspecification. This figure compares the performance of single bias-corrected estimators with the performance of their corresponding baseline estimators, absent model misspecification. The six single estimation methods are: (1) OLS, (2) standard fixed effects (FE) estimation, (3) Arellano and Bond's (1991) difference GMM (AB), (4) Blundell and Bond (1998) system GMM (BB), (5) Huang and Ritter (2009) 4-period long differencing (LD4), and (6) least squares dummy variable correction (LSDVC, Bruno, 2005; Kiviet, 1995). For each γ value ($\lambda = 1 - \gamma$, where λ denotes SOA), 500 dynamic panels are generated. Each panel consists of 6,000 firm-year observations (firm $N = 500$ and time $T = 12$). The top panel shows the bias comparison, the middle panel shows the standard deviation comparison, while the bottom panel illustrates the RMSE comparison.

extreme values of SOA, we generate the simulated dataset under a range of hypothetical values in the range [0.1, 1.0] for the true value of γ (i.e., $1 - \text{SOA}$) with increments of 0.1. We summarize the simulation data-generating process in [Appendix C](#).

3.2. Simulation evidence assuming correctly specified leverage dynamics

In [Fig. 1](#), we depict the biases that arise if corporate leverage dynamics are correctly specified and no other problematic data features are incorporated into the simulated dataset. These biases exclusively arise from dynamic panel bias. The solid lines represent baseline estimates, while the dashed lines indicate the bias-corrected estimates. As shown in [Fig. 1](#), the biases of the six baseline estimators approximate linear functions of the true γ value for γ values less than 0.8, which correspond to annual leverage speeds of adjustment greater than 20%. However, the biases become distorted as the true γ values approach 1.0; in other words, distortions are evident if little or no true leverage adjustment behavior exists. This finding suggests that estimates of SOA ($1 - \gamma$) are severely biased if actual SOA values are close to 0. In other words, all six of the examined single estimators provide unreliable estimates in cases of negligible or nonexistent adjustment behavior.

Among these single estimators, consistent with the findings of [Flannery and Hankins \(2013\)](#), the conventional OLS and FE estimation approaches produce the greatest biases. However, these two approaches are biased in opposite directions for true γ values below 0.8, suggesting that the OLS and FE estimates define reasonable bounds for SOA estimates. The system GMM (BB) and LSDVC approaches are the best-performing standalone estimators, producing only negligible biases for all assumed true values. As the true γ values increase to values exceeding 0.8, the biases of AB and LD4 estimates sharply increase, breaching the bounds defined by the OLS and FE estimates, whereas the biases of the BB and LSDVC estimates only mildly increase.

Based on our simulation analysis, we further decompose the root mean squared error (RMSE) into the two components of bias and standard deviation (Std.Dev.). We present the characteristics of these components in [Table 1](#). We observe from [Table 1](#) that for each estimator, the bias effects are much greater than the standard deviation effects. Thus, since bias is the predominant driver of the overall inaccuracy of SOA estimates, this situation is ideal for the application of bias-correction methods.

Accordingly, we perform LBC aiming to correct biases for each of the six single baseline estimators. We observe that the bias correction approach greatly reduces the biases of the OLS, FE, and LD4 estimators, as indicated by the fact that the dashed lines in [Fig. 1](#) are closer to zero than the counterpart solid lines for each approach. The bias correction method also improves the GMM (both AB and BB) and LSDVC estimates, but to a lesser extent. Notably, the bias-corrected OLS and FE estimates exhibit smaller biases than the GMM approach, even in situations where γ values exceed 0.9 (i.e., where SOA values are lower than 10%), which as noted above is generally the scenario with the least accurate SOA estimates. The bias-corrected FE approach performs best if the true γ is less than 0.95 (i.e., SOA is greater than 5%). In contrast, the standard deviation component of RMSE in the

Table 1

Simulation evidence for single baseline estimators of the partial adjustment model absent model misspecification.

True γ		0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
OLS	Mean Estimated Coef.	0.313	0.418	0.517	0.613	0.701	0.784	0.859	0.924	0.984	1.044
	Bias	0.213	0.218	0.217	0.213	0.201	0.184	0.159	0.124	0.084	0.044
	Std.Dev.	0.014	0.013	0.012	0.010	0.009	0.007	0.006	0.004	0.003	0.001
	RMSE	0.213	0.218	0.217	0.213	0.201	0.184	0.159	0.124	0.084	0.044
FE	Mean Estimated Coef.	0.022	0.115	0.209	0.303	0.397	0.492	0.587	0.681	0.781	0.936
	Bias	-0.078	-0.085	-0.091	-0.097	-0.103	-0.108	-0.113	-0.119	-0.119	-0.064
	Std.Dev.	0.012	0.012	0.012	0.012	0.011	0.011	0.010	0.009	0.009	0.005
	RMSE	0.079	0.085	0.092	0.098	0.103	0.108	0.114	0.120	0.119	0.064
AB	Mean Estimated Coef.	0.098	0.198	0.297	0.397	0.496	0.594	0.691	0.784	0.767	0.998
	Bias	-0.002	-0.002	-0.003	-0.003	-0.004	-0.006	-0.009	-0.016	-0.133	-0.002
	Std.Dev.	0.017	0.017	0.017	0.018	0.019	0.019	0.022	0.026	0.078	0.008
	RMSE	0.017	0.017	0.017	0.019	0.019	0.020	0.023	0.031	0.154	0.009
BB	Mean Estimated Coef.	0.103	0.203	0.304	0.405	0.505	0.607	0.710	0.818	0.941	1.037
	Bias	0.003	0.003	0.004	0.005	0.005	0.007	0.010	0.018	0.041	0.037
	Std.Dev.	0.016	0.016	0.016	0.016	0.015	0.014	0.014	0.014	0.008	0.002
	RMSE	0.016	0.017	0.016	0.016	0.016	0.016	0.017	0.023	0.042	0.037
LD4	Mean Estimated Coef.	0.130	0.232	0.333	0.436	0.539	0.642	0.747	0.851	1.014	1.009
	Bias	0.030	0.032	0.033	0.036	0.039	0.042	0.047	0.051	0.114	0.009
	Std.Dev.	0.018	0.018	0.018	0.019	0.018	0.019	0.018	0.023	0.172	0.010
	RMSE	0.035	0.037	0.037	0.041	0.043	0.047	0.050	0.056	0.206	0.014
LSDVC	Mean Estimated Coef.	0.099	0.199	0.298	0.398	0.497	0.596	0.694	0.788	0.872	0.993
	Bias	-0.001	-0.001	-0.002	-0.002	-0.003	-0.004	-0.006	-0.012	-0.028	-0.007
	Std.Dev.	0.013	0.014	0.013	0.013	0.012	0.012	0.011	0.011	0.011	0.006
	RMSE	0.013	0.014	0.014	0.014	0.013	0.013	0.013	0.016	0.030	0.009

For each value of γ ($\lambda = 1 - \gamma$, where λ denotes SOA), 500 dynamic panels are generated. Each panel consists of 6,000 firm-year observations (with cross-section $N = 500$ and time $T = 12$). This table indicates the performance of the examined single estimation methods in terms of the bias, standard deviation and RMSE values for each examined estimator absent model misspecification. The six estimation methods are: (1) OLS, (2) standard fixed effects (FE) estimation, (3) Arellano and Bond's (1991) difference GMM (AB), (4) Blundell and Bond (1998) system GMM (BB), (5) [Huang and Ritter \(2009\)](#) 4-period long differencing (LD4), and (6) least squares dummy variable correction (LSDVC, [Bruno, 2005](#); [Kiviet, 1995](#)). The "Mean Estimated Coef." rows present the average γ estimates across 500 panels.

bias-corrected estimates remain largely unchanged from the counterparts in the baseline estimates. Therefore, the use of bias correction greatly reduces overall RMSE in situations involving correctly specified leverage dynamics.

To further investigate whether and to what extent SOA estimation biases are detrimental to economic inferences, we tabulate the calculated baseline SOA estimates and their corresponding implied “half-life” adjustments (in parentheses) in Panel A of Table 2. The counterpart information for each bias-corrected estimator is presented in Panel B of Table 2. Panel A of Table 2 indicates that under conditions involving a correctly specified model and the absence of endogeneity or other data issues, the examined baseline estimates exhibit only negligible biases that do not adversely affect economic inferences. The magnitudes of the observed biases are not sufficient to deleteriously impact inferences regarding firms’ leverage adjustment behavior. For example, in the absence of adjustment behavior (i.e., if the true SOA is 0%), the baseline estimates provided by the OLS, FE, AB, BB, LD4, and LSDVC approaches are –4.44%, 6.41%, 0.20%, –3.72%, –0.94%, and 0.75%, respectively. These estimates generally lead to the correct conclusion that a firm is engaging in “no” or “negligible” leverage adjustment behavior. As such, adjustment behavior-related inferences produced by the examined approaches remain accurate – even for the troublesome zone of true SOA values (less than 10%).

Panel B of Table 2 indicates that the use of bias correction greatly reduces bias levels and produces more accurate SOA estimates. Thus, short panel bias can be greatly reduced by the application of the proposed bias correction method.

In sum, our results imply that although the single baseline estimators are biased under conditions involving correctly specified corporate leverage dynamics and no endogeneity issues, these biases do not unduly affect the final conclusions regarding the speed of leverage adjustment. Under these (albeit unrealistic) conditions, bias correction is likely to provide only marginal improvement to empirical corporate finance studies.

3.3. Simulation evidence assuming misspecified leverage dynamics

In stark contrast to the preceding analysis based on correctly specified models, the simulation results from misspecified models are inconsistent with the findings from prior studies. As illustrated in Fig. 2, if leverage dynamics are misspecified, all six of the examined baseline estimators represented by the solid lines in the figure are severely biased, and the conjecture that OLS and FE estimates conveniently provide the upper and lower bounds, respectively, for γ (e.g., Flannery and Rangan, 2006; Huang and Ritter, 2009) no longer holds. Instead, under conditions involving model misspecification, the direction of the bias in OLS estimation becomes ambiguous. In particular, for true γ values less than 0.6 (i.e., SOA values above 40%), OLS estimation biases

Table 2

The economic meaning of estimated SOA from simulations with correctly specified models.

True SOA	90.00%	80.00%	70.00%	60.00%	50.00%	40.00%	30.00%	20.00%	10.00%	0.00%
	(0.30)	(0.43)	(0.58)	(0.76)	(1.00)	(1.36)	(1.94)	(3.11)	(6.58)	(NA)
<i>Panel A: Baseline SOA estimates</i>										
OLS	68.72%	58.24%	48.31%	38.75%	29.91%	21.60%	14.13%	7.58%	1.63%	–4.44%
	(0.60)	(0.79)	(1.05)	(1.41)	(1.95)	(2.85)	(4.55)	(8.80)	(42.29)	(NA)
FE	97.80%	88.45%	79.14%	69.71%	60.27%	50.76%	41.34%	31.95%	21.88%	6.41%
	(0.18)	(0.32)	(0.44)	(0.58)	(0.75)	(0.98)	(1.30)	(1.80)	(2.81)	(10.46)
AB	90.23%	80.23%	70.31%	60.31%	50.38%	40.60%	30.87%	21.55%	23.29%	0.20%
	(0.30)	(0.43)	(0.57)	(0.75)	(0.99)	(1.33)	(1.88)	(2.86)	(2.61)	(339.76)
BB	89.70%	79.66%	69.64%	59.53%	49.46%	39.34%	29.03%	18.16%	5.93%	–3.72%
	(0.30)	(0.44)	(0.58)	(0.77)	(1.02)	(1.39)	(2.02)	(3.46)	(11.33)	(NA)
LD4	87.02%	76.79%	66.74%	56.36%	46.09%	35.75%	25.30%	14.91%	–1.39%	–0.94%
	(0.34)	(0.47)	(0.63)	(0.84)	(1.12)	(1.57)	(2.38)	(4.29)	(NA)	(NA)
LSDVC	90.09%	80.13%	70.22%	60.23%	50.31%	40.36%	30.62%	21.18%	12.76%	0.75%
	(0.30)	(0.43)	(0.57)	(0.75)	(0.99)	(1.34)	(1.90)	(2.91)	(5.08)	(92.32)
<i>Panel B: Bias-corrected SOA estimates</i>										
OLS	93.90%	81.63%	70.00%	58.81%	48.47%	38.74%	30.00%	22.33%	15.37%	8.27%
	(0.25)	(0.41)	(0.58)	(0.78)	(1.05)	(1.41)	(1.94)	(2.74)	(4.15)	(8.03)
FE	89.77%	79.86%	70.00%	60.02%	50.04%	39.97%	30.00%	20.06%	9.44%	–6.57%
	(0.30)	(0.43)	(0.58)	(0.76)	(1.00)	(1.36)	(1.94)	(3.10)	(6.99)	(NA)
AB	90.20%	80.05%	70.00%	59.86%	49.79%	39.87%	30.00%	20.54%	22.14%	–1.08%
	(0.30)	(0.43)	(0.58)	(0.76)	(1.01)	(1.36)	(1.94)	(3.01)	(2.77)	(NA)
BB	89.75%	79.87%	70.00%	60.04%	50.12%	40.16%	30.00%	19.29%	7.21%	–2.28%
	(0.30)	(0.43)	(0.58)	(0.76)	(1.00)	(1.35)	(1.94)	(3.24)	(9.26)	(NA)
LD4	89.55%	79.69%	70.00%	59.98%	50.07%	40.09%	30.00%	19.97%	4.02%	4.83%
	(0.31)	(0.43)	(0.58)	(0.76)	(1.00)	(1.35)	(1.94)	(3.11)	(16.89)	(14.00)
LSDVC	90.07%	80.00%	70.00%	59.91%	49.88%	39.84%	30.00%	20.45%	11.94%	–0.17%
	(0.30)	(0.43)	(0.58)	(0.76)	(1.00)	(1.36)	(1.94)	(3.03)	(5.45)	(NA)

This table presents estimated SOAs with their associated “half-lives” in parentheses. A half-life represents the number of years that an average firm requires to move halfway toward its target leverage after a one-unit shock to the error term (Huang and Ritter, 2009). For each value of γ ($\lambda = 1 - \gamma$, where λ denotes SOA), 500 dynamic panels are generated. Each panel consists 6,000 firm-year observations (with cross-section $N = 500$ and time $T = 12$). The indicated SOAs in Panel A are estimated from the six baseline estimation methods summarized in B, while SOAs in Panel B are bias-corrected estimates. The results in this table are from simulations imposing a correctly specified model.

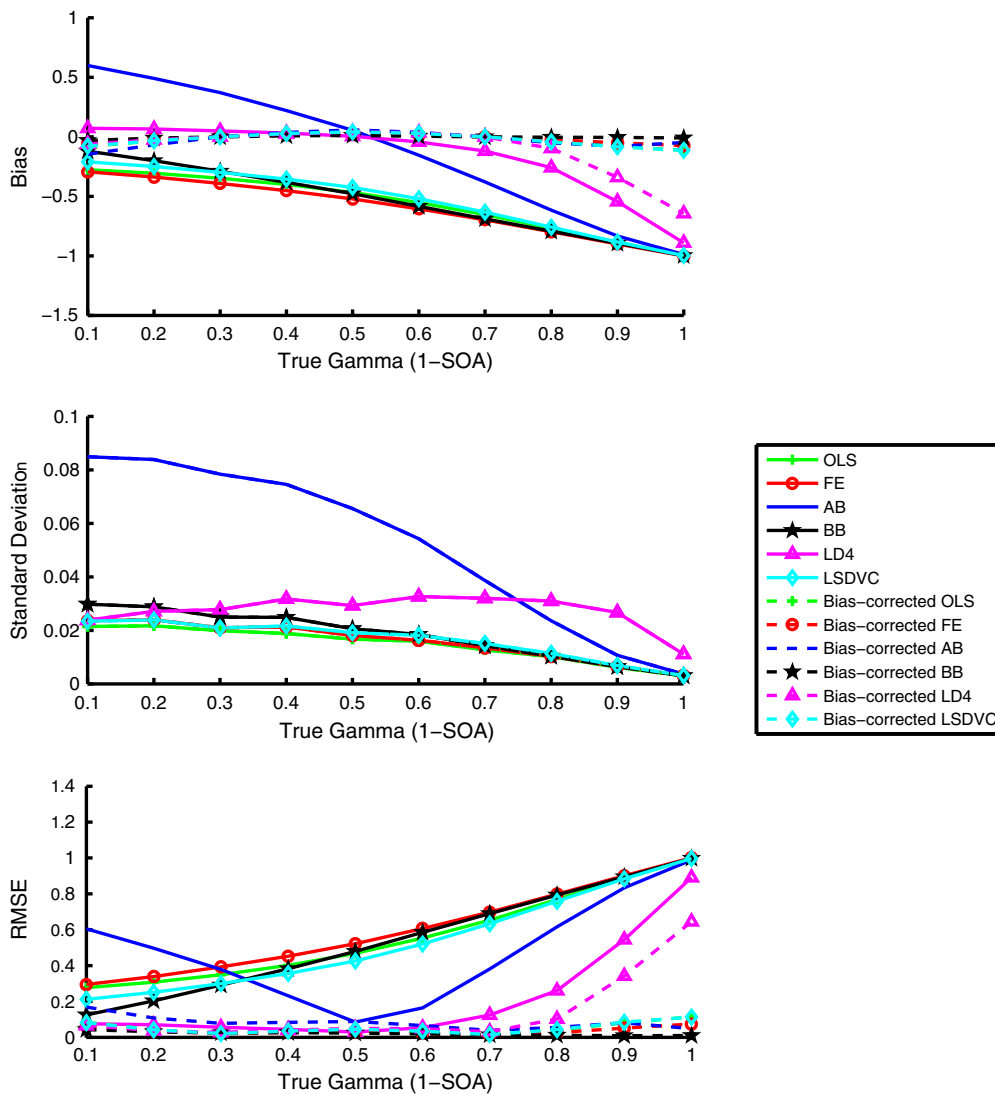


Fig. 2. Simulated performance of bias-corrected vs. baseline single estimators of the partial adjustment model with model misspecification. This figure compares the performance of single bias-corrected estimators with the performance of their corresponding baseline estimators, imposing model misspecification. The six single estimation methods are: (1) OLS, (2) standard fixed effects (FE) estimation, (3) Arellano and Bond's (1991) difference GMM (AB), (4) Blundell and Bond (1998) system GMM (BB), (5) Huang and Ritter (2009) 4-period long differencing (LD4), and (6) least squares dummy variable correction (LSDVC, Bruno, 2005; Kiviet, 1995). For each γ value ($\lambda = 1 - \gamma$, where λ denotes SOA), 500 dynamic panels are generated. Each panel consists of 6,000 firm-year observations (firm $N = 500$ and time $T = 12$). The top panel shows the bias comparison, the middle panel shows the standard deviation comparison, while the bottom panel illustrates the RMSE comparison.

lead to the overestimation of γ and the underestimation of SOA. In contrast, for γ values greater than 0.6 (i.e., SOA values below 40%), these biases become negative, resulting in the underestimation (overestimation) of γ (SOA).

This result undermines the notion that OLS and FE estimates uniformly specify a reasonable range for SOA. However, in accordance with our intuitive beliefs, even under conditions involving model misspecification, the FE approach consistently underestimates γ and overestimates SOA; thus, FE estimates continue to provide an upper bound on SOA values. As such, based on our simulation analysis in the more realistic setting that leverage dynamics are misspecified, there are no lower bounds on SOA, and the true SOA value can fall far below the SOA estimates generated by the OLS approach. This phenomenon provides a rationale for the slow leverage adjustment behavior (e.g., Iliev and Welch, 2010) observed within the partial adjustment framework. In addition, although the OLS approach produces the largest biases from our chosen set of estimation methods in the scenario involving correctly specified models, in the scenario with misspecified models, the OLS approach produces smaller biases than either the GMM or LSDVC approaches for γ values greater than 0.6 (i.e., SOA values below 40%).

In Table 3, based on our simulation analysis, we summarize the RMSE decomposition results, for the misspecified model situation. The table clearly indicates that in this more realistic setting, similar to the scenario involving correctly specified models,

Table 3

Simulation evidence for single baseline estimators of the partial adjustment model with model misspecification.

True γ		0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
OLS	Mean Estimated Coef.	-0.176	-0.106	-0.048	0.000	0.033	0.047	0.046	0.032	0.013	0.003
	Bias	-0.276	-0.306	-0.348	-0.400	-0.467	-0.553	-0.654	-0.768	-0.887	-0.997
	Std.Dev.	0.021	0.022	0.020	0.019	0.017	0.016	0.013	0.010	0.006	0.003
	RMSE	0.277	0.307	0.349	0.401	0.468	0.553	0.654	0.768	0.887	0.997
FE	Mean Estimated Coef.	-0.194	-0.138	-0.092	-0.052	-0.022	-0.006	0.002	0.002	-0.001	-0.001
	Bias	-0.294	-0.338	-0.392	-0.452	-0.522	-0.606	-0.698	-0.798	-0.901	-1.001
	Std.Dev.	0.024	0.024	0.021	0.021	0.018	0.016	0.013	0.010	0.006	0.003
	RMSE	0.295	0.339	0.392	0.452	0.522	0.606	0.698	0.798	0.901	1.001
AB	Mean Estimated Coef.	0.699	0.690	0.671	0.619	0.555	0.445	0.321	0.184	0.066	0.011
	Bias	0.599	0.490	0.371	0.219	0.055	-0.155	-0.379	-0.616	-0.834	-0.989
	Std.Dev.	0.085	0.084	0.078	0.075	0.066	0.054	0.039	0.024	0.011	0.004
	RMSE	0.605	0.497	0.379	0.232	0.085	0.164	0.381	0.616	0.834	0.989
BB	Mean Estimated Coef.	-0.021	-0.001	0.010	0.018	0.022	0.015	0.011	0.007	0.006	0.002
	Bias	-0.121	-0.201	-0.290	-0.382	-0.478	-0.585	-0.689	-0.793	-0.894	-0.998
	Std.Dev.	0.030	0.029	0.025	0.025	0.021	0.018	0.014	0.010	0.006	0.003
	RMSE	0.125	0.203	0.291	0.383	0.479	0.585	0.689	0.793	0.895	0.998
LD4	Mean Estimated Coef.	0.171	0.265	0.348	0.431	0.504	0.557	0.580	0.541	0.356	0.110
	Bias	0.071	0.065	0.048	0.031	0.004	-0.043	-0.120	-0.259	-0.544	-0.890
	Std.Dev.	0.024	0.027	0.028	0.032	0.029	0.033	0.032	0.031	0.027	0.011
	RMSE	0.075	0.070	0.056	0.044	0.030	0.054	0.124	0.261	0.545	0.890
LSDVC	Mean Estimated Coef.	-0.110	-0.049	0.001	0.045	0.075	0.080	0.067	0.042	0.016	0.003
	Bias	-0.210	-0.249	-0.299	-0.355	-0.425	-0.520	-0.633	-0.758	-0.884	-0.997
	Std.Dev.	0.023	0.024	0.021	0.022	0.019	0.018	0.015	0.011	0.007	0.003
	RMSE	0.211	0.251	0.300	0.356	0.426	0.521	0.633	0.759	0.884	0.997

For each value of γ ($\lambda = 1 - \gamma$, where λ denotes SOA), 500 dynamic panels are generated. Each panel consists 6,000 firm-year observations (with cross-section $N = 500$ and time $T = 12$). This table indicates the performance of the examined single estimation methods in terms of the bias, standard deviation and RMSE values for each estimator, imposing model misspecification. The six estimation methods are: (1) OLS, (2) standard fixed effects (FE) estimation, (3) Arellano and Bond's (1991) difference GMM (AB), (4) Blundell and Bond (1998) system GMM (BB), (5) Huang and Ritter (2009) 4-period long differencing (LD4), and (6) least squares dummy variable correction (LSDVC, Bruno, 2005; Kiviet, 1995). The "Mean Estimated Coef." rows present the average γ estimates across 500 panels.

bias effects dominate the standard deviation effects, with a median bias/Std.Dev. ratio of 30 across the examined baseline estimation methods. Therefore, bias correction should reduce RMSE even if leverage dynamics are misspecified.

As before, we correct for the biases in the simulated six baseline estimators using LBC bias correction. Similar to Fig. 1, in Fig. 2, the dashed lines represent bias-corrected estimates. As we can see from the figure, under conditions involving the misspecification of leverage dynamics, the bias correction approaches also greatly reduce the bias for all six baseline estimators. As depicted in Fig. 2, except for LD4, all of the bias-corrected estimation methods are centered around 0 and only exhibit negligible biases across all tested true SOAs. In addition, the bias-correction approach works well for LD4 when γ is less than 0.8 (i.e., the true SOA is greater than 20%). Further, the application of the proposed bias-correction approach does not materially alter the efficiencies (the standard deviations) of the six single estimators. Thus, bias correction greatly improves overall estimation accuracy, with five (OLS, FE, AB, BB, and LSDVC) bias-corrected estimators exhibiting RMSE values close to 0. The bias-corrected LD4 estimates have negligible errors for γ values less than 0.8.

More importantly, if the underlying models are misspecified and the examined dataset possesses problematic characteristics, biases in the SOA estimates dramatically impact conclusions regarding leverage adjustment behavior. As indicated in Panel A of Table 4, even in the total absence of (true) adjustment behavior, all six of the examined estimators tend to produce relatively high estimates for SOA; thereby providing grossly misleading support for the trade-off theory. Moreover, in this misspecification setting, no discernible pattern is observed between estimated SOA and true SOA. Therefore, misguided empirical conclusions are very likely based on such biased SOA estimates.

Our simulation analysis clearly shows that bias correction is economically meaningful in cases involving the potential misspecification of models. In this regard, Panel B of Table 4, summarizes the bias-corrected SOA estimates and their associated implied "half-life" adjustments (in parentheses) for the scenario with misspecified models. As expected, we observe that the bias-corrected approaches are more accurate. For example, if the true SOA is 0% indicating a total absence of actual adjustment behavior, the (unadjusted) baseline estimators produce SOA estimates of approximately 90%, incorrectly suggesting that rapid adjustment behavior occurs. In contrast, the bias-corrected estimates are much closer to the true SOA (with one major exception), consistently producing the accurate conclusion that adjustment behavior is non-existent or slow. Specifically, if the true SOA is 0%, the bias-corrected estimates produced by the OLS, FE, AB, BB, LD4, and LSDVC approaches are 11.41%, 7.39%, 4.79%, 0.99%, 64.49%, and 11.34%, respectively. Thus, with the exception of the bias-corrected LD4 estimate,⁷ the bias-corrected estimates produce the correct inference regarding leverage adjustment behavior. However, the bias-corrected LD4 estimates are only quite accurate for true SOA values greater than 20%.

⁷ As shown in Fig. 2, the bias function of LD4 becomes highly non-linear when SOA goes below 20%, thus LBC is quite a poor approximation for the bias of LD4 in this low-SOA region.

Table 4

The economic meaning of estimated SOA from simulations with misspecified models.

True SOA	90.00%	80.00%	70.00%	60.00%	50.00%	40.00%	30.00%	20.00%	10.00%	0.00%
	(0.30)	(0.43)	(0.58)	(0.76)	(1.00)	(1.36)	(1.94)	(3.11)	(6.58)	(NA)
<i>Panel A: Baseline SOA estimates</i>										
OLS	117.62%	110.63%	104.81%	100.05%	96.75%	95.30%	95.36%	96.83%	98.67%	99.68%
	(NA)	(NA)	(NA)	(NA)	(0.20)	(0.23)	(0.23)	(0.20)	(0.16)	(0.12)
FE	119.38%	113.78%	109.19%	105.19%	102.18%	100.61%	99.76%	99.79%	100.07%	100.07%
	(NA)	(NA)	(NA)	(NA)	(NA)	(NA)	(0.12)	(0.11)	(NA)	(NA)
AB	30.14%	31.05%	32.95%	38.06%	44.55%	55.48%	67.88%	81.56%	93.37%	98.86%
	(1.93)	(1.86)	(1.73)	(1.45)	(1.18)	(0.86)	(0.61)	(0.41)	(0.26)	(0.15)
BB	102.11%	100.11%	98.99%	98.21%	97.82%	98.46%	98.90%	99.27%	99.45%	99.83%
	(NA)	(NA)	(0.15)	(0.17)	(0.18)	(0.17)	(0.15)	(0.14)	(0.13)	(0.11)
LD4	82.85%	73.51%	65.15%	56.91%	49.56%	44.27%	41.95%	45.88%	64.42%	89.04%
	(0.39)	(0.52)	(0.66)	(0.82)	(1.01)	(1.19)	(1.27)	(1.13)	(0.67)	(0.31)
LSDVC	111.02%	104.95%	99.90%	95.52%	92.54%	92.03%	93.30%	95.85%	98.40%	99.69%
	(NA)	(NA)	(0.10)	(0.22)	(0.27)	(0.27)	(0.26)	(0.22)	(0.17)	(0.12)
<i>Panel B: Bias-corrected SOA estimates</i>										
OLS	98.09%	83.46%	70.00%	57.60%	46.66%	37.58%	30.00%	23.83%	18.03%	11.41%
	(0.18)	(0.39)	(0.58)	(0.81)	(1.10)	(1.47)	(1.94)	(2.55)	(3.49)	(5.72)
FE	95.48%	82.23%	70.00%	58.36%	47.71%	38.49%	30.00%	22.40%	15.03%	7.39%
	(0.22)	(0.40)	(0.58)	(0.79)	(1.07)	(1.43)	(1.94)	(2.73)	(4.26)	(9.03)
AB	104.66%	86.83%	70.00%	56.38%	44.14%	36.34%	30.00%	24.95%	18.03%	4.79%
	(NA)	(0.34)	(0.58)	(0.84)	(1.19)	(1.54)	(1.94)	(2.41)	(3.49)	(14.13)
BB	93.08%	81.10%	70.00%	59.24%	48.87%	39.54%	30.00%	20.39%	10.59%	0.99%
	(0.26)	(0.42)	(0.58)	(0.77)	(1.03)	(1.38)	(1.94)	(3.04)	(6.19)	(69.73)
LD4	96.10%	82.56%	70.00%	57.55%	46.01%	36.52%	30.00%	29.73%	44.07%	64.49%
	(0.21)	(0.40)	(0.58)	(0.81)	(1.12)	(1.53)	(1.94)	(1.96)	(1.19)	(0.67)
LSDVC	97.82%	83.40%	70.00%	57.28%	45.94%	37.08%	30.00%	24.20%	18.40%	11.34%
	(0.18)	(0.39)	(0.58)	(0.82)	(1.13)	(1.50)	(1.94)	(2.50)	(3.41)	(5.76)

This table presents estimated SOAs with their associated “half-lives” in parentheses. A half-life represents the number of years that an average firm requires to move halfway toward its target leverage after a one-unit shock to the error term (Huang and Ritter, 2009). For each value of γ ($\lambda = 1 - \gamma$, where λ denotes SOA, 500 dynamic panels are generated. Each panel consists 6,000 firm-year observations (with cross-section $N = 500$ and time $T = 12$). The SOAs in Panel A are estimated from the six baseline estimation methods summarized in B, while SOAs in Panel B are bias-corrected estimates. The results in this table are from simulations imposing a misspecified model. 6 cm.

The current demonstration utilizes a worst-case scenario that combines model misspecification and many other data-related issues (e.g., endogeneity, serial correlation, an unbalanced panel, and missing data). Actual corporate studies might not suffer from all of these issues and, therefore, such situations will involve lower levels of bias than modeled in this paper. We use our simulated scenarios to demonstrate that our bias correction method can produce economically meaningful improvement relative to baseline estimates, even under the worst possible conditions.

3.4. A consensus SOA estimate

Empirical research to date is conflicted regarding whether the SOA convincingly pulls toward a real target financial leverage or not. For example, Welch (2004) concludes that firms do not adjust toward the target capital structure, whereas Fama and French (2002) estimate a relatively low SOA of 7%–18% per year. In contrast, Lemmon et al. (2008) estimate a relatively rapid speed of 25% per year, and Flannery and Rangan (2006) an even faster adjustment speed above 30% annually, while Huang and Ritter (2009) estimate an SOA range of 17%–23%.

Biases and various empirical problems, including model misspecification, make the identification of a consistently superior estimate – even after bias correction, guesswork. But, we offer a simple solution. We propose a global minimum variance (GMV) combined estimator to approximate a consensus SOA estimate. As such, we effectively reconcile the single estimates of the leverage speed of adjustment (SOA) using a “pooling” approach. Our paper contrasts with other recent SOA “reconciliation papers” (see Dang et al., 2013; Flannery and Hankins, 2013), which adopt a “horse race” approach.

Bias corrections are first applied to each single estimator, and the resulting unbiased estimators are then combined. Because both of these steps involve linear transformation, the order in which these procedures are performed is irrelevant to the final outcome. We solve the combination weights by minimizing the mean squared error of the combined estimator, defined as follows:

$$E(\hat{\gamma}_i - \gamma_0)^2 = E[b_i(\gamma_0, n) + v_i(\gamma_0, n)]^2. \quad (8)$$

Assuming that biases are not correlated with random errors, we obtain the following expression:

$$E(\hat{\gamma}_i - \gamma_0)^2 = b_i(\gamma_0, n)^2 + v_i(\gamma_0, n)^2. \quad (9)$$

In a finite sample, we cannot simultaneously eliminate both terms of Eq. (9) for a single estimator. Lower variance (bias) is necessarily associated with greater bias (variance); thus, we are faced with a bias/variance dilemma. This trade-off between bias and variance is critical to reducing overall mean square error. For a single estimator, we can use bias-correction techniques to reduce bias; however, these approaches will inflate variance. Thus, the average result of a bias-corrected single estimator may be a “true” estimate of SOA, but this estimator can generate an extremely unreliable SOA estimate for a given sample. However, the use of a combination of bias-corrected single estimators can reduce both bias and variance relative to the use of a single estimator alone.

The aforementioned trade-off between bias and variance is analogous to the mean-variance (return-risk) trade-off in modern portfolio theory, which states that portfolio variance can be reduced by combining different assets with optimal portfolio weights. In this spirit, we propose to improve SOA estimation accuracy by constructing a pooled estimator that combines various single estimators. The basic idea underlying this approach is to minimize Std.Dev. for a given bias level and subsequently correct for biases. The resulting pooled estimator will therefore have the smallest possible Std.Dev. but will also exhibit relatively little bias. We use GMV weights for the combination of our single estimators because these weights minimize estimation error. Appendix D outlines a derivation of the weights for our proposed GMV-based pooled estimator.

Our approach is characterized in Fig. 3, in which estimator bias (on the y-axis) is plotted against estimator Std.Dev. (on the x-axis). The scattered internal dots represent the status of diverse individual estimators that exhibit various levels of bias and Std.Dev. Building on the trade-off approach, we generate a hypothetical “estimation frontier”. Point G represents a combination of single estimators that produces minimum Std.Dev., and point U represents an unbiased combination of single estimators. The consensus SOA estimator should feature negligible bias and minimum Std.Dev., which is represented by point O in Fig. 3. Point O indicates the ideal situation of an unbiased estimator with minimum variance. This ideal condition cannot be feasibly achieved by any single individual estimator. In essence, our strategy for achieving outcome O is to use a GMV weighting scheme to create an optimal combination of individual bias-corrected estimators.

It is important to understand that we are not proposing a new estimator nor are we highlighting new pitfalls of SOA estimation. Given that each single estimator can outperform other estimators under certain (unobservable) conditions, the pooling of SOA estimates in lieu of selecting a single estimation approach represents a superior strategy to address situations in which we lack knowledge regarding the true underlying processes.

To illustrate the approximation of consensus SOA values, we employ both GMV-weighted and simple averaging, using the simulation settings specified in the previous section. Figs. 4 and 5 graphically display the results. From Fig. 4, we see that in cases involving correctly specified models and no endogeneity problems, simple averaging and GMV-weighted averaging produce extremely similar outcomes, with simple averaging yielding slightly better results than GMV-weighted averaging. However, as shown in Fig. 5 for cases involving model misspecification, endogeneity, unbalanced panels, and missing data, smaller biases and RMSEs are produced by GMV-weighted averaging than are produced by simple averaging across all examined true values of SOA. When compared with single estimates, we can see that the consensus estimate delivers smaller bias, Std.Dev., and RMSE. Crucially, this negligible bias allows more reliable inferences about the underlying economic process.

4. Further investigation using empirical corporate data

4.1. Sample selection and variables

4.1.1. Sample selection

The initial sample includes all firms recorded in the Compustat North America Fundamentals Annual database between 1965 and 2006. In accordance with typical conventions, we exclude financial firms (SIC 6000–6999) and regulated utilities (SIC

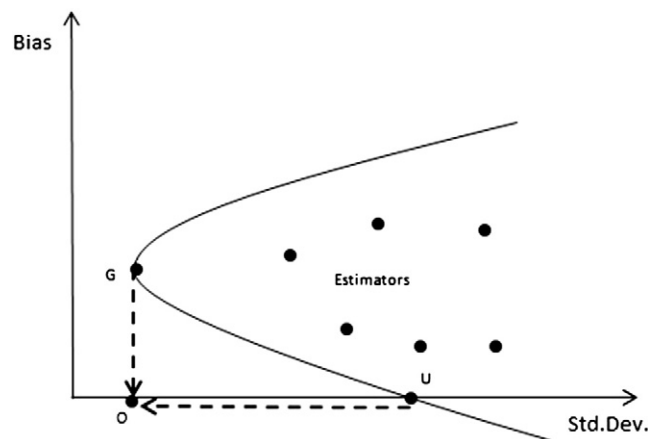


Fig. 3. Bias/variance trade-off framework.

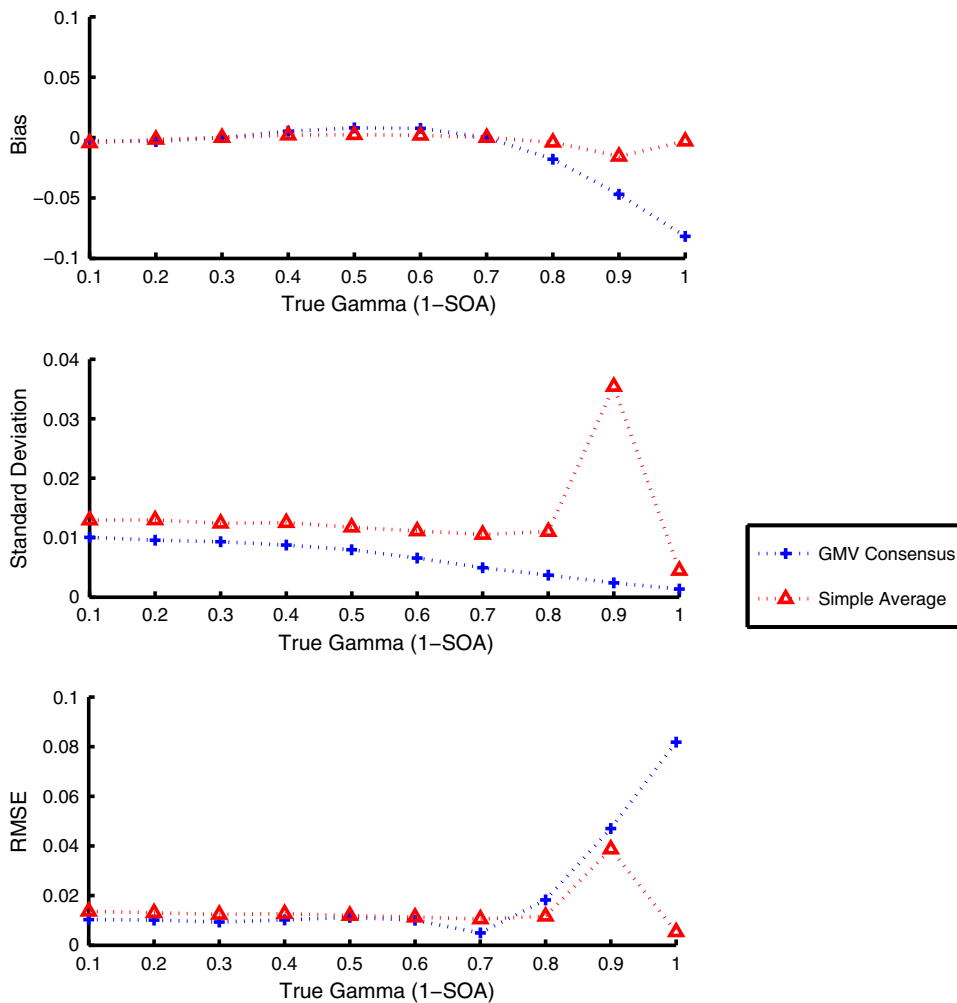


Fig. 4. Performance comparison of simulated consensus estimator of the partial adjustment model absent model misspecification. This figure compares the performance of the GMV-weighted consensus estimator with the performance of the simple averaged estimator, absent model misspecification. For each γ value ($\lambda = 1 - \gamma$, where λ denotes SOA), 500 dynamic panels are generated. Each panel consists of 6,000 firm-year observations (firm $N = 500$ and time $T = 12$). Estimation results of combined estimates for the 500 panels are stored. The bias, standard deviation and RMSEs are computed from the average estimates of 500 samples and are plotted against true γ values to illustrate how these parameters change as γ values increase. The GMV-weighted consensus estimator combines six single bias-corrected estimates with global minimum variance portfolio weights. The six single estimation methods are: (1) OLS, (2) standard fixed effects (FE) estimation, (3) Arellano and Bond's (1991) difference GMM (AB), (4) Blundell and Bond (1998) system GMM (BB), (5) Huang and Ritter (2009) 4-period long differencing (LD4), and (6) least squares dummy variable correction (LSDVC, Bruno, 2005; Kiviet, 1995). The top panel shows the bias comparison, the middle panel shows the standard deviation comparison, while the bottom panel illustrates the RMSE comparison.

4900–4999) from the examined sample. Firms with undefined Compustat formats and foreign firms (format codes 4, 5, 6) are also omitted from our sample. Furthermore, in accordance with the approach used in prior research (Huang and Ritter, 2009), we eliminate extremely small companies by excluding firms with beginning-of-year book assets of less than \$10 million, measured in terms of 1998 purchasing power, from the sample. In addition, firm-year observations reflecting accounting changes due to the adoption of Statement of Financial Accounting Standards (SFAS) No. 94 are excluded from the sample because the capital structure decisions of these firms could be affected by this change in accounting standards.⁸ Furthermore, we exclude firm-years with negative book values of equity from the sample. To reduce the potential impact of outliers, the dependent and independent variables are Winsorized at the 1st and 99th percentiles. Finally, we exclude firms with less than four consecutive years of data because the LD4 estimation method requires a 4 period lag of the dependent variable for the estimation of SOA. The final sample consists of 166,365 firm-year observations.

⁸ As mentioned by Huang and Ritter (2009), the issuance of SFAS No. 94 (Consolidation of All Majority-Owned Subsidiaries) by the Financial Accounting Standards Board (FASB) in late 1987, which required firms to consolidate off-balance sheet financing subsidiaries, produced the greatest effects on heavy equipment manufacturers and merchandise retailers because these firms extensively used unconsolidated financing subsidiaries. Thus, we exclude 201 relevant firm-year observations identified by Compustat footnote codes.

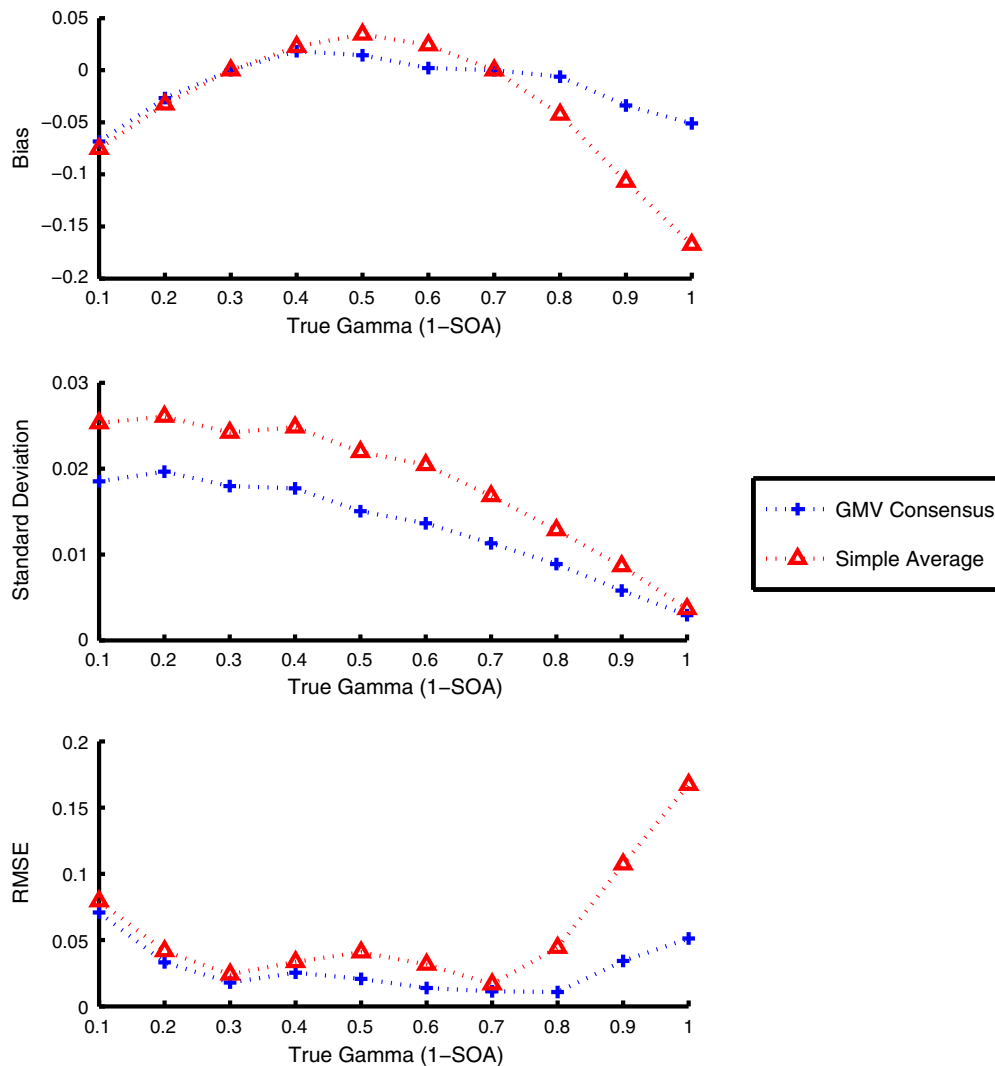


Fig. 5. Performance comparison of simulated consensus estimator of the partial adjustment model with model misspecification. This figure compares the performance of the GMV-weighted consensus estimator with the performance of the simple averaged estimator, imposing model misspecification. For each γ value ($\lambda = 1 - \gamma$, where λ denotes SOA), 500 dynamic panels are generated. Each panel consists of 6,000 firm-year observations (firm $N = 500$ and time $T = 12$). Estimation results of combined estimates for the 500 panels are stored. The bias, standard deviation and RMSEs are computed from the average estimates of 500 samples and are plotted against true γ values to illustrate how these parameters change as γ values increase. The GMV-weighted consensus estimator combines six single bias-corrected estimates with global minimum variance portfolio weights. The six single estimation methods are: (1) OLS, (2) standard fixed effects (FE) estimation, (3) Arellano and Bond's (1991) difference GMM (AB), (4) Blundell and Bond (1998) system GMM (BB), (5) Huang and Ritter (2009) 4-period long differencing (LD4), and (6) least squares dummy variable correction (LSDVC, Bruno, 2005; Kiviet, 1995). The top panel shows the bias comparison, the middle panel shows the standard deviation comparison, while the bottom panel illustrates the RMSE comparison.

4.1.2. Variable definitions

We use the market debt ratio (MDR)⁹ as the dependent variable in Eq. (4). The remaining firm characteristic variables in Eq. (4) are defined as described by Flannery and Rangan (2006). We consider seven observable firm characteristic variables, including earnings before interest and taxes scaled by total assets (EBIT_TA), market to book (MB), depreciation scaled by total assets (DEP_TA), the natural log of total assets (Ln(TA)), fixed assets scaled by total assets (FA_TA), R&D expense scaled by total assets (R&D_TA), and the industry median debt ratio (Ind_Median).

⁹ The differences between passive leverage adjustments and active, manager-driven leverage adjustments are not relevant to the current examination because the proposed bias correction method is equally applicable to both types of adjustments.

4.2. The divergence and validity of baseline SOA estimates

The literature provides rather divergent estimates of SOA. In this study, we compare the six documented estimation methods for the estimation of the partial adjustment model specified by Eq. (4). We also utilize several statistical tests to provide a simple assessment of the validity of these estimates. The estimation results are provided in Table 5.

The single estimation approaches produce γ values ranging from 0.616 to 0.873, which correspond to SOA estimates ranging from 12.7% to 38.4%. Following Huang and Ritter (2009), we use the concept of a “half-life”, which represents the number of years that a firm requires to move halfway toward its target leverage after a one-unit shock to the error term. Our results suggest an average half-life between 5.1 and 1.4 years. Although we lack a quantitative null hypothesis for testing adjustment behavior (Graham and Leary, 2011), given the median panel time span of 12 years for the sampled firms, literature sources typically suggest that a half-life of 5.1 years is too lengthy to support the belief that meaningful adjustment behavior is occurring. In contrast, at the other extreme of the obtained range, a half-life of 1.4 years is generally considered to be evidence supporting the occurrence of adjustment behavior.

The divergent nature of the calculated estimates produces controversy among researchers who employ different estimation methods with respect to the occurrence/strength of leverage adjustment behavior. Conventional least squares estimators (e.g., OLS and FE) exhibit fundamental flaws in the context of partial leverage adjustment models, whereas the validity of the GMM (AB and BB) approaches is dependent on assumptions regarding the serial correlation of residuals and the appropriate specification of instruments. We use the second and third lags of the leverage ratio as instruments for the first lag of the leverage ratio in our GMM (AB and BB) estimations. As indicated in Table 5, the null of no second-order serial correlation and the null of joint validity of the moment conditions are both rejected at the 1% significance level. The second-order serial correlation (AR(2)) and overidentification (Hansen J and Sargan) test results suggest rejecting the null hypotheses of no serial correlation and valid instruments. These issues are not easily resolved through the use of longer lags as instruments; for example, the AR(3) and AR(4) test results imply that the null hypothesis of no serial correlation should be rejected. Therefore, the SOA estimates produced by the GMM (AB and BB) approaches have dubious validity.

4.3. The bias-corrected minimum-variance consensus estimator

We estimate linear bias functions for the six examined single estimators by evaluating appendix Eq. (A.7) at two points. We choose the initial estimate and the constant bias-corrected estimate as the two points, and we can then solve for the intercept and slope of the bias function for each estimator. To estimate the biases of these two points, we use two sets of simulations, and in each case we generate 500 samples.¹⁰

We combine the six bias-corrected single estimators using GMV-specified weights. The key input for the estimation of these weights is the covariance matrix for these single estimators — we use industry sub-samples to estimate this covariance matrix.¹¹ To ensure the accuracy of this covariance matrix estimate, we adopt the robust shrinkage approach developed by Schäfer and Strimmer (2005) for covariance matrix estimation. By substituting our estimated covariance matrix into appendix Eq. (D.3), we obtain GMV weights for the single estimation methods. We use these weights to combine the single estimators and compare the resulting GMV consensus estimate with a benchmark estimate generated using simple arithmetic averaging. The results are presented in Table 6.

Table 6 indicates that the bias-corrected GMV-based consensus estimate for SOA is 35.84%, which corresponds to a half-life of 1.6 years. The GMV weighting assigns the greatest weight to the OLS estimator because this approach has the smallest variance among the examined single estimators. Thus, the conventional least squares estimator is the best choice for a baseline estimator for additional bias correction. We also observe from Table 6 that bias correction lowers the FE estimate for SOA from 38.4% to 26.27% but increases the OLS estimate for SOA from 15.20% to 39.46%. Thus, the bias correction approach alleviates the overestimation and underestimation issues associated with FE and OLS estimates of SOA, respectively, in a dynamic partial adjustment model of leverage.

5. Discussion

As shown in our simulations, under conditions involving the misspecification of leverage dynamics, the presumption that OLS estimates constitute a lower bound for SOA values no longer holds. However, even under conditions of model misspecification, FE estimates continue to serve as an upper bound on SOA. Therefore, we can conclude from our empirical estimation results that the true SOA for the examined dataset does not exceed 38.40%. This finding contrasts existing studies in which SOA values are believed to lie in a range with discernible upper and lower limits.

¹⁰ The LSDVC method is difficult to apply to large datasets due to the substantial computer memory requirements of this approach (Flannery and Hankins, 2013). Fortunately, because corporate finance datasets typically include adequate cross-sectional data, convergent results are achievable with relatively small numbers of simulations. In particular, (unreported) results similar to the described findings are rapidly achieved from the simulation of just 30 samples.

¹¹ We use the Fama–French 48-industry classification scheme. After the data screening described in Section 4.1, our final sample includes 42 industries. A detailed list of these industries and each industry's SOA estimate is available from the authors upon request.

Table 5

Empirical results from estimations of the partial adjustment model of financial leverage.

	AB	BB	FE	OLS	LD4	LSDVC
Lag MDR	0.873*** (55.75)	0.758*** (91.84)	0.616*** (141.86)	0.848*** (448.49)	0.873*** (266.67)	0.708*** (175.70)
EBIT_TA	0.307*** (28.56)	0.0770*** (6.90)	−0.0966*** (−15.66)	−0.0750*** (−18.13)	−0.0157 (−1.80)	−0.0878*** (−8.09)
MB	0.0837*** (40.65)	0.0248*** (14.81)	0.00395*** (4.63)	0.00736*** (14.65)	0.0271*** (24.56)	0.00247* (2.20)
DEP_TA	0.119 (1.94)	0.00211*** (6.98)	−0.486*** (−14.01)	−0.302*** (−16.82)	0.0691*** (10.87)	−0.480*** (−11.88)
Ln(TA)	0.00525* (2.08)	0.0308** (2.80)	0.0201*** (23.26)	0.00246*** (32.05)	0.000446*** (15.62)	0.0142*** (77.15)
FA_TA	−0.0736*** (−5.96)	−0.423*** (−15.70)	0.0731*** (12.45)	0.0231*** (10.90)	−0.00494 (−0.69)	0.0689*** (7.94)
R&D_TA	0.355*** (8.70)	0.0348*** (3.30)	−0.0911*** (−3.74)	−0.231*** (−27.23)	0.0309 (1.01)	−0.0997*** (−3.37)
Ind_Median	−0.0764*** (−6.37)	−0.265*** (−3.86)	0.0923*** (14.61)	0.0524*** (15.69)	−0.00806 (−1.12)	0.0689*** (7.70)
Adj. speed (SOA)	12.7%	24.2%	38.4%	15.2%	12.7%	29.2%
AR(2)	−4.24 [0.000]	−2.96 [0.003]				
Sargan	1493.44 [0.000]	3350.26 [0.000]			56.657 [0.000]	
Hansen J test	1493.44 [0.000]	1600.99 [0.000]				

This table summarizes SOA estimations generated by the six single estimation methods: (1) OLS, (2) standard fixed effects (FE) estimation, (3) Arellano and Bond's (1991) difference GMM (AB), (4) Blundell and Bond (1998) system GMM (BB), (5) [Huang and Ritter \(2009\)](#) 4-period long differencing (LD4), and (6) least squares dummy variable correction (LSDVC, [Bruno, 2005](#); [Kiviet, 1995](#)). The data are drawn from the fundamental Compustat annual dataset. This sample consists of US firms from 1965 to 2006, comprising 166,365 firm-year observations. The first pair of rows provides estimated coefficients for γ , (and t -statistic), relating to lagged market leverage (MDR); where the speed of adjustment (SOA) is $\lambda = 1 - \gamma$. The following 7 pairs of rows provide estimated coefficients (and associated t -statistics) for the firm characteristic variables: (1) earnings before interest and taxes scaled by total assets (EBIT_TA), (2) market to book (MB), (3) depreciation scaled by total assets (DEP_TA), (4) the natural log of total assets (Ln(TA)), deflated to 1983 dollars), (5) fixed assets scaled by total assets (FA_TA), (6) R&D expense scaled by total assets (R&D_TA), and (7) the industry median debt ratio for the firm's [Fama and French \(1997\)](#) industry (Ind_Median). The final three pairs of rows report results for the AR(2) test for the null of no second-order serial correlation and the Sargan and Hansen tests for the null of joint validity of the moment conditions (over-identifying restrictions). *, ** and *** indicate significance at 1%, 5% and 10%, respectively. Values enclosed in parentheses are the t statistics for coefficients, and values in square brackets are the p -values for test statistics.

Table 6

An empirical comparison of speed of adjustment estimates for financial leverage.

			<u>AB</u>	<u>BB</u>	<u>FE</u>	<u>OLS</u>	<u>LD4</u>	<u>LSDVC</u>
	GMV weights		9.71%	1.58%	0.72%	90.36%	3.85%	−6.21%
Panel A: Without bias correction	Adj. speed (SOA)		12.70% (8.11)	24.20% (29.32)	38.40% (88.43)	15.20% (80.39)	12.70% (38.79)	29.20% (72.46)
			“1/N” consensus			GMV consensus		
			22.07% (69.52)			14.30% (143.02)		
Panel B: With bias correction	Bias function	C (intercept)	−0.858	0.023	−0.169	0.490	−0.749	0.002
	parameter	S (slope)	0.893	0.163	0.064	−0.409	0.880	0.029
	Adj. speed (SOA)		8.57% (6.00)	36.77% (45.26)	26.27% (60.93)	39.46% (397.26)	13.68% (43.41)	31.20% (72.62)
			“1/N” consensus			GMV consensus		
			24.95% (122.76)			35.84% (716.89)		

This table presents speed of adjustment (SOA) estimates for leverage produced by the empirical application of six single estimation methods and two consensus methods. The six estimation methods are: (1) OLS, (2) standard fixed effects (FE) estimation, (3) Arellano and Bond's (1991) difference GMM (AB), (4) Blundell and Bond (1998) system GMM (BB), (5) [Huang and Ritter \(2009\)](#) 4-period long differencing (LD4), and (6) Least Squares Dummy Variable Correction (LSDVC, [Bruno, 2005](#); [Kiviet, 1995](#)). The two consensus methods are the simple average consensus ("1/N") and the global minimum variance consensus (GMV). The data are drawn from the fundamental Compustat annual dataset. This sample consists of US firms from 1965 to 2006, comprising 166,365 firm-year observations. Target leverage is modeled as a function of the following firm characteristic variables: (1) earnings before interest and taxes scaled by total assets (EBIT_TA), (2) market to book (MB), (3) depreciation scaled by total assets (DEP_TA), (4) the natural log of total assets (Ln(TA)), deflated to 1983 dollars), (5) fixed assets scaled by total assets (FA_TA), (6) R&D expense scaled by total assets (R&D_TA), and (7) the industry median debt ratio for the firm's [Fama and French \(1997\)](#) industry (Ind_Median). The t -statistic associated with each SOA estimate is provided in parentheses below the associated estimate.

We use simulation to approximate the bias function. Because there are large samples of cross-sectional data in corporate finance settings, we only require relatively small simulated samples to obtain convergent-bias approximations. Hence, simulation-based bias correction is not computationally demanding for empirical studies in corporate finance.

The bias-corrected estimates will be completely unbiased if the bias function is linear and will be nearly unbiased if the bias function is non-linear. This characteristic implies that bias-corrected SOA estimates will be unbiased for true SOA values greater than 0.2 but slightly biased for true SOA values less than 0.2. Therefore, we are likely to obtain more accurate estimates of SOA after implementing bias correction, even in situations involving rather slow actual adjustment behavior. This feature of linear bias correction is highly meaningful for empirical analyses because there are growing concerns that current popular estimation methods spuriously support the existence of adjustment behavior (see [Chang and Dasgupta, 2009](#); [Elsas and Florysiak, 2011](#); [Iliev and Welch, 2010](#)).

The primary focus of our paper is the estimation of SOA. However, the long-run relationship between a target leverage and its determinants has important effects on leverage adjustment behavior in a partial adjustment framework. Meaningful leverage adjustments are based on a well-defined, long-run target ([Dang et al., 2013](#)). Because bias in SOA estimates deleteriously affects the estimation of the influence of firms' characteristics on leverage adjustment speed, bias correction approaches should be extended to the determination of factor loadings for firm characteristic variables.

For investigations beyond leverage adjustment, the accurate estimation of firm characteristic variables, particularly with respect to the influence of endogenous variables, is of greater importance than the factor loadings attaching to lagged dependent variables. For example, in the corporate governance arena and for studies that focus on how corporate board structure affects firm performance, the main point of interest is the estimated coefficients on board structure proxies (e.g., [Wintoki et al., 2012](#)), whereas factor loadings relating to past firm performance are not a major focus. In these studies, inferences derived from a dynamic panel model regarding the endogenous relationships of interest could be rather biased due to the endogeneity between corporate board structure and firm performance, model misspecification, and unobserved firm heterogeneities. The use of bias correction for other factor loadings is relatively important in this context.

The bias correction method proposed in our paper can be extended to the estimation of various parameters of interest by correcting biases for a vector of estimates. Although we focus solely on SOA estimates, studies addressing other topics can adopt procedures similar to the approach proposed in the current investigation¹² to improve the reliability of inferences drawn by corporate empiricists. Additionally, it should be noted that we include two simulated scenarios in our analysis, and our proposed method works well in these contexts. The empirical data can involve other, more complicated data features. For example, biases are also likely to arise from the cross-sectional dependence of firms in the same industry or when firms are correlated due to exposure to the same macro factor. We leave the examination of this more complicated setting for future research.

6. Conclusion

Empirical corporate finance panel datasets are limited in the time dimension. As a result, dynamic panel bias is a serious issue in estimations using the types of models that are designed to address many currently unanswered corporate finance questions. Our study is the first investigation in the field of corporate finance to illustrate which situations produce levels of bias that are detrimental to economic inferences regarding corporate behavior and to examine the severity of dynamic panel bias when it is combined with model misspecification bias.

Using a two-step procedure, we correct for the bias inherent in existing panel data estimation methods and then combine the corrected estimates using the GMV procedure to produce an efficient, unbiased estimator. We evaluate the performance of the proposed bias correction method and minimum variance combined estimation procedure in the context of a widely-researched capital structure question, namely, the SOA estimation in the partial adjustment model. As demonstrated in simulation analysis, our bias-corrected, minimum-variance combined estimation method provides more accurate estimates with a negligible bias, thus, leading to reliable economic inferences. We also include a discussion on generalizing our methods to many other areas of corporate finance research.

Our results demonstrate that although the absolute magnitudes of estimation errors caused purely by dynamic panel biases are clearly evident, these types of biases generally do not induce economically important effects on inferences regarding SOA unless the true speed of adjustment is close to 0. In this scenario, baseline and bias-corrected estimates produce the same conclusions regarding leverage adjustment speed. However, under more realistic conditions involving endogenous variables and misspecified leverage dynamics, all six of the examined baseline estimates (OLS, FE, AB, BB, LD4, and LSDVC) are severely biased, and these biases are detrimental to the accuracy of economic inferences regarding corporate behavior. More importantly, monotonic relationships between these biases and true SOA values are not evident in situations featuring potential model misspecification. In these situations, the six bias-corrected estimates are not only more accurate than their corresponding baseline estimates but also produce negligible biases despite the presence of model misspecification, endogeneity, imbalanced panels, and missing data. The inferences derived from bias-corrected estimates are consistent with the conclusions obtained using true SOA values.

The big advantage of our estimation method is that it can be used to reduce the biases of numerous alternative estimation methods. Moreover, the resulting bias-corrected estimators can retain some of the advantages presented by their corresponding initial estimators. For instance, it is well established that conventional least squares estimation procedures (such as OLS and FE)

¹² The Stata program for implementing the proposed bias correction method in the context of corporate finance is available from the authors upon request.

exhibit very little dispersion relative to many consistent estimators. More importantly, the proposed bias-correction approach is not computationally taxing for corporate dynamic panel models. As indicated by our simulations, all six of the examined estimation methods have small variance when using realistic corporate data; thus, a small number of simulated paths suffice for the accurate calibration of the bias function required for bias correction.

Our study is the first to discuss the intricacies of bias correction in a corporate finance setting. Moreover, our proposed minimum-variance combined estimation procedure is readily applicable to many other corporate finance questions in which empirical researchers are confronted with divergent estimates and competing theories or models. Exploring such broad applications is left to future research.

Acknowledgments

We thank Tom Smith, Anthony W. Lynch, Petko Kalev, Mardi Dungey, and Ignacio Requejo for their many helpful comments on the development of the methodology of this paper. We also would like to express our thanks to Rongbing Huang for kindly providing us the four-period Long Differencing estimation program.

The first author is grateful for the financial support from NSFC (71372163), the scientific research foundation of the humanities and social planning project of Chinese Ministry of Education (13YJA630081) and the Specialized Research Fund for the Doctoral Program of Higher Education (20130201110019).

Appendix A. Bias correction methods

As documented by MacKinnon and Smith (1998), there are three general methods for correcting the biases of estimators: constant bias correction (CBC), linear bias correction (LBC), and non-linear bias correction (NBC). Since the first two bias-correction methods are most relevant to our chosen setting, in this appendix, we summarize just these two, CBC and LBC.

A.1. Constant bias correction (CBC)

Constant bias correction (CBC) assumes a constant bias function, $b(\gamma, n) = b(n)$ for all γ . To estimate the constant bias function, we generate J samples using the initial estimate $\hat{\gamma}$ and then re-estimate γ for all J samples. We calculate the arithmetic average of the J estimates $\bar{\gamma}$ as follows:

$$\bar{\gamma} \equiv \frac{1}{J} \sum_{j=1}^J \hat{\gamma}_j. \quad (\text{A.1})$$

The bias $b(n)$ can be estimated as the difference between the average estimate and the initial estimate:

$$\hat{b} \equiv \hat{b}(n) = \bar{\gamma} - \hat{\gamma}. \quad (\text{A.2})$$

The CBC estimator is thus given by

$$\tilde{\gamma} \equiv \hat{\gamma} - \hat{b} = 2\hat{\gamma} - \bar{\gamma}. \quad (\text{A.3})$$

A.2. Linear bias correction (LBC)

Linear bias correction (LBC) assumes a linear bias function:

$$b(\gamma) = C + S\gamma. \quad (\text{A.4})$$

By evaluating Eq. (A.4) at two points, we can solve for C , the intercept of the bias function, and S , the slope of the bias function. To implement this, we can perform a set of simulations that differ in the point at which the data-generating process is evaluated. We can use the initial estimate $\hat{\gamma}$ and CBC estimate $\tilde{\gamma}$. C and S can be solved as

$$\hat{C} = \hat{b} - \frac{\hat{b} - \tilde{b}}{\hat{\gamma} - \tilde{\gamma}} \hat{\gamma} \quad \text{and} \quad \hat{S} = \frac{\hat{b} - \tilde{b}}{\hat{\gamma} - \tilde{\gamma}}. \quad (\text{A.5})$$

As the number of simulations is increased, \hat{C}_i and \hat{S}_i will converge to C_i and S_i . The bias-corrected estimator $\check{\gamma}$ must be equal to $\hat{\gamma}$ minus the bias function evaluated at $\check{\gamma}$ itself. Thus, it is the solution to the equation:

$$\check{\gamma} = \hat{\gamma} - \hat{C} - \hat{S} * \check{\gamma}. \quad (\text{A.6})$$

Thus,

$$\tilde{\gamma} = \frac{1}{1+S}(\hat{\gamma} - \hat{C}). \quad (\text{A.7})$$

For a linear bias function, we have $E(b(\gamma)) = b(\gamma_0)$; thus, the following will be true:

$$E(\tilde{\gamma}) = E\left(\hat{\gamma} - b(\hat{\gamma})\right) = \gamma_0 - b(\gamma_0) - b(\gamma_0) = \gamma_0. \quad (\text{A.8})$$

The LBC estimator $\tilde{\gamma}$ will be unbiased whenever the bias function is linear, and the variance of the LBC estimator is

$$V(\tilde{\gamma}) = \frac{1}{(1+S)^2} V(\hat{\gamma}). \quad (\text{A.9})$$

Hence, whether the variance of the LBC estimator will be greater or less than that of γ will depend on whether S is less than or greater than zero. When $S < 0$, the unbiased LBC estimator $\tilde{\gamma}$ can have greater MSE than the initial estimator $\hat{\gamma}$ if the following condition holds:

$$\frac{1}{(1+S)^2} V(\hat{\gamma}) > (C + S\gamma)^2 + V(\hat{\gamma}). \quad (\text{A.10})$$

If $V(\hat{\gamma})$ is relatively small compared to the bias $(C + S\gamma)$ or if the bias function is upward sloping, the condition (A.10) cannot be satisfied. Thus, the LBC estimator will have smaller MSE when the variance of the initial estimator is small or when the bias function slopes upward. As shown in Dang et al. (2013), the estimation variance of γ is far less than the bias component; hence, we apply LBC to correct biases for single estimators.

Appendix B. Estimation procedures for single estimators

Broadly based on the extant literature, the selected single estimation methods and implementation details in Stata are summarized as follows:

- OLS Ordinary least squares. We use the Stata procedure “reg”.
- FE Fixed effects. We use the Stata procedure “xtreg, fe”.
- AB Arellano and Bond's (1991) difference GMM. We use the Stata procedure “xtabond”. In the simulation, we use the default first lag as the instrument. For the empirical analysis, we use the option to specify the maximum lag 3 as the instrument.
- BB Blundell and Bond's (1998) system GMM estimates. We use the Stata procedure “xtdpdysys” and the Stata procedure “xtabond”. In the simulation, we use the default first lag as the instrument. For the empirical analysis, we use the option to specify the maximum lag 3 as the instrument.
- LD4 Four-period Long Differencing replicates Huang and Ritter's (2009) implementation of Hahn et al. (2007)'s estimator. Rongbing Huang kindly provided us with the Stata code for implementing the estimation.
- LSDVC Least squares dummy variable correction corrects the biased FE-estimated coefficients. We use the “xtlsdvc” (Bruno, 2005) estimation procedure and use BB as the initial estimate.

Appendix C. Simulated data-generating process

The basic benchmark data-generating process is as follows:

$$y_{it} = \gamma y_{it-1} + \sum_{j=1}^7 \beta_j x_{jit} + \eta_i + \varepsilon_{it} \quad (\text{C.1})$$

where the independent firm characteristic variables are generated as

$$x_{jit} = \rho_j x_{jit-1} + \alpha_1 y_{it-1} + \alpha_2 \eta_i + \xi_{jit} \quad (\text{C.2})$$

and the residual terms are generated as

$$\varepsilon_{it} = \delta_1 \varepsilon_{it-1} + \delta_2 \varepsilon_{it-2} + \omega_{it}. \quad (\text{C.3})$$

Assigning different sets of parameter values in Eqs. (C.2) and (C.3) allows us to incorporate various realistic corporate finance data features into our datasets. Following Flannery and Rangan (2006), we consider seven observable firm characteristic variables: X_i including earnings before interest and taxes scaled by total assets (EBIT_TA), market to book (MB), depreciation

scaled by total assets (DEP_TA), the natural log of total assets (Ln(TA)), fixed assets scaled by total assets (FA_TA), R&D expense scaled by total assets (R&D_TA), and the industry median debt ratio (Ind_Median).

As a general principle, we start with $x_{j0} = 0$ and $y_{j0} = 0$ generate a panel length $T + 10$ for each firm, and then drop the first 10 observations. Under each parameterization, we generate 500 samples (following Flannery and Hankins, 2013). We fix $T = 12$ and the number of firms to 500 for each sample. Thus, each sample has 6,000 firm-year observations. We set all seven $\beta = 0.2$ and calibrate the correlation coefficients of seven independent variables using the same values as Flannery and Hankins (2013), where $\rho = [\rho_1 \ \rho_2 \ \rho_3 \ \rho_4 \ \rho_5 \ \rho_6 \ \rho_7]' = [0.455 \ 0.25 \ 0.085 \ 0.844 \ 0.254 \ 0.197 \ 0.690]'$. We generate firm-level fixed effects from a uniform distribution, $\eta_i \sim U[-1, 1]$, and the innovation terms of Eqs. (C.1) and (C.2), ε_{it} and ω_{it} are generated from (0, 1) normal distributions separately.

We perform two groups of simulations. 1) The empirical model is correctly specified. In this scenario, the explanatory variables x_{jt} s are generated independently, and the innovation terms in Eq. (C.2) sample from a (0, 1) normal distribution. There are no other problematic issues. We set α_1 and α_2 and δ_1 and δ_2 all equal to 0; thus, there are no endogeneity and serial correlation problems. 2) The empirical model is misspecified. In this scenario, the innovation terms in Eq. (C.2) are distributed as $\xi_{ijt} \sim N(0, \Sigma_0)$, where Σ_0 is the covariance matrix of the seven independent variables calibrated using actual Compustat data. We use the calibration value from Flannery and Hankins (2013) to make our results comparable to theirs. We set $\delta_1 = 0.10$ and $\delta_2 = 0.05$ to generate second-order serial correlation in residuals as a simulated type of model misspecification because model misspecification generally affects our estimation from residual terms. Additionally, we assign 0.01 to both α_1 and α_2 to incorporate the endogeneity problem. Because the Compustat firms generally have different lengths of data and the panel is unbalanced, to mimic more realistic empirical corporate finance dataset features, we maintain a constant average $T = 12$ but vary the panel length so that half of the firms have $T = 6$ and the other half have $T = 18$, and the panel lengths are randomly assigned.

Appendix D. Derivation of GMV pooled estimator weights

In estimating the SOA, our objective is to minimize the variance (bias) for a given level of bias (variance). The single estimator weights can be estimated by solving the following minimization problem:

$$\min_x \frac{1}{2} \omega' \Sigma \omega \quad (D.1)$$

s.t.

$$B = \omega' \mathbf{b} \quad (D.2)$$

where ω is the single estimator weights (ω); Σ is the covariance matrix of the single estimators; B is the bias; and \mathbf{b} is the bias vector of single estimators. The “efficient estimator pool frontier” can be derived analogously to the asset portfolio frontier derivation of Merton (1972), producing the well-known hyperbolic function. Along the frontier, all of the combined estimators will have the smallest variance for a given bias level. Because the global minimum variance point has the smallest variance and can be more accurately estimated empirically (see Frahm and Memmel, 2010), we use the global minimum variance (GMV) portfolio weights as our pooled estimator weights and call this case the GMV weighting scheme. The bias can then be calculated, and we can correct for the bias. Specifically,

$$\omega = \frac{\Sigma^{-1} \mathbf{1}}{\mathbf{1}' \Sigma^{-1} \mathbf{1}} \quad (D.3)$$

and

$$B = \frac{\mathbf{b}' \Sigma^{-1} \mathbf{1}}{\mathbf{1}' \Sigma^{-1} \mathbf{1}}. \quad (D.4)$$

Then, the combined estimator γ_c takes the following general form:

$$\hat{\gamma}_c = \omega'_{N \times 1} * \hat{\gamma}_{N \times 1} - B \quad (D.5)$$

where

$$\hat{\gamma}_{N \times 1} = \begin{bmatrix} \hat{\gamma}_1 \\ \vdots \\ \hat{\gamma}_N \end{bmatrix} \quad (D.6)$$

is an estimator set containing N estimates.

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