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Dynamic Firm Performance and Estimator Choice: A Comparison of Dynamic Panel Data Estimators

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ABSTRACT

Dynamic panel data models are increasingly and extensively used in operational research and performance analysis as researchers seek to better understand the dynamic behaviors of firms. However, estimation of the lagged dependent variable in conjunction with the time-invariant individual effect leads to a number of econometric issues. While several methodologies exist to overcome such complexities, there is little consensus on the appropriate method of estimation. In this paper, we evaluate the performance of different dynamic panel estimators across a range of common settings experienced by researchers. Instead of focusing on one single criterion of assessment, we employ multiple evaluative metrics across multiple experiments to provide a more extensive analysis of dynamic panel estimators. Taking all simulations into account, we find the quasi-maximum likelihood estimator to be the most robust and reliable estimator across empirical settings. We illustrate our findings with two empirical applications and show that the choice of estimator significantly affects the interpretation of firms' productivity and efficiency persistence.

Keywords: Dynamic Panel Data Models, Monte Carlo Simulations, Total Factor Productivity, Efficiency

JEL Classification Numbers: C23, C33, C53

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1 Introduction

Dynamic panel data (DPD) models are now widely used all over the spectrum including operational research (OR). In particular, DPD models have become an essential method of evaluation in supply chain management as researchers and practitioners seek to better understand the dynamic nature of firms' decisions and their impact on the production process. Estimates of productivity and (in)efficiency persistence are of particular importance for decision makers who need to evaluate the performance impact of input changes on the production process, such as, the introduction of genetic enhancements on agricultural production (e.g., Ali et al. (2021)) or the value-enhancing effects of new information technology (e.g., Lin and Kao (2014) and Lin et al. (2019)). Similarly, in other areas of supply chain management, estimates of revenue persistence are useful for decision-makers who need to optimize distribution and sales strategies (e.g., Chung et al. (2019)) or for decision-makers who are looking to evaluate the effects of online reviews on consumer demand and firms' financial performance (e.g., Archak et al. (2011) and Symitsi et al. (2021)).

In all of the above applications, the precise estimation of DPD models and the autoregressive parameter is paramount in order to examine the persistence of firms' (in)efficiency, the intertemporal transition towards optimal input combinations and the speed of adjustment (SOA) towards target outputs. However, precise estimation of the *true* autoregressive coefficient can be difficult for several reasons. First, empirical datasets in the OR and firm performance literature typically consist of a large number of firms (N), often over a small, and infrequent, number of time periods (T). Second, due to the correlation between the lagged dependent variable and the time-invariant component, the common fixed-effect (FE) or within-transformed estimator can also produce biased estimates of the autoregressive coefficient when the panel length, T, is short (Nickell, 1981)[1]. Thus, it is clear that the implications of cross-sectional heterogeneity and finite sample bias are of significant importance to both researchers and practitioners, as incorrect estimation of the autoregressive coefficient can give rise to spurious economic conclusions and the possible mismanagement of firms' supply chain and production process.

In order to reinforce one's findings in practice, empirical researchers should naturally examine the robustness of their findings against a series of robust estimation procedures. However, despite the existence of several different DPD estimators, there is, surprisingly, little consensus on the most appropriate method of estimation in the OR literature. As a result, researchers often employ DPD estimators and report their findings without questioning the appropriateness/efficacy of the estimator itself. In this paper, we address the ambiguity of estimator choice in the OR and firm performance literature by examining the economic implications of different DPD estimators via a series of Monte Carlo experiments. Specifically, we investigate and compare the statistical properties of eight different DPD estimator, namely, the OLS estimator, the FE estimator, the two-step first-difference generalized method of moments (FD-GMM) estimator of Arellano and Bond (1991), the two-step non-linear GMM estimator of Ahn and Schmidt (1995) (AS-GMM), the two-step system GMM (SYS-GMM) estimator of Blundell and Bond (1998), the lag difference four (LD4) estimator of Huang and Ritter (2009), the least square dummy variable correction (LSDVC) estimator of Kiviet (1995) and the quasi-maximum

[1] Judson and Owen (1999) show that the FE estimator can still be severely biased when T = 30.

likelihood (QML) fixed effect estimator of Hsiao et al. (2002).

The main objective of this paper is to identify the most appropriate and robust method of DPD estimation. Whilst many sections of the supply chain contain dynamic processes, we focus our application on the production stage. We do this for two reasons. First, given the presence of adjustment costs, DPD models play a natural role in evaluating the production stage of firms' operations, as intertemporal input adjustments are extremely common in practice[2]. Second, there exists a large and well-established theoretical and empirical literature on the dynamics and persistence of firms' productivity and (in)efficiency. For example, initially modeled by Ahn and Sickles (2000)[3], DPD models have been used to investigate the degree (in)efficiency persistence across a large number of sectors, such as, the agricultural sector (e.g., Souza and Gomes (2015) and Ali et al. (2021)), the manufacturing sector (e.g., Jin et al. (2019)), and the financial sector (e.g., Staub et al. (2010), Galán et al. (2015), Zhang and Jiao (2015), Kai et al. (2018) and Delis et al. (2020)).

To undertake our investigation, we conduct a series of experiments consistent with the common empirical datasets, characteristics and issues experienced by researchers in the OR and firm performance literature. Specifically, we focus our panel data design on the dimensions of a short time-series (T) and large cross-sectional (N) panel dataset, as this reflects the panel datasets most frequently encountered in practice by operational and firm performance researchers. Indeed, we are not the first to pursue this avenue, with studies in other fields, such as management and finance, also considering the efficacy of DPD estimators in similar empirical settings (e.g., Abdallah et al. (2015), Flannery and Hankins (2013) and Dang et al. (2015)). However, our paper differs in a number of key respects. First, our paper overcomes the limitations of existing studies, by evaluating multiple competing DPD estimators across multiple evaluative metrics. In particular, we employ four evaluative metrics, namely, coefficient bias (Bias), the standard deviation of bias (SD), the root mean square error (RMSE), and a Wald test metric (Wald), across simulations of low, medium and high levels of dynamic persistence. Moreover, we also document the trade-off between bias and variance – analogous to that of the mean-variance trade-off in modern portfolio theory – by utilizing non-parametric kernel (bias) density plots for each estimator. Second, existing studies, such as Abdallah et al. (2015) and Chung et al. (2019), have predominately focused on the performance of the popular FD- and SYS-GMM estimators whilst our study considers a range of competing methods, from alternative GMM and instrumental variable estimators to bias correction and quasi maximum likelihood approaches. Finally, we examine the statistical robustness of our DPD estimators to a series of empirical issues in the OR and firm performance literature, such as the impact of varying panel dimensions, the degree of cross-sectional heterogeneity, the extent of panel unbalancedness, the size and functional form of the idiosyncratic disturbance term and the presence of predetermined and endogenously determined regressors.

Taking all experiments into account, our simulations show that the QML estimator consistently

[2]For example, in the presence of rapid technological change, firms seek to adjust production inputs in order to maximize discounted cash flows or to minimize discounted costs. However, the existence of institutional rigidity, quasi-fixity of inputs, transaction and information costs, among other factors, prevent firms from making instantaneous adjustments towards optimal input combinations. As a result, firms may not only be inefficient at a given point of time, but they may decide to remain partly inefficient in the short-run as they transition towards new production states. This makes the decision process dynamic.

[3]Note this approach has recently been extended by Lai and Kumbhakar (2020).

produces the most accurate and efficient estimates of the autoregressive coefficient. Our tests reveal that the QML estimator is largely robust to changes panel dimensions and the degree of cross-sectional heterogeneity, and outperforms competing DPD estimators in unbalanced panel settings and when the variance of the residual is non-constant. Moreover, the QML estimator also perform reasonably in the presence of predetermined regressors. Our simulations find that in a number of settings, the LSDVC estimator performs similarly to the QML estimator in terms of Bias; although, the estimator often proves unreliable in the inferential Wald tests. As expected, we find the OLS and FE estimators perform poorly throughout our experiments. However, most alarmingly, we find the FD-GMM and SYS-GMM estimators to be highly sensitive to a range of issues. More specifically, we find the performance of the FD-GMM and SYS-GMM estimators to be affected by the size of cross-sectional heterogeneity, the degree of panel unbalanedness and the size and functional form of the idiosyncratic disturbance term, with the FD-GMM estimator typically underestimating the *true* autoregressive coefficient, especially when the degree of dynamic persistence is high. We find the AS-GMM estimator often performs well in terms of bias - especially in the presence of an endogenous regressor - however, at the cost of relatively low efficiency with the AS-GMM estimator often producing high levels of SD and RMSE compared to competing DPD estimators.

To verify our simulation results and to further stress the importance of accurate DPD estimation in practice, we present two empirical illustrations of dynamic persistence. Using a large sample of Indian manufacturing firms from 2000-2017, we examine the degree of dynamic persistence in firms' total factor productivity (TFP) and non-radial efficiency. We focus on firms' TFP and efficiency, as both measures are commonly employed in the OR literature and are frequently used in the analysis of productivity persistence (e.g., Souza and Gomes (2015), Galán et al. (2015), Casu et al. (2016) and Ali et al. (2021)). Our results show that the autoregressive coefficient estimates for TFP and efficiency range considerably across estimators from 0.57-0.92 and 0.43-0.75, respectively. We find the LSDVC and QML estimators produce the most plausible estimates while, in both applications, the estimates from the GMM estimators typically cluster downwards towards the biased estimates of the FE estimator.

The findings from our simulations as well as our two empirical applications have highly important implications for OR and supply chain management. As our first contribution, we show that several DPD estimators, of which many have been employed in the OR literature, are severely biased, especially when the dependent variable in question is highly persistent. For instance, our findings are of particular importance for likes of Archak et al. (2011), Elkamhi et al. (2014), Souza and Gomes (2015), Galán et al. (2015) Tsionas (2016), Irresberger et al. (2018), Belghitar et al. (2019), Chung et al. (2019), Boubaker et al. (2020), Ali et al. (2021) and Symitsi et al. (2021), of whom all estimate DPD models in the OR literature via FD- and/or SYS-GMM estimators. Ultimately, our findings bring these works, among others, into question, as the conclusions and policy recommendations advocated may indeed be based on inaccurate or spurious estimates of the *true* autoregressive coefficient. As this paper's second contribution, we show in our empirical applications that the choice of the DPD estimator has a significant effect on the degree of estimated persistence in TFP and efficiency, and that the degree of variation is non-trivial. Accordingly, researchers and practitioners concerned with the production process of the supply chain may need to consider reassessment, as it is more than possible that production input adjustments have been implemented based on biased empirical estimations. Finally, and perhaps most importantly, our paper contributes to the OR and firm performance literature by highlighting for future studies currently one of the most accurate and robust methods of DPD estimation in the QML estimator.

The remainder of this paper is organized as follows. In Section 2 we provide a review of the dynamic partial adjustment model and surveys the existing methods of DPD estimation. Section 3 introduces the data generating process used for our simulations and details our experiment designs. In Section 4 we report the findings from our experiments and Section 5 reports the results from our empirical applications. Section 6 concludes.

2 Dynamic Panel Data Models and Estimation

2.1 A Traditional Dynamic Panel Data Model

In the OR literature, empirical researchers often examine the dynamics of firms' performance variables via the estimation of DPD models (e.g., Galán et al. 2015, Boubaker et al. 2020, Symitsi et al. 2021). In such models, the lagged dependent (performance) variables are included on the right-hand side as regressors to capture firms' adjustment towards optimal input and/or output combinations or the degree of persistence in firms' performance measures. More specifically, since the theory of partial adjustment was introduced by Nerlove (1958), many studies have employed dynamic partial adjustment models to examine firms' (and other decision-making units) target adjustment behavior. For example, Lin et al. (2010), Lin and Kao (2014) and Lin et al. (2019) employ a dynamic partial adjustment framework to evaluate the value-enhancing affects of information technology adoption in the production process, Chen et al. (2012), Öztekin and Flannery (2012) and Elkamhi et al. (2014) examine the adjustment of firms' corporate financial policies, and Kumbhakar et al. (2002) and Hendricks et al. (2014) adopt the framework to model firms' labour input adjustments and agricultural production, respectively.[4] The traditional dynamic partial adjustment model is specified as follows:

$$y_{i,t} - y_{i,t-1} = \theta(y^*_{i,t} - y_{i,t-1}) + \eta_i + \upsilon_{i,t} \tag{1}$$

where $y_{i,t}$ and $y^*_{i,t}$ denote the actual (observed) and optimal (unobserved) preference of firm i at time t, η_i is the time-invariant individual effect and $\upsilon_{i,t}$ is the idiosyncratic error term. In equation (1), θ approximates the adjustment rate from the current position to the optimal target. Note, the optimal target, $y^*_{i,t}$, is not directly observed, but could be deterministic on a set of deterministic characteristics ($X_{i,t}$):

$$y^*_{i,t} = \Omega' X_{i,t} \tag{2}$$

where $X_{i,t}$ denotes the $k \times 1$ vector of explanatory variables. Given the generated regressor problem resulting in invalid inference (Pagan, 1984), it is common practice to adopt the single-stage approach

[4] Other applications of partial adjustment models in empirical research range from the demand for natural gas (Lin et al., 1987) and cigarettes (Baltagi and Levin, 1992) to the production of lumber (Lin, 1986) and the pricing of initial public offerings (Chiang et al., 2010). See Lin and Kao (2014) for an extensive review.

by substituting equation (2) into equation (1) which gives:

$$y_{i,t} = \lambda y_{i,t-1} + \beta' X_{i,t} + \eta_i + \upsilon_{i,t} \tag{3}$$

where $\lambda = 1 - \theta$ and $\beta = \theta\Omega$. The single lag DPD model in equation (3) can be considered the traditional specification used to investigate the adjustment process of firms' towards their optimal targets, where the model allows for the simultaneous single-stage estimation of the SOA, $\hat{\theta} = 1 - \hat{\lambda}$, and the long run parameter coefficients for the optimal target, $\hat{\Omega} = \frac{\hat{\beta}}{1-\hat{\lambda}}$. Whilst higher order lag models have been adopted in the OR and firm performance literature, the single lag specification is both theoretically and empirically the most common[5] and is thus the main focus in our paper. Given this, the challenge that remains for empirical researchers is how to precisely estimate the *true* autoregressive coefficient λ.

2.2 Dynamic Panel Data Estimators

A number of different econometric methods have been proposed to estimate DPD models. Among the traditional approaches, it is well known that due to the presence of the time-invariant effect, η_i, in equation (3), the OLS estimator yields upwardly biased estimates of the autoregressive coefficient resulting in inaccurate conclusions about the *true* speed of partial adjustment. Furthermore, whilst the FE estimator addresses this issue, the within-data transformation induces a correlation between the lagged regressor and the error term, resulting in downwardly biased estimates of the autoregressive parameter, especially when the panel length, T, is short (Nickell, 1981).

To overcome the finite-sample bias associated with the FE estimator, many empirical studies have adopted more advanced econometric techniques. Notably, as affirmed by Ali et al. (2021), it has now become standard practice in OR literature to employ GMM estimators to estimate DPD models. For example, Chung et al. (2019) and Symitsi et al. (2021) adopt the FD-GMM estimator to examine the degree of persistence in pharmaceutical sales and firm profitability, respectively. Similarly, the SYS-GMM estimator has been employed across a range of topics in the OR literature from agricultural production (e.g., Souza and Gomes 2015 and Ali et al. 2021) to the analysis of financial instruments (e.g, Irresberger et al. 2018); and from online customer reviews (e.g., Archak et al. 2011) to the degree of persistence in firms' performance (e.g., Belghitar et al. 2019 and Boubaker et al. 2020). Unlike the other estimators evaluated in this paper, one of the main motivations for the GMM estimators is their ability, in practice, to potentially address both the bias in the lagged dependent variable as well as other potentially predetermined or endogenously determined regressors.

Despite the extensive use of GMM estimators in the OR and firm performance literature, they are known to be widely prone to a number of empirical issues. For instance, the FD-GMM estimator is known to perform poorly in finite samples and in the presence of weak correlation of the level instruments with that of the first differences. This often arises empirically when the dependent variable is highly persistent and/or the variance of η_i is large relative to the variance $\upsilon_{i,t}$ (Blundell and Bond,

[5] See, for example, Lee et al. (2000), Lokshin et al. (2008), Chen and van Dalen (2010), Archak et al. (2011), Akan et al. (2013), Sabitha et al. (2016), Irresberger et al. (2018), Belghitar et al. (2019), Boubaker et al. (2020), Lai and Kumbhakar (2020), Kalaitzoglou et al. (2020), and Symitsi et al. (2021).

1998). Moreover, whilst the AS-GMM and SYS-GMM estimators were proposed to address such concerns, Bun and Windmeijer (2010) show that at high levels of persistence, the SYS-GMM estimator equally struggles to estimate accurately the *true* autoregressive coefficient. Furthermore, Levine et al. (2000) argues that given equation (3) is conceptually in levels differencing may reduce the variation of explanatory variables as well as the statistical power of empirical tests in GMM estimators.

Given such shortcomings, the recent empirical has turned to alternative dynamic panel estimators in an attempt to gain a more precise estimate of the autoregressive coefficient, namely: the fourth-period difference estimator (LD4) of Huang and Ritter (2009)[6], the LSDVC estimator of Kiviet (1995) and finally, the QML estimator of Hsiao et al. (2002). Despite the favorable properties of the LSDVC estimator evidenced in the extensions of Bun and Kiviet (2003) and Bruno (2005), to date, only a few empirical studies have employed the methodology empirically, for example, Öztekin and Flannery (2012) and Dang et al. (2015). Similarly, in comparison to the vastly popular GMM estimators of Arellano and Bond (1991) and Blundell and Bond (1998), the QML fixed-effect estimator has received considerably less attention in the operational and performance literature, with the studies of Lokshin et al. (2008) and Chen and van Dalen (2010) being noteworthy exceptions. Thus, our documentation of both estimators in this paper contributes to the overall discussion of DPD estimators and dynamic persistence in the operational and firm performance literature.

3 Data and Experiment Design

3.1 Data Generating Process

In this section, we introduce the parameter definitions and the data generating process used for our Monte Carlo experiments. Motivated by Section 2.1, we consider the following DPD model:

$$y_{i,t} = \lambda y_{i,t-1} + \beta x_{i,t} + \eta_i + \nu_{i,t} \tag{4}$$

$$x_{i,t} = \rho x_{i,t-1} + \xi_{i,t} \tag{5}$$

$$\nu_{i,t} \sim N(0, \sigma_\nu^2) \tag{6}$$

$$\xi_{i,t} \sim N(0, \sigma_\xi^2) \tag{7}$$

Following Arellano and Bond (1991) and Kiviet (1995), we consider three different values of λ in order to encapsulate different degrees of dynamic persistence, namely, $\lambda = 0.2$ (low persistence), $\lambda = 0.5$ (moderate persistence) and $\lambda = 0.8$ (high persistence)[7]. We set β=1-λ which means that changes to λ only effect the relationship between x and y in the short run and the long run relationship is kept at unity ($\beta/1 - \lambda$). We allow for correlation between η_i and $x_{i,t}$ and follow Dang et al. (2015) and Elsas and Florysiak (2015) and set η_i to be correlated with the explanatory variable. We define $\eta_i = \mu(1 - \lambda)\Omega_i$, where $\Omega_i = (\bar{x}_i - \bar{x}) + 1$ and $\bar{x}_i$ and $\bar{x}$ are the within and overall means, respectively. Finally, we set $\sigma_\nu^2 = 1$, and $\rho = 0.5$ in equation (5) across all simulations.

[6] Following the longest difference estimator of Hahn et al. (2007).

[7] These coefficient values are typically common of the empirical OR and firm performance literature, for example, Lokshin et al. (2008), Souza and Gomes (2015), Belghitar et al. (2019) and Boubaker et al. (2020).

For our data generating process, we follow the more efficient procedure designed by McLeod and Hipel (1978) for time-series simulations and adopted by Kiviet (1995), Bun and Kiviet (2003), Bruno (2005) and Dang et al. (2015) for the panel data setting.[8] Following Kiviet (1995), we set L as the lag operator for equation (4) and define:

$$y_{i,t} = \lambda L y_{i,t} + \beta x_{i,t} + \eta_i + \nu_{i,t} \tag{8}$$

factorizing and rearranging we have:

$$y_{i,t} = \frac{\beta}{(1-\lambda L)} x_{i,t} + \frac{\eta_i}{(1-\lambda L)} + \frac{\nu_{i,t}}{(1-\lambda L)} \tag{9}$$

following the same process for $x_{i,t}$ we can define $y_{i,t}$ as the combination of an AR(2) and AR(1) processes:

$$y_{i,t} = \frac{\beta}{(1-\lambda L)(1-\rho L)} \xi_{i,t} + \frac{\eta_i + \nu_{i,t}}{(1-\lambda L)} = \beta \varphi_{i,t} + \psi_{i,t} + \frac{\eta_i}{(1-\lambda L)} \tag{10}$$

where $\varphi_{i,t} = (\rho + \lambda)\varphi_{i,t-1} - \rho\lambda\varphi_{i,t-2} + \xi_{i,t}$ and $\psi_{i,t} = \lambda\psi_{i,t-1} + \nu_{i,t}$. We can obtain the initial start values for the AR(1) process by drawing from the randomly generated $\xi_{i,t}$ and $\nu_{i,t}$:

$$x_{i,0} = \xi_{i,0}(1-\rho^2)^{-1/2} \tag{11}$$

$$\psi_{i,0} = \nu_{i,0}(1-\lambda^2)^{-1/2} \tag{12}$$

and finally, we obtain the initial values of the AR(2) process as:

$$\varphi_{i,0} = \xi_{i,0} var(\varphi_{i,t})^{1/2} \tag{13}$$

$$\varphi_{i,1} = \varphi_{i,0} corr(\varphi_{i,t}, \varphi_{i,t-1}) + \xi_{i,1} var(\varphi_{i,t})^{1/2} + \{1 - corr[(\varphi_{i,t}, \varphi_{i,t-1})^2]\}^{1/2} \tag{14}$$

where the var($\varphi_{i,t}$), corr($\varphi_{i,t}, \varphi_{i,t-1}$) and corr($\varphi_{i,t}, \varphi_{i,t-2}$) are defined as:

$$var(\varphi_{i,t}) = \sigma_\xi^2 [1 - (\lambda + \rho) corr(\varphi_{i,t}, \varphi_{i,t-1}) + \lambda\rho corr(\varphi_{i,t}, \varphi_{i,t-2})]^{-1} \tag{15}$$

$$corr(\varphi_{i,t}, \varphi_{i,t-1}) = \frac{\lambda + \rho}{1 + \lambda\rho} \tag{16}$$

$$corr(\varphi_{i,t}, \varphi_{i,t-2}) = \frac{(\lambda + \rho)^2}{1 + \lambda\rho} - \lambda\rho. \tag{17}$$

As discussed by Kiviet (1995), the advantage of this style of data generating process is that it avoids a number of practical issues, namely, the waste of random numbers, slow convergence issues, and small sample non-stationarity problems, as the initial values for the AR(1) and AR(2) processes are generated via a combination of random numbers ($\xi_{i,0}$ and $\nu_{i,0}$) and defined parameter values (namely, λ and ρ). To maintain the rigor of Kiviet (1995), Bun and Kiviet (2003), Bruno (2005) and Dang et al. (2015), we control for two specific elements, namely the factor loading of the time-invariant individual effect, η_i, denoted as μ, and the signal-to-noise ratio, which we denote as ζ.

[8] See Kiviet (1995) for the associated problem with the data generating process in Arellano and Bond (1991) and Flannery and Hankins (2013) .

The loading factor reflects the impact of η_i on the dependent variable, $y_{i,t}$, with respect to the error competent, $\nu_{i,t}$. Kiviet (1995) and Dang et al. (2015) show that the size of the time-invariant effect can cause significant bias in estimator performance. The signal-to-noise ratio measures the variance ratio of the regressors with respect to the error term. Defining the latent variable, $z_{i,t} = \beta\varphi_{i,t} + \psi_{i,t} = y_{i,t} + \eta_i/(1-\lambda)$, one can express the signal-to-noise ratio as $\zeta = \sigma_s^2/\sigma_v^2$ where σ_s^2 is variance of the signal $s_{i,t} = z_{i,t} - \nu_{i,t}$. Kiviet (1995), Bruno (2005) and Dang et al. (2015) have found that the signal-to-noise ratio impacts the level of parameter bias in the autoregressive coefficient, yet, the outcome of which is often mixed.

3.2 Experiment Design and Evaluation

To examine the effective performance of our DPD estimators we conduct a series of experiments consistent with the common empirical datasets, characteristics, and issues experienced by researchers in the OR and firm performance literature. We begin our analysis with our benchmark simulation where we set $T = 12$ and $N = 500$. These panel dimensions largely reflect the short T and large N datasets typically encountered in the firm-level operational and performance literature. We consider three values of λ: $\lambda = 0.2, 0.5, 0.8$ and set $\beta = 1 - \lambda$, $\rho = 0.5$, $\mu = 1$ and $\zeta = 5$ with a repetition rate of $R = 500$. Naturally, our baseline simulations are used as a point of reference throughout the duration of the paper.

For our first experiment, we test the impact of changes in time-series length (T) and cross-section size (N) as the statistical performance of DPD estimators depends on the relative values of both panel components (Alvarez and Arellano, 2003). Therefore, in experiment one we vary the panel dimensions of T and N, separately, to $T = 6$, $T = 18$, $N = 100$ and $N = 250$. For our next set of experiments, we examine the impact of cross-sectional heterogeneity and panel unbalancedness. The degree of both cross-sectional heterogeneity and panel unbalancedness are common issues in the operational and firm performance literature. For experiment two, we consider two forms of η_i, one with zero correlation between $x_{i,t}$ and η_i, and one where $\mu = 3$ capturing the impact of increased cross-sectional heterogeneity. For experiment three, we consider two different levels of panel unbalancedness (ω), namely, low ($\omega = 90\%$) and high ($\omega = 50\%$) levels of panel unbalancedness. In our final set of experiments, we examine the impact of the idiosyncratic error component on DPD estimator performance. In our fourth experiment, we follow Kiviet (1995) and evaluate the impact of the size of the residual by considering two values of ζ: $\zeta = 2$ and $\zeta = 8$. For our fifth experiment, we examine the effect of non-constant variance in the disturbance term by testing the performance of our DPD estimators in the presence of cross-sectional heteroskedasticity and time-series heteroskedasticity. In our sixth and final experiment, we examine the effect of correlation between an additional regressor and the error term. Specifically, we examine, separately, the impact of a predetermined and an endogenously determined regressor on the performance of our DPD estimators.[9]

[9] As an additional test, we examine the impact of non-stationarity in the dependent variable. Following a similar data generating process to Blundell and Bond (1998), we find the performance of the FD-GMM and AS-GMM estimators improves considerably when the initial conditions are non-stationary. We find the SYS-GMM and LSDVC estimators to perform poorly in such settings while overall, the QML estimator remains the most robust, outperforming all other estimators in terms of Bias, SD and Wald. The full set of simulations can be made available upon request.

Instead of focusing on a single criteria to assess the relative performance of each estimator, we employ a number of evaluative metrics, namely, coefficient bias (Bias)[10], the standard deviation of bias (SD)[11], the root mean square error (RMSE)[12] and a Wald based inference statistic (Wald), which reports the rejection rate from individual Wald tests, where for each simulation we test whether the 95% confidence interval of λ_i contains the true parameter set in the data generating process (i.e., whether in 5% cases it fails to include the true parameter)[13]. Finally, we supplement our assessment by visualizing the relationship between bias and variance – akin to the mean-variance (return-risk) trade-off of modern portfolio theory – where we utilize non-parametric kernel (bias) density plots for each estimator.

4 Monte Carlo Experiments

4.1 Benchmark Simulations

Table 1 reports the simulation statistics for λ, Table 2 reports the simulation statistics for β, Table 3 reports the inferred rate of adjustment (i.e. SOA) and finally Figure 1 illustrates the bias density plots for λ.[14]

Table 1 shows that the performance of the OLS and FE estimators are consistent with the work of Kiviet (1995) and Judson and Owen (1999). The OLS (FE) estimator consistently overestimates (underestimates) the autoregressive coefficient. Furthermore, our results show that the bias for the OLS (FE) estimator decreases (increases) with the level of persistence – with the highest level of reported Bias being 0.194 (-0.112) when $\lambda = 0.2$ (0.8). Regarding the other evaluative metrics, we find both estimators to have relatively low levels of SD, however, both the OLS and FE estimators perform poorly in terms of RMSE and the Wald test. For example, when $\lambda = 0.2$, we find the FE estimator reports a Wald rejection rate of 96.4%. Therefore, out of 500 repetitions, the 95% confidence interval of the parameter did not contain the true parameter 482 times. Finally, for β (Table 2), the OLS estimator shows moderate levels of bias while the FE estimator generally performs better.

With the GMM estimators, we find that the FD-GMM, AS-GMM and SYS-GMM estimators outperform the traditional estimators in terms of Bias. For instance, when $\lambda = 0.5$ we report Bias of -0.011, -0.006 and 0.018, respectively. Consistent with Blundell and Bond (1998), we document that the bias associated with all the three estimators increases with the level of persistence. The SYS-GMM estimator notably outperforms the FD-GMM estimator regarding RMSE while the AS-GMM estimator performs surprisingly well in the Wald test[15].

[10] Bias= $\frac{1}{R}\sum_{i=1}^{R}(\hat{\lambda}_i - \lambda)$, where $\hat{\lambda}_i$ is the estimated autoregressive coefficient and λ is set in the data generating process.

[11] SD= $\sqrt{\frac{1}{R}\sum_{i=1}^{R}(\hat{\lambda}_i - \bar{\lambda})^2}$ where $\hat{\lambda}_i$ is the estimated autoregressive coefficient and $\bar{\lambda}$ is the average bias.

[12] RMSE= $\sqrt{\frac{1}{R}\sum_{i=1}^{R}(\hat{\lambda}_i - \lambda)^2}$ where $\hat{\lambda}_i$ is the estimated autoregressive coefficient and λ is set in the data generating process.

[13] For example, when λ is set to 0.8 in the data generating process, the Wald rejection rate reflects the percentage of simulations where the estimated confidence interval does not include 0.8 at the 5% significance level.

[14] For brevity, in later experiments we shall only report the simulation statistics and bias density plots for λ in the main text. All other corresponding Tables can be found in the appendix.

[15] It is important to note, given their instrumental variable design, the GMM estimators often perform well in the Wald test due to increased standard errors.

Looking at the alternative estimators, we find the performance of the LD4 estimator to be inversely affected by the degree of dynamic persistence. At low to moderate levels of persistence, the LD4 estimator performs worse than the traditional estimators across most evaluative metrics. However when $\lambda = 0.8$, the LD4 estimator outperforms both the FD-GMM and SYS-GMM estimators in terms of reported Bias. Thus, with highly persistent λ, the LD4 estimator might be advantageous in estimating the true autoregressive coefficient, however, at the cost of the inconsistent and biased estimates of β. Finally, we find the LSDVC and QML estimators to be superior across all values of λ, with the performance of both estimators being weakened by the degree of dynamic persistence. However, unlike the GMM-estimators, we see the LSDVC and QML estimators still estimate λ with negligible reported Bias when $\lambda = 0.8$. While the performance of the LSDVC estimator is unsurprising given the work of Flannery and Hankins (2013) and Dang et al. (2015) we are, to the best of our knowledge, the first to document the estimation properties of the QML estimator in an evaluative comparison approach. Furthermore, our benchmark simulations indicate that the performance of the QML estimator edges the LSDVC estimator, particularly in terms of the Wald test.

To visualize the impact of dynamic persistence in Table 1, Figure 1 illustrates the role of λ and its influence on reported Bias and SD. When the degree of persistence is low, the GMM and alternative estimators (apart from the LD4 estimator) are centered close to zero, with the LSDVC and QML estimators having the narrowest bandwidths. However, as the degree of persistence increases to $\lambda = 0.8$, the density and bandwidths of the aforementioned estimators worsen considerably (especially in the GMM-estimators) resulting in wider bias curves and less consistent estimates.

In sum, we find the degree of dynamic persistence to have a significant impact on the properties of estimators, where in most cases, higher levels of persistence result in increased estimation bias. As expected, our benchmark simulations establish that the OLS and FE estimators are inadequate methods of estimation as both estimators produce severely biased estimates of the autoregressive coefficient, λ. The economic implications (Table 3) of the OLS and FE estimators reflect their inability to estimate the true SOA. For example, where the SOA= 20% the OLS and FE estimator, on average, estimate the SOA to be 13.60% and 31.30%, respectively. We find the GMM and alternative estimators prove more reliable in this regard, however, the GMM and LD4 estimators are highly sensitive to the degree of dynamic persistence. Overall, the LSDVC and QML estimators provide the most accurate estimates for the SOA, even when $\lambda = 0.8$, the implied SOA is 21.1% and 21.1%, respectively.

[Insert Tables 1-3 and Figure 1 about here]

4.2 Experiment One: The Impact of Panel Data Dimensions

For our first experiment, we examine the performance of our DPD estimators to changes in both time-series length (T) and cross-sectional size (N). Our first experiment is motivated by the increasing availability and use of micro-panel datasets in OR and other fields, where often the panel dimensions are fixed and non-negligible. For example, operational researchers often look to exploit the uniqueness of newly available, short panel datasets to expand the literature's understanding of persistence in firms' production processes (e.g., Souza and Gomes (2015)). To conduct our first experiment and to begin our search for the most robust DPD estimator(s), we consider four different variations of our baseline specification, namely, $T = 6$, $T = 18$, $N = 100$ and $N = 250$.

The results corresponding to varying time-series length (T) and cross-sectional size (N) can be found in Table 4 and Table 5, respectively. At a broad level, we show that the statistical performance of our DPD estimators are largely impacted by time-series length, with most estimators performing considerably worse in the shorter panel data setting. In contrast, cross-sectional size tends to have little effect on the reported Bias of most DPD estimators, but it does however effect the standard deviation and thus consistency of parameter estimates across simulations. In line with Judson and Owen (1999), we find that both the OLS and FE estimators exhibit significant performance improvements as T increases, however, they do still remain severely biased at high levels of persistence. For instance, our simulations show that when $\lambda = 0.8$ and $T = 6$, the OLS (FE) estimator, on average, has a bias of 0.071 (-0.274), whereas when $T = 18$, the autoregressive coefficient estimate is biased by 0.056 (-0.068), thus reiterating that the OLS and FE estimators' inability to estimate the *true* autoregressive coefficient precisely.

Our simulations show that the performance of the AS-GMM estimator deteriorates in terms of SD and RMSE when $T = 6$, while the SYS-GMM estimator also increases in reported Bias when $T = 6$. We find the performance of both the FD-GMM and LD4 estimators to be impacted by changes in both panel dimensions, with both estimators displaying considerable increases in reported Bias, SD and RMSE when $T = 6$ and when $N = 100$.[16] Focusing on the LSDVC and QML estimators, at low to moderate levels of persistence, both estimators perform well, with only minor performance reductions as a result of the changes in time-series length and cross-sectional size. At high levels of persistence, when $T = 6$, we find the reported Bias of the LSDVC and QML estimators increases to moderate levels of -0.032 and -0.030, respectively, with the LSDVC estimator, also performing poorly in terms of the Wald statistic. Thus, the QML estimator generally edges the LSDVC estimator in small panel data settings.

The overall performance of our DPD estimators across different panel data settings is most clearly summarized in Figure 2 and Figure 3. Comparing the two figures, it is clear that the time-series component of panel datasets has the greatest impact on the performance of our DPD estimators. The implications of our first experiment are particularly important for researchers and practitioners, as frequently, the panel datasets used in practice are short in length. Thus, in such short panel data settings, empirical researchers should pay particular attention to the type of DPD estimator employed, as we evidence, the estimates of the autoregressive coefficient can vary considerably.

[Insert Table 4-5 and Figure 2-3 about here]

4.3 Experiment Two: The Impact of The Time-Invariant Individual Effect

For our second experiment, we examine the impact of the time-invariant individual effect on the performance of our DPD estimators. In practice, operational and firm performance researchers are often concerned with the production processes and management of firms across different industries

[16] Note, that while the LD4 estimator performs uncharacteristically well when $\lambda = 0.5$, but distorted by the presence of extreme outliers, with an estimated range of $[0.086, 1.742]$.

and/or countries (e.g., Shi and Zhang (2010), Öztekin and Flannery (2012), Tsionas (2016) and Casu et al. (2016)). In such settings, the degree of cross-sectional heterogeneity is often large as firms face significant structural differences and time-invariant constraints, such as, different legal systems, different natural resources and different technology environments. To examine the impact of the time-invariant individual effect, we consider two distinct settings. First, we illustrate the effect of zero correlation between the regressor and the time-invariant individual effect. We set $\eta_i \sim N(0, \sigma_\eta^2)$ where $\sigma_\eta = \mu(1-\lambda)\sigma_\nu$ and we maintain $\mu = 1$ to allow for direct comparison with our benchmark simulations. Second, we evaluate the impact of increased cross-sectional heterogeneity on estimator performance. Here we revert to our default definition of the fixed-effect component, whereby $x_{i,t}$ is correlated η_i, and we set $\mu = 3$. Thus, η_i is set three times larger than our baseline simulations.

The results of our simulations are reported in Table 6. Starting with our first test, we find the OLS estimator reduces in reported Bias and RMSE across all degrees of persistence, while comparatively, the FE estimator remains unaffected by the change in definition. We document that both the FD-GMM and SYS-GMM estimators display favorable results when η_i is uncorrelated with x_{it}, especially with $\lambda = 0.8$, where the SYS-GMM estimator reports minimal Bias of -0.005. In terms of the alternative estimators, the LD4 estimator displays marginal gains across all evaluative metrics whereas the LSDVC estimator reacts unfavorably, with deterioration in both reported Bias, RMSE and Wald, especially when the degree of dynamic persistence is high. Finally, in comparison to the benchmark simulations, the QML estimator is relatively unaffected across all metrics and therefore can be considered robust to different types of time-invariant individual effects, both correlated and uncorrelated.

Regarding the second set of simulations, as expected, we find that the OLS estimator performs poorly at high levels of cross-sectional heterogeneity, with extreme Bias and RMSE of 0.497 when $\lambda = 0.2$. Furthermore, given the SYS-GMM estimator does not completely deal with the time-invariant individual effect, η_i, in the system-equation (Wintoki et al., 2012), we also report heightened levels of Bias of 0.093 when $\lambda = 0.8$. Comparatively, the FD-GMM estimator displays opposing behavior in terms of bias, however, at the cost of increased SD and RMSE, relative to our benchmark simulations. Regarding the alternative estimators, while the LD4 estimator reports considerable increases across all evaluative metrics, the LSDVC estimator performs favorable to heightened levels of cross-sectional heterogeneity, with reductions in reported Bias, RMSE and Wald. Finally, the QML estimator remains unaffected to changes μ, and therefore continues to be robust across simulation settings. The implications on reported Bias and SD are visualized in Figure 4 with only the LSDVC and QML estimators showing any degree of reliability when $\lambda = 0.8$ and $\mu = 3$.

[Insert Table 6 and Figure 4 about here]

4.4 Experiment Three: The Impact of Panel Unbalancedness

Next, we examine the impact of panel unbalancedness on estimator performance. In practice, the degree of panel unbalancedness is a common issue in the operational and firm performance literature, with considerable attention being given to whether or not empirical researchers should separate productivity estimates into balanced and unbalanced sub-samples when the initial panel dataset is unbalanced (e.g., Kerstens and Van de Woestyne (2014) and Jin et al. (2020)). Naturally, the degree of parameter bias encountered in the presence of unbalanced panel data is subject to the method of estimation employed. To test the performance of our DPD estimators, we conduct two tests based on the degree of panel unbalancedness, namely, low ($\omega = 90\%$), and high ($\omega = 50\%$) levels of panel unbalancedness. To conduct our experiment, we split the number of cross-sections into three groups and thereafter remove a set number of time periods. For example, for high panel unbalancedness when $\omega = 50\%$, we remove the first 8 time periods for the first 200 cross-sections, for the middle 200 cross-sections we remove the first 7 time periods and we leave the final 100 cross-sections untouched, i.e., $T = 12$. For low unbalancedness, when $\omega = 90\%$, we remove the first 2 time periods for the first 200 cross-sections, for the middle 200 cross-sections we remove the first 1 time period and we again leave the final 100 cross-sections untouched. The main results from our simulations can be found in Table 7.

We find the performance of both the OLS and FE estimators deteriorate across all evaluative metrics as the degree of panel unbalancedness increases. In terms of the GMM-estimators, at low to moderate levels of dynamic persistence, we observe notable performance reductions in SD, RMSE and Wald, yet the effect on reported dynamic coefficient Bias is moderate. When $\lambda = 0.8$ however, the impact of panel unbalancedness is more pronounced. We find the levels of reported Bias in the FD-GMM and AS-GMM estimators to be positively correlated with the severity of panel unbalancedness and we report high levels of Bias when $\omega = 50\%$. The SYS-GMM estimator performs relatively well in terms of reported Bias as the degree of panel unbalancedness increases, however, this comes at the cost of efficiency losses with the SYS-GMM estimator reporting sizable increases in SD and RMSE. For the alternative estimators, we find the bias of the LD4 estimator to be relatively unaffected by the degree of unbalancedness, however, we document substantial increases in SD and RMSE. For the LSDVC, we document increases in all four evaluative metrics as the degree of panel unbalancedness increases – consistent with the simulations of Bruno (2005). Finally, the QML estimator shows similar qualities with notable increases in reported Bias, SD, RMSE and Wald, however, the estimator outperforms the LSDVC estimator across all metrics, especially the Wald test.

In terms of economic implications, we find the SYS-GMM, LSDVC and QML estimators to estimate, on average, the rate of adjustment with the highest degree of accuracy. For example, when $\omega = 50\%$ and $\lambda = 0.8$ the SYS-GMM, LSDVC and QML estimators estimate the rate of adjustment at 18.6%, 22.6% and 22.5%, respectively. Note, however, the SYS-GMM estimator does produce notably higher levels of SD relative to its counterparts. This trade-off is particularly evident in Figure 5 as we observe the bandwidths of all estimators to be severely impeded by the degree of unbalancedness.

In sum, we show that the degree of panel unbalancedness has a substantial impact on the performance of DPD estimators, where in most cases, higher levels of panel unbalancedness result in increases in all evaluative metrics. These findings are of particular concern to empirical researchers, as many datasets employed in the OR and firm performance literature are typically unbalanced. We find the QML estimator to continues to perform favourably across all evaluative metrics and, when compared to it's competitors, only reports moderate levels of Bias when the degree of panel unbalancedness is high.

[Insert Table 7 and Figure 5 about here]

4.5 Experiment Four: The Impact of Changes in Signal to Noise Ratio

In our forth experiment, we examine how our DPD estimators perform subject to changes in the signal-to-noise ratio (i.e. the power of regressors relative to the error term). In practice, the explanatory power of regressors can vary considerably, especially in the firm performance literature where the variance explained by the unobserved time-invariant component, η_i, is often large when compared to observed factors (e.g., Öztekin and Flannery (2012)). To conduct our experiment, we consider two values of ζ; low explanatory regressor power, $\zeta = 2$, and high explanatory regressor power, $\zeta = 8$.

In Table 8 we report our results. Relative to our benchmark simulations, we find the reported Bias of the OLS and FE estimators display opposing reactions to the level of ζ, with the OLS (FE) estimator increasing (decreasing) in Bias and RMSE when ζ increases. For the GMM-estimators, we find variation in ζ has little impact on reported Bias and only small improvements in SD and RMSE at low to moderate levels of persistence. However, when $\lambda = 0.8$, the performance of the GMM-estimators surprisingly deteriorates. Out of the three estimators, the AS-GMM estimator is most preferable, as we document low levels of dynamic Bias, while comparatively, the FD-GMM estimator performs least favorably with the level of reported Bias being three times larger when $\zeta = 8$ (-0.050) relative to when $\zeta = 2$ (-0.015). These findings are consistent with Kiviet (1995). Finally, we find both the LSDVC and QML estimators display significant efficiency gains as ζ increases with notable improvements in SD and RMSE. Moreover, consistent with Bruno (2005), we find the LSDVC estimator also reduces in reported Bias at high values of ζ.

All in all, we document that at low to moderate levels of persistence greater explanatory power in regressors results in efficiency improvements for most estimators. However, at high levels of persistence, the properties of our DPD estimators become less clear, with improvements in SD and RMSE being offset by increased levels of reported dynamic coefficient Bias. In Figure 6 we document significant increases in coefficient densities as ζ increases, with the densities of some estimators more than doubling when $\zeta = 8$. Overall, the LSDVC and QML estimators are the most robust and appropriate estimators in terms of bias and efficiency, however, LSDVC estimator continues to perform poorly in the Wald test, especially when the power of regressors relative to the error term is low.

[Insert Table 8 and Figure 6 about here]

4.6 Experiment Five: The Impact of Cross-sectional and Time-series Heteroskedasticity

In our penultimate experiment, we examine the performance of our DPD estimators in the presence of two different forms of heteroskedasticity. Thus far, the design of our idiosyncratic error component has been homoskedastic, yet, in practice, empirical researchers frequently encounter regression models that display some form of non-constant variance in the disturbance term. For example, in two-stage data envelopment analysis, the residuals of firms are often correlated across time and incorrect second-stage estimation can result in inconsistent parameter estimates and invalid inference issues (Simar and Wilson (2011) and Uchôa et al. (2014)). Given this, it is not surprising that the presence of heteroskedasticity has been widely evaluated in the firm performance literature (e.g., Bojani et al.

(1998), Banker et al. (2004), McDonald (2009), Uchôa et al. (2014) and Badunenko and Kumbhakar (2017)).

To conduct our experiment and to complement the above studies, we evaluate the two of most common forms of heteroskedasticity in empirical firm analysis, specifically, cross-sectional heteroskedasticity and time-series heteroskedasticity. For cross-sectional heteroskedasticity, we follow Hayakawa and Pesaran (2015) and define the variance structure of our disturbance term as $\sigma_{i,t} = \sigma_i = U(0.5, 1.5)$, and for time-series heteroskedasticity we follow Bun and Carree (2005) and Bun and Carree (2006) and specify the variance structure as $\sigma_{i,t} = \sigma_t = 0.95 - 0.05T + 0.1t$. Both cross-sectional and time-series specifications ensure that $\frac{1}{N}\sum_{n=1}^{N}\sigma_i \approx 1$ and $\frac{1}{T}\sum_{t=1}^{T}\sigma_t = 1$, respectively, and therefore are comparable to our baseline (homoskedastic) simulations.

The results from our experiment are reported in Table 9. We find the presence of time-series heteroskedasticity to be the most impactful on estimator performance, especially when the degree of dynamic persistence is high. Focusing on these simulations, we find the FD- and SYS-GMM estimators perform considerably worse across all evaluative metrics. Moreover, we document significant increases in SD and RMSE for the AS-GMM and LD4 estimators. These findings are not surprising given both the AS-GMM and LD4 estimators are based on the assumption of homoskedasticity. Consistent with Bun and Carree (2005), we find the LSDVC estimator generally performs worse in the presence of time-series heteroskedasticity, however, the detrimental effects on performance are modest, with marginal increases in SD, RMSE and Wald. Overall, as observed in Figure 7, the QML estimator proves to be the most robust in the presence of cross-sectional and time-series heteroskedasticity.

[Insert Table 9 and Figure 7 about here]

4.7 Experiment Six: The Impact of Predetermined and Endogenous Regressors

For our final experiment, we examine how predetermined and endogenously determined regressors impact the performance of our DPD estimators.[17] Endogeneity is arguably one of the most pervasive issues confronting the accuracy of empirical firm performance and efficiency research. Given that endogeneity can lead to both biased and inconsistent parameter estimates, it is not surprising that over the past two decades the estimation of predetermined and endogenously determined regressors has received considerable attention from the OR and firm performance researchers (e.g, Levinsohn and Petrin (2003), Cordero et al. (2015), Kutlu et al. (2020) and Lai and Kumbhakar (2021)). Based on our experiments thus far, the QML estimator has proven to be arguably the most appropriate and robust DPD estimator across evaluative metrics. However, unlike the GMM estimators, that can control for the presence of additional endogenous regressors via instrumental variables, the QML estimator assumes all explanatory variables (other than the lagged dependent variable) to be strictly exogenous (i.e. zero correlation between the explanatory variables and the error term). To examine the impact of the presence of i) a predetermined regressor and ii) an endogenously determined regressor, on the performance of our DPD estimators, we draw from the studies of Blundell et al. (2001), Bun et al. (2015) and Hayakawa and Nagata (2016) and extend our simulation design to include the following

[17] We thank an anonymous referee for this valuable suggestion.

variable:

$$z_{i,t} = \varrho z_{i,t-1} + \tau\eta_i + \phi\nu_{i,t} + \delta\nu_{i,t-1} + \varepsilon_{i,t} \tag{18}$$

$$\varepsilon_{i,t} \sim N(0, \sigma_\varepsilon^2). \tag{19}$$

For the predetermined specification, similar to the work of Bun et al. (2015), we set $\varrho = 0.5$, $\tau = 0$, $\phi = 0$ and $\delta = 0.05$, and therefore $z_{i,t}$ is determined by $z_{i,t-1}$ and the previous periods error term, $\nu_{i,t-1}$. To examine the impact of an endogenously determined regressor, consistent with Blundell et al. (2001), Bun et al. (2015) and Hayakawa and Nagata (2016), we set $\varrho = 0.5$, $\tau = 0.25$, $\phi = 0.1$ and $\delta = 0.05$, and thus $z_{i,t}$ is determined by $z_{i,t-1}$, the time-invariant individual effect, η_i, and the current and previous periods error term, $\nu_{i,t}$ and $\nu_{i,t-1}$. In both tests, $z_{i,t}$ enters equation (4) with the parameter value β (the same as $x_{i,t}$) to allow for equal comparison and to ensure that changes to λ only effect the relationship between z and y in the short run and the long run relationship is kept at unity $(\beta/1 - \lambda)$.

The results from our final experiment are reported in Table 10. First, relative to our other experiments, we find the presence of the endogenously determined regressor most severely impacts the performance of our DPD estimators, with many estimators reporting their highest levels of Bias, RMSE and Wald. As expected, for both the predetermined and endogenously determined regressor settings, we find the OLS and FE estimators to be inadequate, however, more alarmingly, we also find that the SYS-GMM estimator performs poorly across simulations, reporting particularly high levels of autoregressive Bias. Comparatively, we find that the FD- and AS-GMM estimators perform relatively well in terms of reported Bias at low to moderate levels of persistence, however, both estimators do display moderate to high levels of SD and RMSE. Furthermore, consistent with the simulations of Flannery and Hankins (2013), we find the GMM estimators generally fail to estimate the predetermined or endogenously determined regressor, $z_{i,t}$, with any form of accuracy, despite the use of instrumental variables.[18]

In the presence of the predetermined regressor, we find both the LSDVC and QML estimators perform relatively well despite the underlying assumptions of strict exogeneity. While both estimators perform very poorly in the Wald statistic, at low to moderate levels of dynamic persistence, we find both estimators report low SD of estimates and only moderate levels of reported Bias and RMSE. Furthermore, at high levels of persistence, we find the LSDVC and QML estimators even outperform the FD- and SYS-GMM estimators in terms of reported Bias. For the endogenous regressor simulations, we observe a similar pattern of results, however, it is clear that the presence of contemporaneous correlation between $z_{i,t}$ and η_i and $\nu_{i,t}$ has a detrimental effect on both estimators in terms of Bias and RMSE. In line with the simulations of Blundell et al. (2001) and Bun et al. (2015), in the presence of an endogenous regressor we conclude that the AS-GMM estimator estimates the autoregressive coefficient with the least bias, however, as shown in our simulations, this does come at a cost of high SD and RMSE.

All in all, it is clear from our simulations why the presence of endogeneity has received considerable attention from the OR and firm performance literature over the past two decades. Our final experiment

[18]The simulation results for $x_{i,t}$ and $z_{i,t}$ can be found in the online appendix.

has showcased the difficulties empirical researchers face, with endogeneity – just one of many empirical challenges documented in this paper – having a significant detrimental effect on the accuracy and efficiency of our DPD estimators. The AS-GMM estimator has shown to be promising in terms of Bias, but as reflected in Figure 8, the large SD could result in unreliable estimates in practice. The QML estimator that has proven reliable thus far also remains a viable option when i) the data is highly persistent or ii) when additional regressors are considered predetermined (i.e. weakly exogenous).

[Insert Table 10 and Figure 8 about here]

5 Empirical Illustration

It is clear from our simulations that the degree of dynamic persistence, cross-sectional heterogeneity, panel unbalancedness and the existence of predetermined or endogenously determined regressors all severely impact the performance of DPD estimators. In this section, we illustrate the economic implications of estimator choice in the OR and firm performance literature via two empirical examples: first estimating the level of persistence in TFP and second that in efficiency. Analysis involving the degree of persistence in TFP is important and has been widely examined in the OR literature (e.g., Souza and Gomes (2015), Casu et al. (2016), Jin et al. (2019) and Ali et al. (2021)). For example, a positive shock to TFP in the form of investment in infrastructure has growth-enhancing attributes; but a negative shock to TFP can be growth retarding. Thus, it becomes crucial to measure the persistence in TFP by estimating the lagged TFP coefficient accurately. If TFP turns out to be highly persistent, then potential policy changes can exert long-lasting effects on the TFP and profitability of firms.

In a similar vein, the firm-efficiency literature argues that superior profitability is a result of the efficiency differences between firms (McGahan and Porter, 1999). The concept of efficiency evolves from the inter-firm differences in supply chain management decisions, technology and/or production inputs. According to neoclassical theory, inter-firm variation in efficiency should disappear over time as production techniques will be imitated and production inputs/costs will be matched given factor mobility. However, the imperfect imitability of technology and/or resource immobility can give rise to persistence in firms' efficiency levels and the perseverance of inter-firm efficiency differences. In practice, evidence of persistence can reflect opportunities for managers to improve operations and the production stage of the supply chain while, from a regulatory perspective, persistence estimates can be used by policy makers to evaluate the contestability of industries/markets.

5.1 Dataset, Variable Construction and Descriptive Statistics

To conduct our empirical analysis of TFP and efficiency persistence, we use a firm-level dataset from Prowess. Prowess is maintained by the Centre for Monitoring the Indian Economy and reports firm-level financial, market and governance variables for both listed and unlisted Indian companies in a standardised format. For our two applications, we focus specifically on listed firms in the manufacturing sector. To clean the dataset, we remove all firms with less than three consecutive observations to ensure a panel data structure. Thereafter, we remove all observations that have missing data and finally we winsorize all explanatory variables at the bottom 1% and top 99%. Our final sample coverage is from 2000-2017, with a total of 3,397 firms and 29,183 firm-year observations. The average panel length in our sample is 8.6 years. All variable names, definitions and summary statistics can be found in Table 11.[19]

To estimate the persistence of TFP and efficiency we adopt a two-stage approach. First, we estimate our measure of TFP via the Levinsohn and Petrin (2003) revenue approach controlling for simultaneity between inputs. For efficiency, we use Russell (1985) input-based measures of technical efficiency under the assumption of variable returns to scale.[20] Given our measures of firm performance, we then estimate the following DPD model:

$$y_{i,t} = \lambda y_{i,t-1} + \beta' X_{i,t} + \eta_i + \omega_t + \upsilon_{i,t} \tag{20}$$

where $y_{i,t}$ denotes our measure of TFP or efficiency for firm i at time t, $X_{i,t}$ is a $K \times 1$ vector of explanatory variables consisting of the most common determinants of firm performance, namely, return on assets, leverage, firm size, firm age, firm age squared, leverage, export intensity, size of the board and the percentage of independent directors.[21] We include firm, η_i, and year, ω_t, fixed effects to account for unobserved factors that may effect TFP and efficiency and $\upsilon_{i,t}$ is the idiosyncratic error component. For both firm performance measures, we estimate equation (20) using each of the DPD estimators examined in our paper.

5.2 Empirical Applications: Total Factor Productivity and Efficiency Persistence

In the production stage of supply chain management, the presence of institutional rigidity, quasi-fixity of inputs, transaction and information costs, among other factors, prevent firms from making instantaneous adjustments towards optimal production input combinations. Accordingly, the analysis of firms' TFP and efficiency at a single point of time, or by a static panel data model, is incomplete, as in reality, firms often remain partly inefficient in the short-run as they transition towards new long-run production states.[22] As outlined in Section 2.1, the associated inertia or persistence present within firms' TFP and efficiency reflects the associated adjustment costs of reallocating and/or upgrading production inputs towards optimal target outcomes. To examine the performance of our DPD estimators in an empirical setting, we examine this phenomena and estimate the degree of TFP and efficiency persistence for our sample of India listed manufacturing firms.

Table 12 and Table 13 report the results from our TFP and efficiency persistence estimates. First, the results clearly illustrate that the autoregressive coefficient and the SOA varies considerably depending on the estimation method employed. Starting with TFP, the OLS and FE estimates are 0.872

[19] For brevity we do not discuss these in detail, yet, they are widely consistent with the literature.

[20] An alternative approach is to compute TFP from the Divisia index which is constructed from the data and does not require any econometric estimation. In this sense it can be viewed as a single-step procedure. The two-step procedure is criticised on the ground that the input variables in the first stage are to be uncorrelated the $X_{i,t}$ variables in (18).

[21] See Chaudhuri et al. (2016) and Delis et al. (2020) for recent papers on the determinants of firm performance.

[22] In the OR literature, many studies have evaluated the effect of input factor changes and the effect of production environments on firms' performance, such as, the introduction of genetic enhancements on agricultural production (e.g., Ali et al. (2021)), the value-enhancing effects of information technology (e.g., Lin and Kao (2014) and Lin et al. (2019)), and the effects of different external financial environments on firms' efficiency (e.g., Zhang and Jiao (2015)).

and 0.574 corresponding to adjustment speeds of 12.8% and of 42.6% (with half-lives of 5.06 and 1.25 years), respectively. Whilst these estimates are likely to be invalid, given the upward (downward) bias of the OLS (FE) estimator reported throughout our simulations, they can be used as parameters bounds for which the *true* autoregressive coefficient is likely to fall. For the GMM estimators, we find all estimates fall within the OLS and FE estimator bounds, however, while all estimates pass the diagnostic tests such as test for 2nd-order autocorrelation in residuals and the Hansen test for overidentifying restriction, their similarity to the FE estimates are concerning from an empirical standpoint. Thus, in our illustration, we conjecture that the GMM estimators have failed to completely mitigate the associated bias. Analogous to this claim, the LD4 estimates the persistence of TFP to be 0.922 (with a half-life of 8.54 years). This estimate seems inappropriate as it does not fall into the range of the OLS and FE estimators. In comparison, the LSDVC and the QML estimates both falls within the desired range, and provide a close similarity of estimates of 0.741 and 0.698 (with half-lives of 2.31 and 1.93), respectively. Given this, we conjecture that these estimates are closest to the *true* autoregressive coefficient and therefore it seems Indian manufacturing firms adjustment towards productivity targets relatively quickly.[23]

For our second set of estimates, we note that our efficiency measure is bounded between 0 and 1.[24] For this reason, we include an additional estimator known as the dynamic panel fractional dependent variable (DPF) estimator of Elsas and Florysiak (2015) which is explicitly designed for fractional dependent variables.[25] Our results widely follow that of our TFP estimates, with the OLS (FE) estimators over (under) estimating the autoregressive coefficient. We find the FD-GMM, AS-GMM and SYS-GMM estimates all lie inside the range of 0.745 and 0.426, but again, are largely similar to that of the FE estimator.[26] Unlike our TFP estimates, we conjecture that the LD4 estimates are more palpable given their closeness to the LSDVC and QML estimates of 0.581 and 0.569 (with half-lives of 2.83 and 2.94 years), respectively. Finally, given the DPF estimator performs similarly to the LSDVC and QML estimators, we claim, in this example, that our estimates are not impeded by the fractional nature of the dependent variable.

Regarding the estimates of the explanatory variables, we observe that return on asset and size are statistically significant across all most all estimates and are positively associated with both TFP and efficiency, thereby supporting the view that larger firms are not only more productive but also more efficient than their smaller counterparts. Aside from the GMM estimates, we find leverage to have a statistically significant and negative effect on both productivity and efficiency, thus suggesting that high debt levels may inhibit firms from obtaining new funds to pursue productivity and/or efficiency-enhancing investment opportunities. In terms of the other determinants, we observe once unobserved time-invariant factors have been adequately controlled for in the form of firm-fixed effects, the effect of exports, board size and board independence, are largely insignificant or enter estimates on an

[23] Note, in comparison, Jin et al. (2019) finds the persistence of TFP for Chinese manufacturing firms to be a lot higher at 0.905, thus corresponding to a speed of adjustment of 9.5% and a half-life of 6.94 years.

[24] We observe that the number of right-censored observations for non-radial TE is 42.

[25] Note that we did not test this estimator in our main simulation study as our data generating process was explicitly designed for continuous dependent variables.

[26] Note in this case, the GMM estimators failed to pass the diagnostic tests such as test for 2nd-order autocorrelation in residuals and the Hansen test for overidentifying restriction except for overidentifying test for AS-GMM estimator.

inconsistent basis.

In sum, our empirical applications evidence that whilst productivity and efficiency persistence exist, the speed in which firms adjust their production process varies considerably given the type of estimator employed. The implications of our two illustrations, and more broadly, our paper, are important for decision-makers, as on more than one instance, the difference between estimated half-life (i.e. the number of years it takes the average firm to adjust halfway toward its target TFP or efficiency) was greater than one year. Thus, depending on the method of estimation employed, managers may indeed underestimate or overestimate the time it takes to restructure and/or update the production process and transition towards the new production state. Moreover, the importance of accurate estimation extends beyond the production stage of operations, as the underestimation of production changes could have broader implications for the overall supply chain and the financial management of a firm. All in all, our empirical illustrations echo the sentiment of this paper and stress the importance of econometric rigor in the OR and firm performance literature.

[Insert Tables 12-13 about here]

6 Conclusion

The aim of this paper was to i) highlight the importance of estimator choice associated with DPD model estimation and ii) identify the most appropriate and robust method of estimation for the empirical settings typical to the OR and firm performance literature. Across a series of experiments, our analysis has illustrated that the degree of dynamic persistence in the dependent variable is a key driver of estimator performance, with highly persistent data proving the most problematic – consistently resulting in the least accurate estimates of the autoregressive coefficient. Furthermore, our paper illustrated that the common characteristics of empirical datasets, such as short panel dimensions, cross-sectional heterogeneity, panel unbalancedness and the existence of predetermined and endogenously determined regressors, all pose unique problems for researchers employing DPD models in the OR and firm performance literature.

Our experiments demonstrated that several estimators employed in the OR and firm performance literature produce severely biased estimates of the autoregressive coefficient. More precisely, our simulations highlighted that at high levels of dynamic persistence the GMM estimators generally perform poorly, with the performance of the FD-GMM and SYS-GMM estimators proving highly sensitive to changes in key control parameters. In specific settings the AS-GMM performed well in terms of reported autoregressive Bias, however, this is largely at the cost of low efficiency with the estimator often reporting high levels of SD and RMSE. Overall, our simulations showed the QML estimator to be generally the most robust and accurate method for estimating the the autoregressive coefficient. The QML estimator proves to be robust to changes in panel dimensions, the degree of cross-sectional and the level of panel unbalancedness. Moreover, compared to the FD and SYS-GMM estimator, the QML estimator also performs favorably in the presence of predetermined regressors. However, it seems clear that endogeneity still remains a pervasive issue in the OR and firm performance literature.

In conclusion, much attention in the OR and firm performance literature has focused on the efficacy of correctly estimating firm performance and (in)efficiency measures, such as the works of Chaudhuri et al. (2016) and Belghitar et al. (2019). However, until now, considerably less attention has been directed to the estimation of such measures via DPD models and their applications in the OR and firm performance literature. By providing a systematic review of DPD estimators our paper evidences the importance of robust empirical analysis in order to avoid spurious economic conclusions and misleading policy recommendations. Future studies may wish to further this line of inquiry by investigating the performance of DPD estimators in the presence of time-varying parameter values or by extending the search of robust DPD estimation as new methods of estimation come to light.

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Table 1: Benchmark Simulations (λ)

	$\lambda = 0.2$				$\lambda = 0.5$				$\lambda = 0.8$			
Estimator	Bias	SD	RMSE	Wald	Bias	SD	RMSE	Wald	Bias	SD	RMSE	Wald
OLS	0.194	0.008	0.194	1.000	0.144	0.006	0.144	1.000	0.064	0.004	0.065	1.000
FE	-0.026	0.007	0.027	0.964	-0.045	0.007	0.046	1.000	-0.113	0.009	0.113	1.000
FD-GMM	-0.002	0.016	0.016	0.062	-0.011	0.020	0.023	0.088	-0.048	0.039	0.062	0.260
AS-GMM	0.001	0.014	0.013	0.070	-0.006	0.017	0.022	0.078	-0.017	0.026	0.039	0.190
SYS-GMM	0.007	0.010	0.014	0.120	0.018	0.012	0.017	0.312	0.037	0.013	0.031	0.776
LD4	0.218	0.068	0.228	0.986	0.104	0.057	0.119	0.896	0.016	0.046	0.049	0.602
LSDVC	-0.004	0.007	0.008	0.284	-0.007	0.008	0.010	0.350	-0.011	0.010	0.015	0.362
QML	-0.001	0.007	0.007	0.064	-0.005	0.008	0.009	0.116	-0.011	0.010	0.015	0.186

Fixed Parameters: $\beta = 1 - \lambda, \rho = 0.5, \zeta = 5$ & $\mu = 1$.

Notes: OLS and FE refer to the pooled OLS and within transformation estimators. FD, AS and SYS-GMM correspond to the two-step first-difference GMM estimators of Arellano and Bond (1991), the two-step first-difference non-linear instrument estimator of Ahn and Schmidt (1995) and the two-step system-GMM estimator of Blundell and Bond (1998). All GMM estimates adopt Windmeijer (2005) finite-sample corrected standard errors. LD4 is long difference estimator with the estimator set of Huang and Ritter (2009) with a distance of 4 lags. LSDVC is the least squares dummy variable correction estimator of Kiviet (1995) and Bruno (2005) and finally QML corresponds to the quasi-maximum likelihood estimator of Hsiao et al. (2002). Bias is the average difference between the estimated and true parameter value. SD is the standard deviation of the estimated parameter. RMSE is the root mean squared error. The wald rejection rate reports the percentage of simulations where the true parameter set in the data generating process falls outside the estimated 95% confidence interval. The panel dimensions are set to $T = 12$ and $N = 500$ with a repetition rate of $R = 500$.

Table 2: Benchmark Simulations (β)

	$\beta = 0.8$				$\beta = 0.5$				$\beta = 0.2$			
Estimator	Bias	SD	RMSE	Wald	Bias	SD	RMSE	Wald	Bias	SD	RMSE	Wald
OLS	0.051	0.008	0.051	1.000	0.032	0.006	0.032	1.000	0.019	0.004	0.019	0.994
FE	0.007	0.006	0.010	0.188	0.007	0.005	0.009	0.254	0.002	0.004	0.005	0.088
FD-GMM	-0.002	0.017	0.017	0.054	0.001	0.015	0.015	0.062	0.006	0.012	0.013	0.106
AS-GMM	-0.004	0.017	0.009	0.060	-0.002	0.014	0.008	0.072	-0.001	0.010	0.007	0.060
SYS-GMM	-0.003	0.009	0.017	0.066	-0.002	0.008	0.014	0.066	-0.002	0.006	0.011	0.070
LD4	-0.631	0.058	0.634	1.000	-0.340	0.036	0.342	1.000	-0.116	0.013	0.117	1.000
LSDVC	0.000	0.007	0.007	0.186	0.001	0.005	0.005	0.164	0.001	0.004	0.004	0.176
QML	0.000	0.007	0.007	0.036	0.001	0.005	0.005	0.042	0.000	0.004	0.004	0.040

Fixed Parameters: $\lambda = 1 - \beta$, $\rho = 0.5$, $\zeta = 5$ and $\mu = 1$.
Notes: OLS and FE refer to the pooled OLS and within transformation estimators. FD, AS and SYS-GMM correspond to the two-step first-difference GMM estimators of Arellano and Bond (1991), the two-step first-difference non-linear instrument estimator of Ahn and Schmidt (1995) and the two-step system-GMM estimator of Blundell and Bond (1998). All GMM estimates adopt Windmeijer (2005) finite-sample corrected standard errors. LD4 is long difference estimator with the estimator set of Huang and Ritter (2009) with a distance of 4 lags. LSDVC is the least squares dummy variable correction estimator of Kiviet (1995) and Bruno (2005) and finally QML corresponds to the quasi-maximum likelihood estimator of Hsiao et al. (2002). Bias is the average difference between the estimated and true parameter value. SD is the standard deviation of the estimated parameter. RMSE is the root mean squared error. The wald rejection rate reports the percentage of simulations where the true parameter set in the data generating process falls outside the estimated 95% confidence interval. The panel dimensions are set to $T = 12$ and $N = 500$ with a repetition rate of $R = 500$.

Table 3: Benchmark Simulations: Implied Speed of Adjustment (SOA)

True SOA	OLS	FE	FD-GMM	AS-GMM	SYS-GMM	LD4	LSDVC	QML
80%	60.6%	82.6%	80.2%	79.9%	79.3%	58.2%	80.4%	80.1%
50%	35.6%	45.5%	48.9%	49.6%	48.2%	39.6%	49.3%	49.5%
20%	13.6%	31.3%	24.8%	21.7%	16.3%	18.4%	21.1%	21.1%

Notes: OLS and FE refer to the pooled OLS and within transformation estimators. FD, AS and SYS-GMM correspond to the two-step first-difference GMM estimators of Arellano and Bond (1991), the two-step first-difference non-linear instrument estimator of Ahn and Schmidt (1995) and the two-step system-GMM estimator of Blundell and Bond (1998). LD4 is long difference estimator with the estimator set of Huang and Ritter (2009) with a distance of 4 lags. LSDVC is the least squares dummy variable correction estimator of Kiviet (1995) and Bruno (2005) and finally QML corresponds to the quasi-maximum likelihood estimator of Hsiao et al. (2002). The implied speed of adjustment (SOA) is calculated as of one minus the average estimated coefficient of the dynamic parameter.

Table 4: Experiment One: The Impact of Changes in Time Series Length

		$T = 6$				$T = 18$			
	Estimator	Bias	SD	RMSE	Wald	Bias	SD	RMSE	Wald
$\lambda = 0.2$	OLS	0.243	0.008	0.243	1.000	0.157	0.007	0.157	1.000
	FE	-0.063	0.011	0.064	1.000	-0.016	0.005	0.017	0.894
	FD-GMM	-0.007	0.041	0.041	0.042	0.000	0.010	0.010	0.048
	AS-GMM	-0.001	0.025	0.042	0.038	0.002	0.009	0.008	0.040
	SYS-GMM	0.034	0.024	0.025	0.330	0.005	0.007	0.010	0.086
	LD4	0.204	0.785	0.810	0.546	0.211	0.047	0.216	1.000
	LSDVC	-0.006	0.012	0.014	0.204	-0.002	0.005	0.005	0.194
	QML	-0.002	0.012	0.012	0.042	0.000	0.005	0.005	0.046
$\lambda = 0.5$	OLS	0.171	0.006	0.171	1.000	0.121	0.005	0.121	1.000
	FE	-0.115	0.013	0.116	1.000	-0.028	0.005	0.028	1.000
	FD-GMM	-0.060	0.076	0.097	0.009	-0.004	0.011	0.012	0.044
	AS-GMM	-0.008	0.045	0.104	0.084	-0.001	0.010	0.010	0.028
	SYS-GMM	0.100	0.027	0.046	0.936	0.007	0.008	0.010	0.122
	LD4	0.000	0.338	0.338	0.724	0.095	0.034	0.101	0.974
	LSDVC	-0.004	0.015	0.016	0.204	-0.004	0.005	0.007	0.254
	QML	-0.011	0.015	0.018	0.134	-0.003	0.005	0.006	0.052
$\lambda = 0.8$	OLS	0.071	0.006	0.071	1.000	0.056	0.003	0.056	1.000
	FE	-0.274	0.018	0.275	1.000	-0.068	0.006	0.068	1.000
	FD-GMM	-0.249	0.194	0.316	0.308	-0.018	0.016	0.024	0.148
	AS-GMM	-0.002	0.085	0.081	0.218	-0.010	0.013	0.017	0.092
	SYS-GMM	0.080	0.015	0.085	0.994	0.014	0.009	0.017	0.286
	LD4	-0.066	0.173	0.185	0.752	0.014	0.020	0.024	0.562
	LSDVC	-0.032	0.018	0.037	0.592	-0.007	0.006	0.009	0.332
	QML	-0.030	0.024	0.039	0.268	-0.006	0.006	0.009	0.124

Fixed Parameters: $\beta = 1 - \lambda, \rho = 0.5, \zeta = 5$ & $\mu = 1$.

Notes: OLS and FE refer to the pooled OLS and within transformation estimators. FD, AS and SYS-GMM correspond to the two-step first-difference GMM estimators of Arellano and Bond (1991), the two-step first-difference non-linear instrument estimator of Ahn and Schmidt (1995) and the two-step system-GMM estimator of Blundell and Bond (1998). All GMM estimates adopt Windmeijer (2005) finite-sample corrected standard errors. LD4 is long difference estimator with the estimator set of Huang and Ritter (2009) with a distance of 4 lags. LSDVC is the least squares dummy variable correction estimator of Kiviet (1995) and Bruno (2005) and finally, QML corresponds to the quasi-maximum likelihood estimator of Hsiao et al. (2002). Bias is the average difference between the estimated and true parameter value. SD is the standard deviation of the estimated parameter. RMSE is the root mean squared error. The wald rejection rate reports the percentage of simulations where the true parameter set in the data generating process falls outside the estimated 95% confidence interval. The panel width is set to $N = 500$ with a repetition rate of $R = 500$.

Table 5: Experiment One: The Impact of Changes in Cross-sectional Size

		$N = 100$				$N = 250$			
	Estimator	Bias	SD	RMSE	Wald	Bias	SD	RMSE	Wald
$\lambda = 0.2$	OLS	0.193	0.017	0.193	1.000	0.193	0.011	0.193	1.000
	FE	-0.026	0.015	0.030	0.392	-0.025	0.009	0.027	0.772
	FD-GMM	-0.008	0.034	0.035	0.064	-0.002	0.022	0.022	0.054
	AS-GMM	0.004	0.035	0.027	0.060	0.002	0.020	0.018	0.062
	SYS-GMM	0.012	0.024	0.035	0.088	0.010	0.015	0.020	0.102
	LD4	0.246	0.187	0.309	0.690	0.219	0.104	0.243	0.902
	LSDVC	-0.002	0.015	0.015	0.172	-0.003	0.009	0.010	0.206
	QML	-0.001	0.015	0.015	0.050	-0.001	0.009	0.009	0.028
$\lambda = 0.5$	OLS	0.143	0.013	0.144	1.000	0.144	0.008	0.144	1.000
	FE	-0.045	0.016	0.048	0.806	-0.045	0.010	0.046	1.000
	FD-GMM	-0.023	0.044	0.049	0.082	-0.014	0.028	0.031	0.074
	AS-GMM	0.000	0.039	0.034	0.054	-0.003	0.023	0.027	0.056
	SYS-GMM	0.018	0.029	0.039	0.120	0.020	0.018	0.023	0.224
	LD4	0.127	0.145	0.192	0.600	0.105	0.084	0.135	0.732
	LSDVC	-0.005	0.017	0.017	0.188	-0.006	0.010	0.012	0.234
	QML	-0.004	0.017	0.017	0.054	-0.004	0.010	0.011	0.064
$\lambda = 0.8$	OLS	0.064	0.009	0.064	1.000	0.064	0.006	0.064	1.000
	FE	-0.113	0.020	0.115	1.000	-0.112	0.012	0.113	1.000
	FD-GMM	-0.091	0.077	0.119	0.204	-0.061	0.053	0.080	0.186
	AS-GMM	-0.023	0.056	0.038	0.100	-0.019	0.035	0.038	0.136
	SYS-GMM	0.015	0.035	0.061	0.122	0.032	0.020	0.039	0.440
	LD4	0.049	0.144	0.152	0.582	0.020	0.065	0.068	0.572
	LSDVC	-0.009	0.021	0.023	0.242	-0.010	0.014	0.017	0.280
	QML	-0.010	0.024	0.026	0.084	-0.010	0.014	0.017	0.108

Fixed Parameters: $\beta = 1 - \lambda, \rho = 0.5, \zeta = 5$ & $\mu = 1$.

Notes: OLS and FE refer to the pooled OLS and within transformation estimators. FD, AS and SYS-GMM correspond to the two-step first-difference GMM estimators of Arellano and Bond (1991), the two-step first-difference non-linear instrument estimator of Ahn and Schmidt (1995) and the two-step system-GMM estimator of Blundell and Bond (1998). All GMM estimates adopt Windmeijer (2005) finite-sample corrected standard errors. LD4 is long difference estimator with the estimator set of Huang and Ritter (2009) with a distance of 4 lags. LSDVC is the least squares dummy variable correction estimator of Kiviet (1995) and Bruno (2005) and finally QML corresponds to the quasi-maximum likelihood estimator of Hsiao et al. (2002). Bias is the average difference between the estimated and true parameter value. SD is the standard deviation of Bias. RMSE is the root mean squared error. The wald rejection rate reports the percentage of simulations where the true parameter set in the data generating process falls outside the estimated 95% confidence interval. Panel length is set to $T = 12$ with a repetition rate of 500.

Table 6: Experiment Two: The Impact of The Time-Invariant Individual Effect

		$\mu = 1$				$\mu = 3$			
	Estimator	Bias	SD	RMSE	Wald	Bias	SD	RMSE	Wald
$\lambda = 0.2$	OLS	0.137	0.010	0.137	1.000	0.497	0.007	0.497	1.000
	FE	-0.026	0.006	0.027	0.980	-0.026	0.007	0.027	0.964
	FD-GMM	-0.001	0.013	0.013	0.042	-0.001	0.018	0.018	0.058
	AS-GMM	0.000	0.013	0.009	0.066	0.005	0.016	0.018	0.070
	SYS-GMM	0.001	0.009	0.013	0.046	0.012	0.013	0.017	0.166
	LD4	0.212	0.065	0.222	0.992	0.299	0.248	0.389	0.990
	LSDVC	-0.001	0.007	0.007	0.188	-0.002	0.007	0.008	0.226
	QML	-0.001	0.007	0.007	0.040	-0.001	0.007	0.007	0.064
$\lambda = 0.5$	OLS	0.079	0.008	0.080	1.000	0.328	0.004	0.328	1.000
	FE	-0.045	0.007	0.046	1.000	-0.045	0.007	0.046	1.000
	FD-GMM	-0.010	0.015	0.018	0.096	-0.004	0.025	0.026	0.040
	AS-GMM	-0.007	0.014	0.010	0.076	0.011	0.021	0.049	0.098
	SYS-GMM	-0.003	0.010	0.016	0.048	0.045	0.020	0.023	0.672
	LD4	0.090	0.049	0.103	0.858	0.243	0.197	0.313	0.936
	LSDVC	-0.005	0.007	0.009	0.222	-0.002	0.008	0.009	0.246
	QML	-0.005	0.007	0.008	0.092	-0.005	0.008	0.009	0.116
$\lambda = 0.8$	OLS	0.025	0.005	0.026	0.992	0.138	0.002	0.138	1.000
	FE	-0.113	0.009	0.113	1.000	-0.113	0.009	0.113	1.000
	FD-GMM	-0.026	0.020	0.033	0.246	-0.035	0.055	0.065	0.060
	AS-GMM	-0.020	0.018	0.014	0.220	0.045	0.057	0.093	0.160
	SYS-GMM	-0.006	0.012	0.027	0.062	0.093	0.011	0.072	1.000
	LD4	0.004	0.029	0.029	0.478	0.063	0.207	0.216	0.904
	LSDVC	-0.015	0.010	0.018	0.468	0.000	0.010	0.010	0.230
	QML	-0.010	0.010	0.015	0.188	-0.011	0.010	0.015	0.186

Fixed Parameters: $\beta = 1 - \lambda, \rho = 0.5$ & $\zeta = 5$.

Notes: OLS and FE refer to the pooled OLS and within transformation estimators. FD, AS and SYS-GMM correspond to the two-step first-difference GMM estimators of Arellano and Bond (1991), the two-step first-difference non-linear instrument estimator of Ahn and Schmidt (1995) and the two-step system-GMM estimator of Blundell and Bond (1998). All GMM estimates adopt Windmeijer (2005) finite-sample corrected standard errors. LD4 is long difference estimator with the estimator set of Huang and Ritter (2009) with a distance of 4 lags. LSDVC is the least squares dummy variable correction estimator of Kiviet (1995) and Bruno (2005) and finally QML corresponds to the quasi-maximum likelihood estimator of Hsiao et al. (2002). Bias is the average difference between the estimated and true parameter value. SD is the standard deviation Bias. RMSE is the root mean squared error. The wald rejection rate reports the percentage of simulations where the true parameter set in the data generating process falls outside the estimated 95% confidence interval. The panel dimensions are set to $T = 12$ and $N = 500$ with a repetition rate of $R = 500$.

Table 7: Experiment Three: The Impact of Panel Unbalancedness

		$\omega = 50\%$				$\omega = 90\%$			
	Estimator	Bias	SD	RMSE	Wald	Bias	SD	RMSE	Wald
$\lambda = 0.2$	OLS	0.199	0.010	0.199	1.000	0.194	0.008	0.195	1.000
	FE	-0.048	0.010	0.049	0.998	-0.026	0.007	0.027	0.970
	FD-GMM	-0.005	0.028	0.028	0.048	-0.001	0.016	0.016	0.066
	AS-GMM	0.001	0.024	0.019	0.046	0.002	0.014	0.012	0.062
	SYS-GMM	0.003	0.019	0.024	0.038	0.004	0.011	0.014	0.060
	LD4	0.234	0.198	0.306	0.668	0.220	0.076	0.233	0.980
	LSDVC	-0.006	0.011	0.013	0.216	-0.004	0.007	0.008	0.214
	QML	-0.001	0.011	0.011	0.042	0.000	0.007	0.007	0.046
$\lambda = 0.5$	OLS	0.150	0.007	0.150	1.000	0.145	0.006	0.145	1.000
	FE	-0.080	0.011	0.081	1.000	-0.045	0.007	0.046	1.000
	FD-GMM	-0.018	0.036	0.040	0.056	-0.009	0.020	0.022	0.060
	AS-GMM	-0.006	0.031	0.024	0.070	-0.001	0.016	0.018	0.050
	SYS-GMM	0.007	0.023	0.032	0.060	0.012	0.013	0.016	0.180
	LD4	0.115	0.143	0.184	0.576	0.111	0.060	0.126	0.890
	LSDVC	-0.010	0.013	0.017	0.262	-0.007	0.008	0.011	0.300
	QML	-0.008	0.012	0.015	0.084	-0.001	0.008	0.008	0.052
$\lambda = 0.8$	OLS	0.069	0.005	0.069	1.000	0.065	0.004	0.065	1.000
	FE	-0.187	0.016	0.187	1.000	-0.115	0.009	0.116	1.000
	FD-GMM	-0.074	0.064	0.097	0.194	-0.042	0.038	0.057	0.184
	AS-GMM	-0.034	0.047	0.032	0.194	-0.012	0.025	0.036	0.110
	SYS-GMM	0.014	0.028	0.058	0.120	0.033	0.015	0.028	0.630
	LD4	0.037	0.127	0.132	0.562	0.034	0.055	0.065	0.642
	LSDVC	-0.026	0.019	0.032	0.456	-0.013	0.011	0.018	0.400
	QML	-0.025	0.018	0.030	0.252	-0.004	0.012	0.013	0.068

Fixed Parameters: $\beta = 1 - \lambda, \rho = 0.5, \zeta = 5$ & $\mu = 1$.

Notes: OLS and FE refer to the pooled OLS and within transformation estimators. FD, AS and SYS-GMM correspond to the two-step first-difference GMM estimators of Arellano and Bond (1991), the two-step first-difference non-linear instrument estimator of Ahn and Schmidt (1995) and the two-step system-GMM estimator of Blundell and Bond (1998). All GMM estimates adopt Windmeijer (2005) finite-sample corrected standard errors. LD4 is long difference estimator with the estimator set of Huang and Ritter (2009) with a distance of 4 lags. LSDVC is the least squares dummy variable correction estimator of Kiviet (1995) and Bruno (2005) and finally QML corresponds to the quasi-maximum likelihood estimator of Hsiao et al. (2002). Bias is the average difference between the estimated and true parameter value. SD is the standard deviation Bias. RMSE is the root mean squared error. The wald rejection rate reports the percentage of simulations where the true parameter set in the data generating process falls outside the estimated 95% confidence interval. The panel dimensions are set to $N = 500$ with a repetition rate of $R = 500$.

Table 8: Experiment Four: The Impact of Changes in Signal Noise

	Estimator	$\zeta = 2$ Bias	SD	RMSE	Wald	$\zeta = 8$ Bias	SD	RMSE	Wald
$\lambda = 0.2$	OLS	0.159	0.009	0.160	1.000	0.205	0.007	0.205	1.000
	FE	-0.048	0.009	0.049	1.000	-0.018	0.006	0.019	0.890
	FD-GMM	-0.002	0.019	0.019	0.060	-0.001	0.013	0.013	0.062
	AS-GMM	0.001	0.018	0.016	0.070	0.001	0.012	0.011	0.068
	SYS-GMM	0.009	0.013	0.018	0.118	0.006	0.009	0.012	0.110
	LD4	0.070	0.035	0.079	0.712	0.461	0.148	0.484	1.000
	LSDVC	-0.006	0.010	0.011	0.268	-0.003	0.006	0.006	0.288
	QML	-0.001	0.010	0.010	0.052	-0.001	0.006	0.006	0.060
$\lambda = 0.5$	OLS	0.113	0.008	0.113	1.000	0.153	0.005	0.154	1.000
	FE	-0.079	0.010	0.080	1.000	-0.033	0.006	0.033	1.000
	FD-GMM	-0.010	0.024	0.026	0.080	-0.011	0.018	0.021	0.096
	AS-GMM	-0.003	0.020	0.022	0.074	-0.005	0.014	0.020	0.086
	SYS-GMM	0.016	0.015	0.021	0.226	0.016	0.011	0.015	0.332
	LD4	0.035	0.031	0.047	0.570	0.170	0.080	0.188	0.952
	LSDVC	-0.008	0.011	0.014	0.286	-0.006	0.006	0.009	0.374
	QML	-0.004	0.011	0.011	0.062	-0.005	0.006	0.008	0.150
$\lambda = 0.8$	OLS	0.014	0.007	0.015	0.464	0.074	0.003	0.074	1.000
	FE	-0.188	0.012	0.188	1.000	-0.083	0.008	0.083	1.000
	FD-GMM	-0.015	0.027	0.031	0.092	-0.050	0.035	0.061	0.304
	AS-GMM	-0.006	0.023	0.015	0.082	-0.016	0.023	0.052	0.204
	SYS-GMM	0.003	0.015	0.024	0.062	0.051	0.011	0.028	0.962
	LD4	0.001	0.025	0.025	0.512	0.041	0.083	0.093	0.678
	LSDVC	-0.022	0.014	0.026	0.534	-0.008	0.008	0.011	0.344
	QML	-0.002	0.018	0.018	0.044	-0.012	0.008	0.015	0.342

Fixed Parameters: $\beta = 1 - \lambda, \rho = 0.5$ & $\mu = 1$.

Notes: OLS and FE refer to the pooled OLS and within transformation estimators. FD, AS and SYS-GMM correspond to the two-step first-difference GMM estimators of Arellano and Bond (1991), the two-step first-difference non-linear instrument estimator of Ahn and Schmidt (1995) and the two-step system-GMM estimator of Blundell and Bond (1998). All GMM estimates adopt Windmeijer (2005) finite-sample corrected standard errors. LD4 is long difference estimator with the estimator set of Huang and Ritter (2009) with a distance of 4 lags. LSDVC is the least squares dummy variable correction estimator of Kiviet (1995) and Bruno (2005) and finally QML corresponds to the quasi-maximum likelihood estimator of Hsiao et al. (2002). Bias is the average difference between the estimated and true parameter value. SD is the standard deviation of Bias. RMSE is the root mean squared error. The wald rejection rate reports the percentage of simulations where the true parameter falls outside the 95% confidence interval. The panel dimensions are set to $T = 12$ and $N = 500$ with a repetition rate of $R = 500$.

Table 9: Experiment Five: The Impact of Cross-sectional and Time-series Heteroscedasticity

		$\sigma_i = U(0.5, 1.5)$				$\sigma_t = 0.95 - 0.05T + 0.1t$			
	Estimator	Bias	SD	RMSE	Wald	Bias	SD	RMSE	Wald
$\lambda = 0.2$	OLS	0.192	0.008	0.192	1.000	0.194	0.008	0.195	1.000
	FE	-0.027	0.008	0.028	0.950	-0.027	0.008	0.028	0.950
	FD-GMM	-0.001	0.016	0.016	0.056	-0.003	0.017	0.018	0.060
	AS-GMM	0.002	0.014	0.014	0.044	0.001	0.016	0.014	0.056
	SYS-GMM	0.008	0.011	0.014	0.128	0.009	0.011	0.016	0.158
	LD4	0.193	0.063	0.203	0.990	0.221	0.068	0.231	0.984
	LSDVC	-0.004	0.008	0.009	0.248	-0.001	0.008	0.008	0.264
	QML	-0.001	0.008	0.008	0.070	0.001	0.008	0.008	0.066
$\lambda = 0.5$	OLS	0.142	0.006	0.143	1.000	0.146	0.006	0.146	1.000
	FE	-0.047	0.008	0.048	1.000	-0.045	0.008	0.046	1.000
	FD-GMM	-0.009	0.020	0.022	0.074	-0.019	0.024	0.031	0.134
	AS-GMM	-0.003	0.017	0.023	0.050	-0.008	0.020	0.027	0.088
	SYS-GMM	0.019	0.014	0.017	0.346	0.023	0.013	0.021	0.396
	LD4	0.095	0.053	0.109	0.866	0.108	0.061	0.124	0.894
	LSDVC	-0.007	0.008	0.011	0.302	0.000	0.009	0.009	0.250
	QML	-0.004	0.008	0.009	0.096	0.000	0.008	0.008	0.066
$\lambda = 0.8$	OLS	0.063	0.004	0.063	1.000	0.069	0.005	0.069	1.000
	FE	-0.116	0.010	0.117	1.000	-0.103	0.011	0.103	1.000
	FD-GMM	-0.046	0.038	0.059	0.214	-0.075	0.058	0.095	0.226
	AS-GMM	-0.018	0.025	0.038	0.154	-0.014	0.031	0.045	0.132
	SYS-GMM	0.036	0.014	0.030	0.704	0.043	0.012	0.034	0.882
	LD4	0.014	0.042	0.044	0.566	0.055	0.142	0.152	0.622
	LSDVC	-0.011	0.010	0.015	0.392	0.014	0.012	0.018	0.492
	QML	-0.010	0.011	0.015	0.158	0.003	0.011	0.011	0.050

Fixed Parameters: $\beta = 1 - \lambda, \rho = 0.5, \zeta = 5$ & $\mu = 1$.

Notes: OLS and FE refer to the pooled OLS and within transformation estimators. FD, AS and SYS-GMM correspond to the two-step first-difference GMM estimators of Arellano and Bond (1991), the two-step first-difference non-linear instrument estimator of Ahn and Schmidt (1995) and the two-step system-GMM estimator of Blundell and Bond (1998). All GMM estimates adopt Windmeijer (2005) finite-sample corrected standard errors. LD4 is long difference estimator with the estimator set of Huang and Ritter (2009) with a distance of 4 lags. LSDVC is the least squares dummy variable correction estimator of Kiviet (1995) and Bruno (2005) and finally QML corresponds to the quasi-maximum likelihood estimator of Hsiao et al. (2002). Bias is the average difference between the estimated and true parameter value. SD is the standard deviation of the estimated parameter. RMSE is the root mean squared error. The wald rejection rate reports the percentage of simulations where the true parameter set in the data generating process falls outside the estimated 95% confidence interval. The panel dimensions are set to $T = 12$ and $N = 500$ with a repetition rate of $R = 500$.

Table 10: Experiment Six: The Impact of Predetermined and Endogenous Regressors

		$\tau = 0.0$ $\phi = 0.0$ $\delta = 0.05$				$\tau = 0.25$ $\phi = 0.10$ $\delta = 0.05$			
	Estimator	Bias	SD	RMSE	Wald	Bias	SD	RMSE	Wald
$\lambda = 0.2$	OLS	0.151	0.007	0.151	1.000	0.135	0.007	0.135	1.000
	FE	-0.047	0.006	0.047	1.000	-0.057	0.006	0.058	1.000
	FD-GMM	-0.020	0.024	0.031	0.136	-0.025	0.024	0.035	0.172
	AS-GMM	-0.011	0.019	0.089	0.084	-0.017	0.019	0.079	0.128
	SYS-GMM	0.085	0.028	0.022	0.900	0.075	0.027	0.026	0.838
	LD4	0.321	0.081	0.331	1.000	0.332	0.083	0.342	1.000
	LSDVC	-0.028	0.007	0.029	0.964	-0.039	0.007	0.039	0.994
	QML	-0.025	0.007	0.026	0.974	-0.036	0.007	0.037	1.000
$\lambda = 0.5$	OLS	0.116	0.006	0.116	1.000	0.104	0.006	0.104	1.000
	FE	-0.072	0.007	0.072	1.000	-0.083	0.007	0.083	1.000
	FD-GMM	-0.020	0.023	0.030	0.138	-0.025	0.024	0.034	0.184
	AS-GMM	-0.011	0.018	0.069	0.098	-0.017	0.019	0.061	0.152
	SYS-GMM	0.066	0.020	0.022	0.918	0.058	0.020	0.025	0.856
	LD4	0.145	0.061	0.157	0.976	0.154	0.063	0.167	0.988
	LSDVC	-0.037	0.008	0.038	0.986	-0.049	0.008	0.050	1.000
	QML	-0.033	0.008	0.034	0.994	-0.046	0.008	0.046	1.000
$\lambda = 0.8$	OLS	0.058	0.004	0.059	1.000	0.052	0.004	0.053	1.000
	FE	-0.124	0.009	0.124	1.000	-0.133	0.010	0.133	1.000
	FD-GMM	-0.053	0.040	0.067	0.280	-0.061	0.041	0.074	0.366
	AS-GMM	-0.018	0.026	0.053	0.172	-0.025	0.026	0.047	0.244
	SYS-GMM	0.052	0.012	0.032	0.972	0.045	0.012	0.036	0.936
	LD4	0.026	0.044	0.051	0.610	0.030	0.047	0.056	0.638
	LSDVC	-0.026	0.010	0.028	0.796	-0.040	0.011	0.042	0.964
	QML	-0.025	0.011	0.027	0.698	-0.039	0.011	0.040	0.962

Fixed Parameters: $\beta = 1 - \lambda, \rho = 0.5, \zeta = 5$, $\mu = 1$ & $\varrho = 0.5$.

Notes: OLS and FE refer to the pooled OLS and within transformation estimators. FD, AS and SYS-GMM correspond to the two-step first-difference GMM estimators of Arellano and Bond (1991), the two-step first-difference non-linear instrument estimator of Ahn and Schmidt (1995) and the two-step system-GMM estimator of Blundell and Bond (1998). All GMM estimates adopt Windmeijer (2005) finite-sample corrected standard errors. LD4 is long difference estimator with the estimator set of Huang and Ritter (2009) with a distance of 4 lags. LSDVC is the least squares dummy variable correction estimator of Kiviet (1995) and Bruno (2005) and finally QML corresponds to the quasi-maximum likelihood estimator of Hsiao et al. (2002). Bias is the average difference between the estimated and true parameter value. SD is the standard deviation of Bias. RMSE is the root mean squared error. The wald rejection rate reports the percentage of simulations where the true parameter set in the data generating process falls outside the estimated 95% confidence interval. The panel dimensions are set to $T = 12$ and $N = 500$ with a repetition rate of $R = 500$.

Table 11: Descriptive Statistics

Variable	Mean	SD	Min	Max
(1) Total Factor Productivity (TFP)	6.25	1.58	-0.72	12.96
(2) Technical Efficiency (TE)	0.47	0.09	0.06	1.00
(3) Return on Assets	0.02	0.27	-0.77	0.68
(4) Leverage	0.40	0.44	0.00	54.59
(5) Firm Size	7.00	1.84	2.70	13.15
(6) Firm Age	29.71	18.18	3.00	99.00
(7) Export Intensity (%)	0.15	0.24	0.00	0.98
(8) Board Size	16.02	9.03	1.00	51.00
(9) Board Independence	0.14	0.11	0.00	0.50

Notes: This table presents the descritive statistics for all variables used in our empirical applications. The sample consists of all manufacturing firms in the annual Prowess database between 2000 and 2017 with nonmissing data for all analysis variables. The final sample consists of 29,183 firm-year observations. (1) TFP based on Levinsohn and Petrin (2003) revenue approach. (2) TE based on Russell (1985) non-radial approach. (3) The sum of earnings before interest and depreciation over total assets. (4) The sum of short and long term borrowing over total assets. (5) The natural logarithm of total assets, (6) The number of years since incorporation. (7) Exports as a percentage of total sales revenue. (8) The total number of members sitting on the board. (9) Total number of independent board members as a percentage of total board size.

Table 12: Empirical Application: Total Factor Productivity (TFP)

	OLS (1)	FE (2)	FD-GMM (3)	AS-GMM (4)	SYS-GMM (5)	LD4 (6)	LSDVC (7)	QML (8)
$\text{TFP}_{i,t-1}$	0.872***	0.574***	0.580***	0.600***	0.631***	0.922***	0.741***	0.698***
	(0.007)	(0.018)	(0.080)	(0.061)	(0.032)	(0.018)	(0.011)	(0.024)
Return on $\text{Assets}_{i,t}$	0.863***	0.838***	0.498***	0.150*	0.506***	0.047	0.867***	0.826***
	(0.038)	(0.053)	(0.058)	(0.090)	(0.058)	(0.055)	(0.010)	(0.058)
$\text{Leverage}_{i,t}$	-0.008	-0.083***	-0.025	-0.331***	-0.020	-0.005	-0.042***	-0.053**
	(0.009)	(0.022)	(0.029)	(0.080)	(0.029)	(0.018)	(0.002)	(0.023)
$\text{Size}_{i,t}$	0.110***	0.295***	0.406***	0.246***	0.389***	-0.051***	0.210***	0.221***
	(0.006)	(0.015)	(0.024)	(0.067)	(0.026)	(0.014)	(0.003)	(0.017)
$\text{Age}_{i,t}$	-0.349***	0.358	0.747	-2.997***	-3.343***	1.205***	0.549	1.477
	(0.042)	(1.111)	(1.908)	(0.595)	(0.511)	(0.435)	(0.935)	(1.402)
$\text{Age}^2_{i,t}$	0.239***	0.261	0.784	-0.105	0.942*	0.410*	0.452***	0.640***
	(0.047)	(0.193)	(0.606)	(0.654)	(0.555)	(0.221)	(0.004)	(0.190)
$\text{Exports}_{i,t}$	-0.026***	0.018	0.035	0.113	0.038	-0.010	0.004	0.017
	(0.009)	(0.039)	(0.066)	(0.109)	(0.067)	(0.048)	(0.061)	(0.044)
Board $\text{Size}_{i,t}$	-0.124***	0.076	-0.046	-0.596***	-0.050	-0.045	-0.005	0.105
	(0.032)	(0.063)	(0.085)	(0.172)	(0.094)	(0.073)	(0.028)	(0.065)
Board $\text{Independence}_{i,t}$	-0.043**	0.079**	0.095**	-0.078	0.097**	0.002	0.075	0.099***
	(0.022)	(0.035)	(0.041)	(0.070)	(0.043)	(0.036)	(0.066)	(0.035)
AR(2) [p-value]	-	-	0.558	0.276	0.534	-	-	-
Hansen-Test [p-value]			0.368	0.972	0.260			
Firm-fixed effect	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Speed of Adjustment (SOA)	12.8%	42.6%	42.0%	40.0%	36.9%	7.8%	25.9%	30.2%
Half life (Years)	5.06	1.25	1.27	1.36	1.51	8.54	2.31	1.93

Notes: OLS and FE refer to the pooled OLS and within transformation estimators. FD, AS and SYS-GMM correspond to the two-step first-difference GMM estimators of Arellano and Bond (1991), the two-step first-difference non-linear instrument estimator of Ahn and Schmidt (1995) and the two-step system-GMM estimator of Blundell and Bond (1998). All GMM estimates adopt Windmeijer (2005) finite-sample corrected standard errors. LD4 is long difference estimator with the estimator set of Huang and Ritter (2009) with a distance of 4 lags. LSDVC is the least squares dummy variable correction estimator of Kiviet (1995) and Bruno (2005) and finally QML corresponds to the quasi-maximum likelihood estimator of Hsiao et al. (2002). The implied speed of adjustment (SOA) is calculated as of one minus the average estimated coefficient of the dynamic parameter $(1-\hat{\lambda})$. Half life is the number of years that the SOA implies for a firm to move halfway toward its target TFP (log(0.5)/log(1-SOA)). Standard-errors are reported in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 13: Empirical Application: Efficiency

	OLS (1)	FE (2)	FD-GMM (3)	AS-GMM (4)	SYS-GMM (5)	LD4 (6)	LSDVC (7)	QML (8)	DPF (9)
$\text{Efficiency}_{i,t-1}$	0.745***	0.426***	0.432***	0.429***	0.491***	0.522***	0.569***	0.581***	0.606***
	(0.009)	(0.015)	(0.026)	(0.033)	(0.040)	(0.018)	(0.022)	(0.011)	(0.007)
$\text{Return on Asset}_{i,t}$	0.071***	0.079***	0.059***	0.060***	0.039***	0.023***	0.073***	0.080***	0.077***
	(0.004)	(0.005)	(0.007)	(0.007)	(0.010)	(0.005)	(0.006)	(0.001)	(0.003)
$\text{Leverage}_{i,t}$	-0.003***	-0.011***	-0.001	-0.000	-0.008	-0.005**	-0.008***	-0.007***	-0.006***
	(0.001)	(0.002)	(0.003)	(0.003)	(0.009)	(0.002)	(0.002)	(0.000)	(0.001)
$\text{Size}_{i,t}$	0.006***	0.003***	0.008***	0.005***	0.020***	-0.002**	0.003***	0.001***	0.002***
	(0.000)	(0.001)	(0.002)	(0.002)	(0.006)	(0.001)	(0.001)	(0.000)	(0.001)
$\text{Age}_{i,t}$	-0.009*	0.115	0.021	-0.155***	-0.152**	0.492***	0.184*	0.088	-0.070***
	(0.005)	(0.089)	(0.166)	(0.053)	(0.065)	(0.057)	(0.100)	(0.116)	(0.021)
$\text{Age}^2_{i,t}$	0.005	-0.123***	-0.013	-0.046	0.125	-0.132***	-0.098***	-0.104***	-0.076***
	(0.006)	(0.023)	(0.064)	(0.063)	(0.094)	(0.028)	(0.022)	(0.003)	(0.018)
$\text{Exports}_{i,t}$	-0.004***	0.002	-0.004	-0.002	-0.003	0.002	-0.002	0.002	0.001
	(0.001)	(0.004)	(0.006)	(0.006)	(0.012)	(0.004)	(0.004)	(0.008)	(0.002)
$\text{Board Size}_{i,t}$	-0.004	-0.007	-0.014*	-0.015*	0.018	0.014*	-0.006	-0.007**	0.000
	(0.004)	(0.007)	(0.008)	(0.008)	(0.021)	(0.008)	(0.007)	(0.003)	(0.006)
$\text{Board Independence}_{i,t}$	-0.007**	0.014***	0.007	0.003	-0.011	0.002	0.009**	0.014*	0.012***
	(0.003)	(0.004)	(0.005)	(0.005)	(0.009)	(0.004)	(0.004)	(0.008)	(0.003)
AR(2)[p-value]	-	-	0.000	0.000	0.000	-	-	-	
Hansen-Test[p-value]			0.000	0.920	0.000				
Firm-fixed effect	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Speed of Adjustment (SOA)	25.5%	57.4%	56.8%	57.1%	50.9%	47.8%	43.1%	41.9%	39.4%
Half life (Years)	5.42	1.87	1.90	1.89	2.24	2.46	2.83	2.94	3.19

Notes: OLS and FE refer to the pooled OLS and within transformation estimators. FD, AS and SYS-GMM correspond to the two-step first-difference GMM estimators of Arellano and Bond (1991), the two-step first-difference non-linear instrument estimator of Ahn and Schmidt (1995) and the two-step system-GMM estimator of Blundell and Bond (1998). All GMM estimates adopt Windmeijer (2005) finite-sample corrected standard errors. LD4 is long difference estimator with the estimator set of Huang and Ritter (2009) with a distance of 4 lags. LSDVC is the least squares dummy variable correction estimator of Kiviet (1995) and Bruno (2005), QML is the quasi-maximum likelihood estimator of Hsiao et al. (2002) and finally DPF corresponds to the dynamic panel fractional dependent variable estimator of Elsas and Florysiak (2015). The implied speed of adjustment (SOA) is calculated as of one minus the average estimated coefficient of the dynamic parameter $(1 - \hat{\lambda})$. Half life is the number of years that the SOA implies for a firm to move halfway toward its target efficiency (log(0.5)/log(1-SOA)). Standard-errors are reported in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Figure 1: Benchmark Simulations: Bias Density Plots

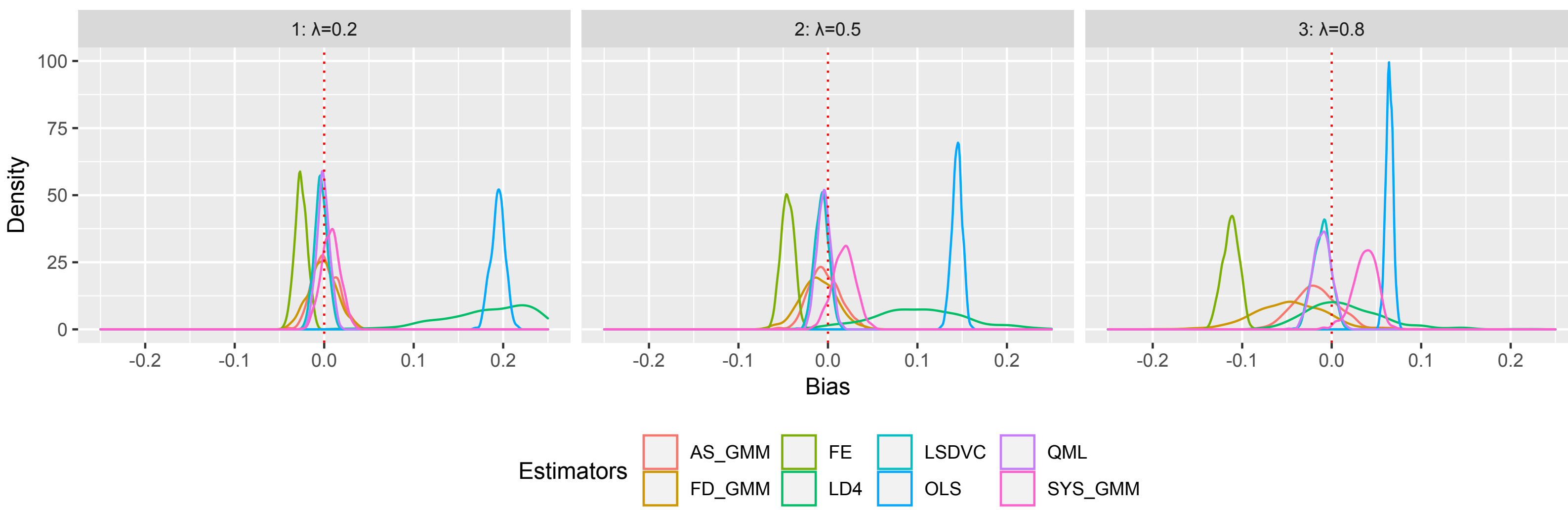


Figure 2: Bias Density Plots: The Impact of Changes in Time Series Length

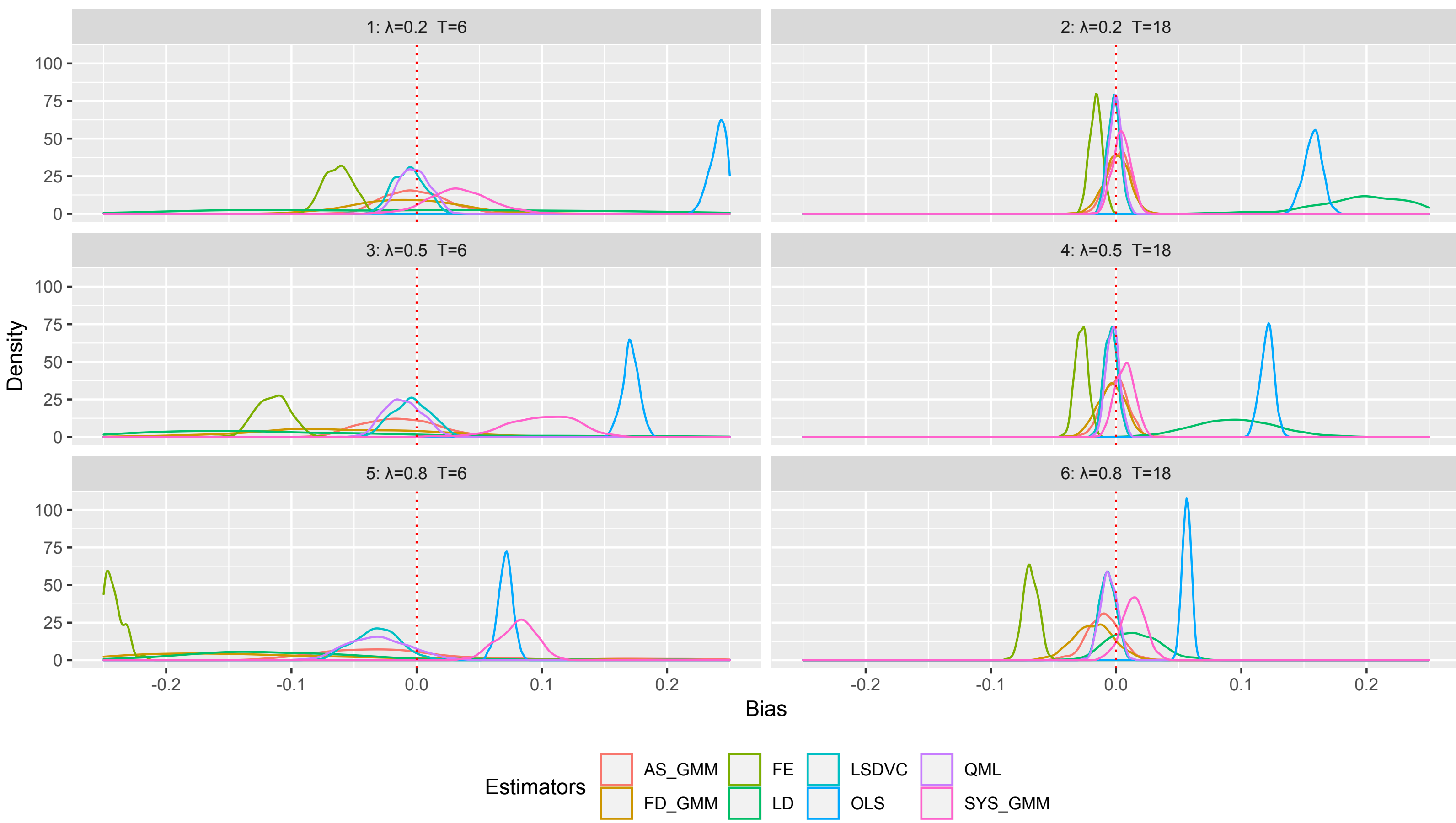


Figure 3: Bias Density Plots: The Impact of Changes in Cross-sectional Size

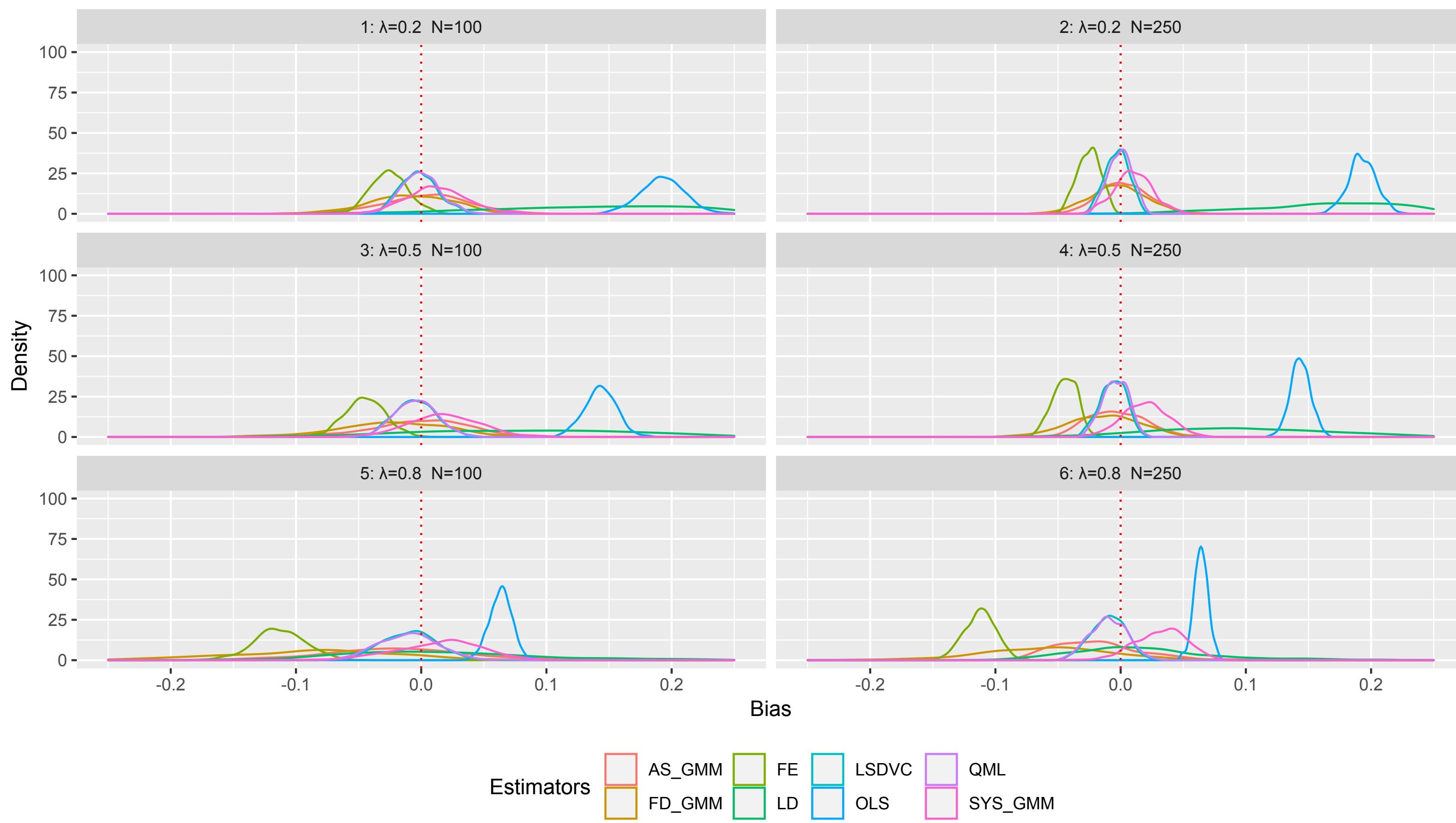


Figure 4: Bias Density Plots: The Impact of The Time-Invariant Individual Effect

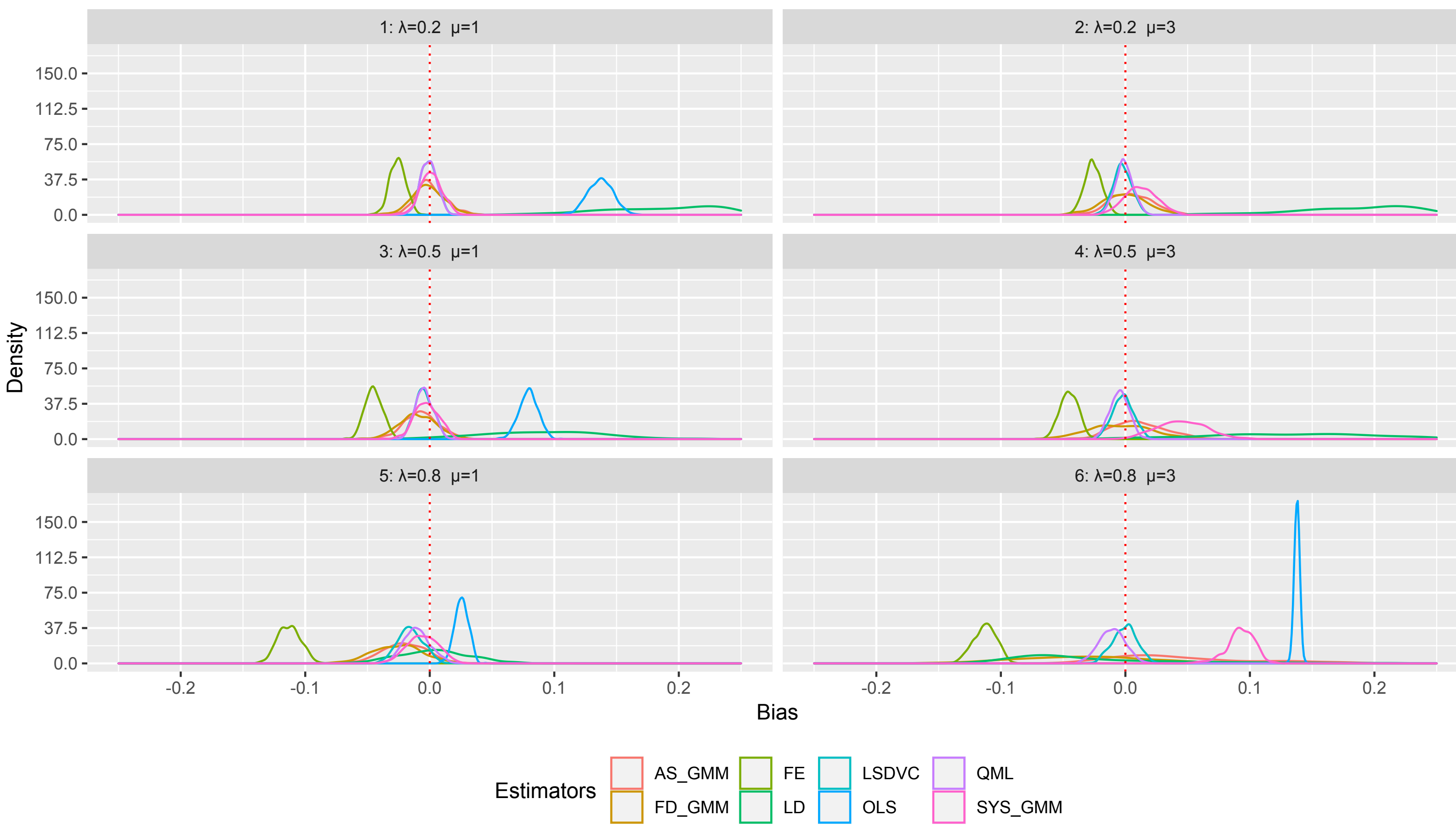


Figure 5: Bias Density Plots: The Impact of Panel Unbalancedness

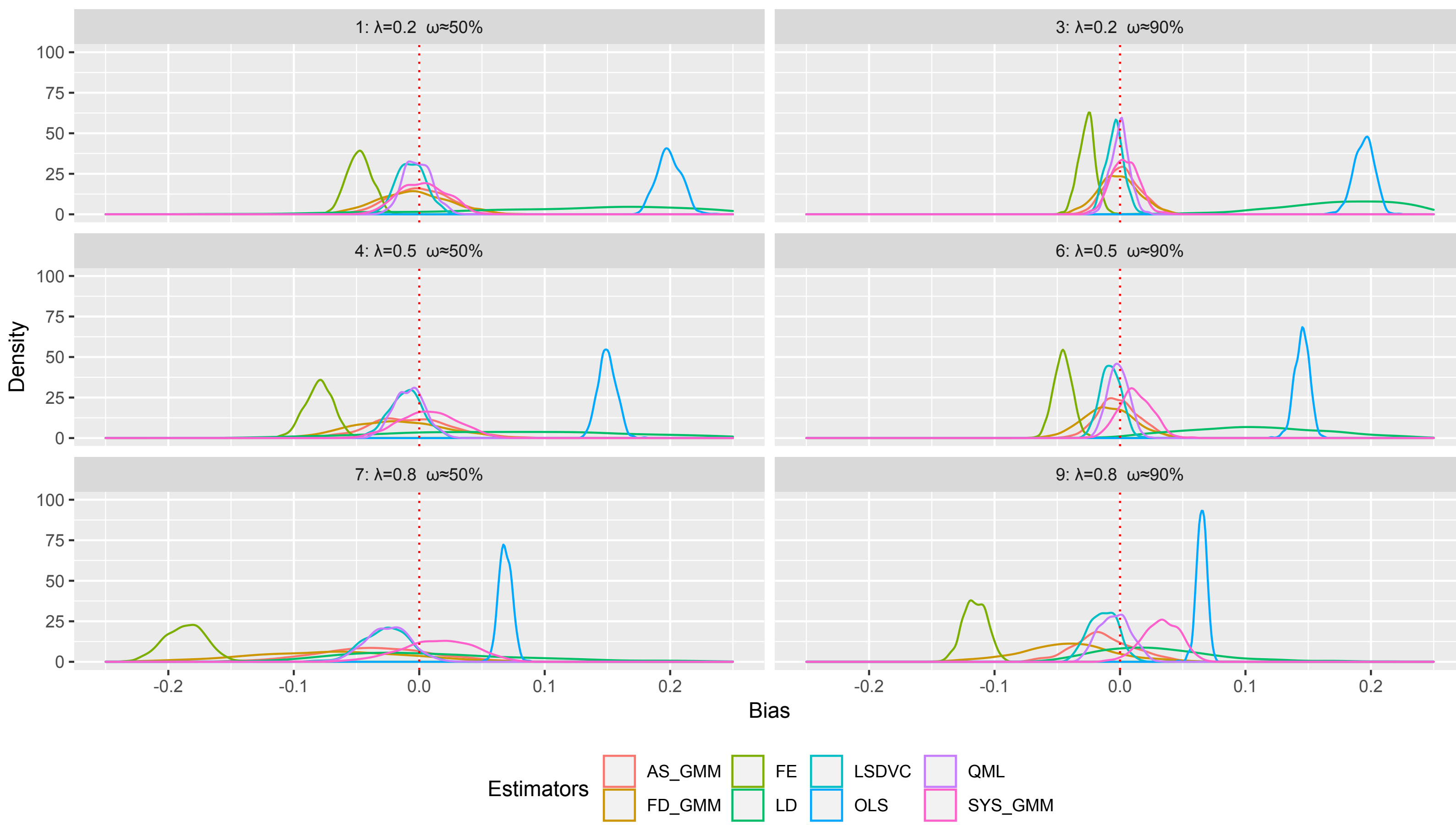


Figure 6: Bias Density Plots: The Impact of Changes in Signal Noise

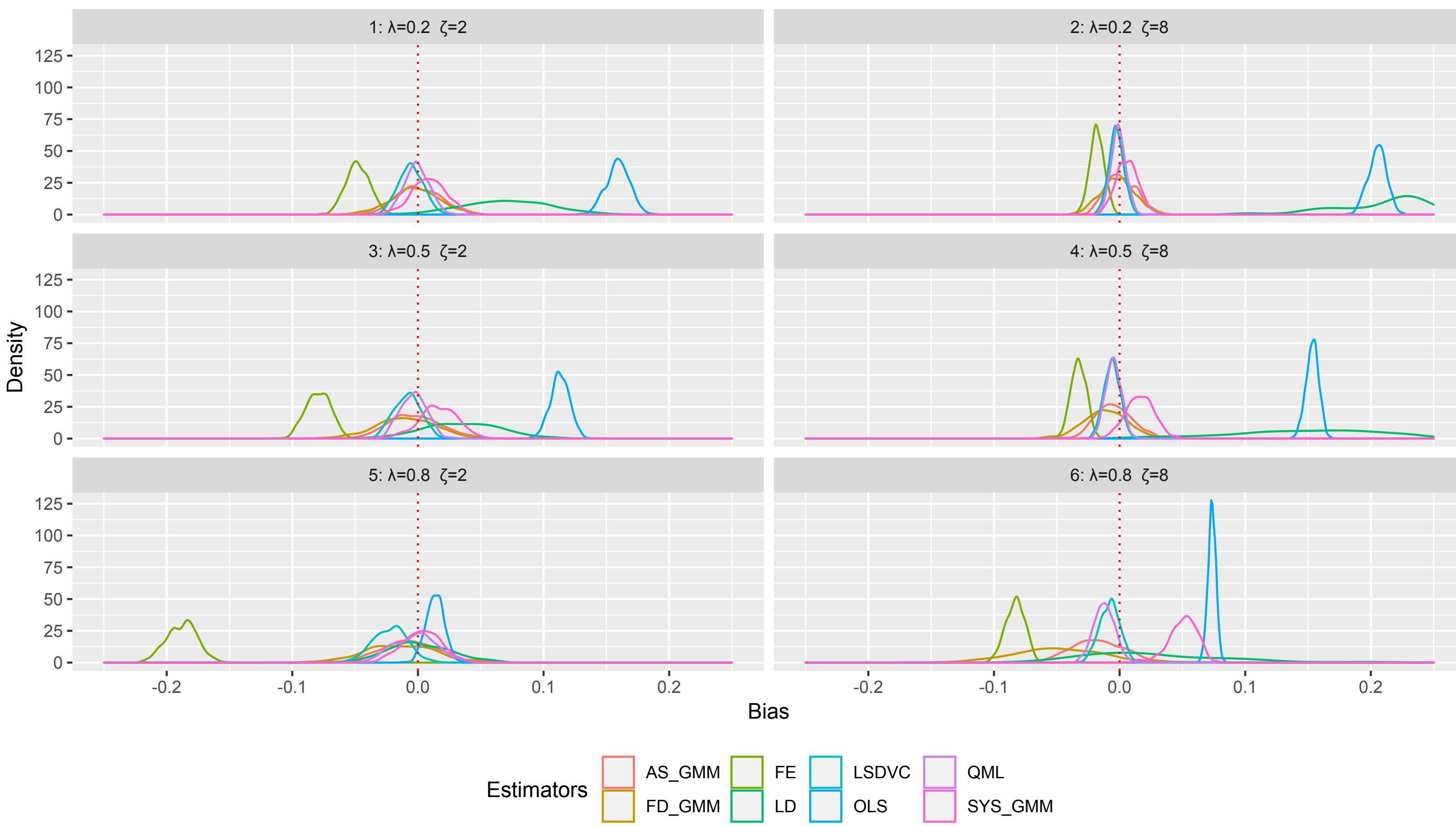


Figure 7: Bias Density Plots: The Impact of Cross-sectional and Time-series Heteroscedasticity

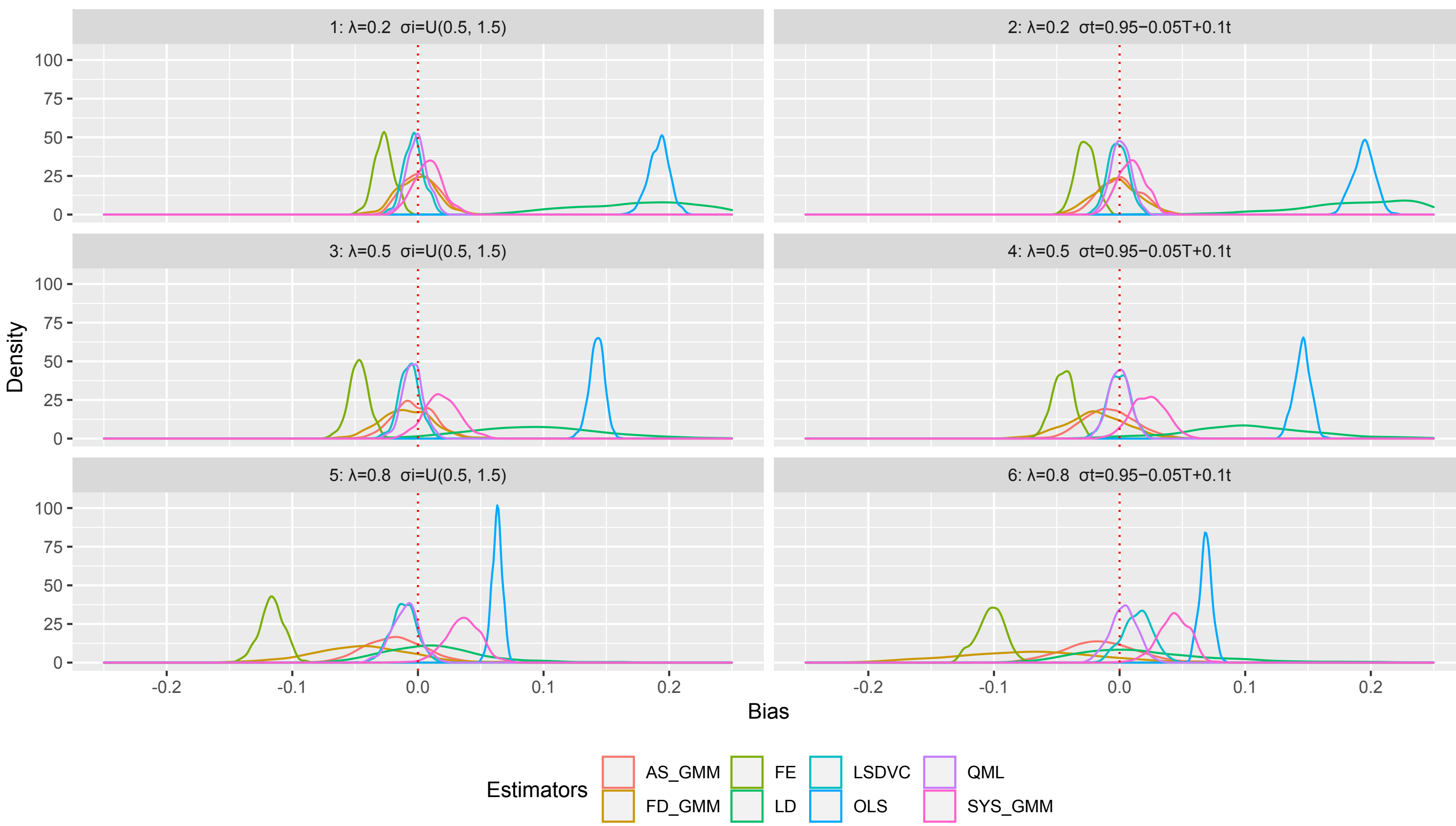
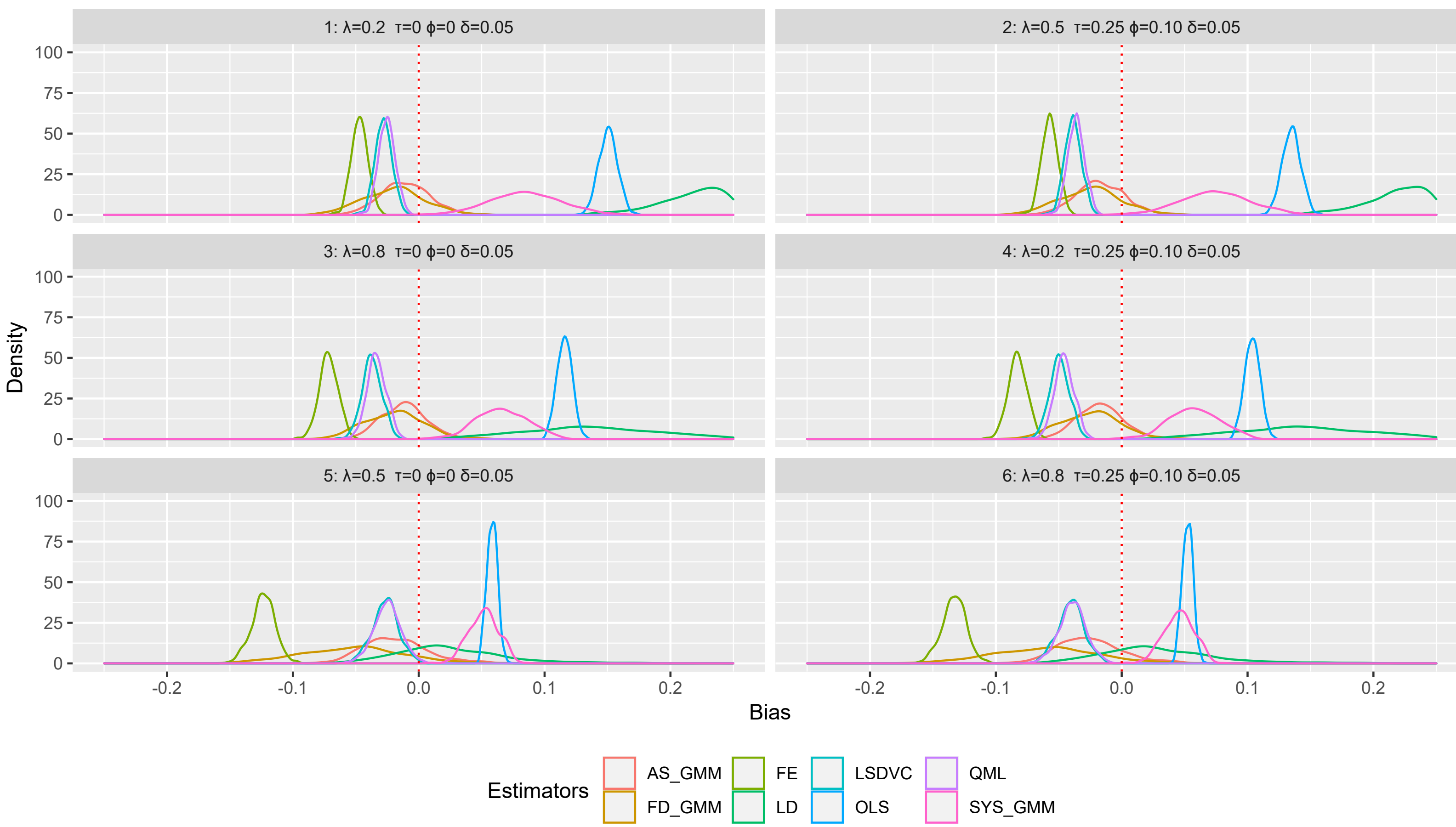


Figure 8: Bias Density Plots: The Impact of Predetermined and Endogenous Regressors



Online Appendix

Dynamic Firm Performance and Estimator Choice: A Comparison of Dynamic Panel Data Estimators

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Online Appendix Table A.1.1: List of Acronyms

Abbreviation	Definition
AR	Autoregressive
AS-GMM	Ahn and Schmidt Generalized Method of Moments
DPD	Dynamic Panel Data
FD-GMM	First Difference Generalized Method of Moments
FE	Fixed Effect
GMM	Generalized Method of Moments
LD4	Long Distance Four
LSDVC	Leaset Square Dummy Variable Correction
OLS	Ordinary Least Squares
OR	Operational Research
QML	Quasi Maximum Likelihood
SOA	Speed of Adjustment
SYS-GMM	System Generalized Method of Moments
TFP	Total Factor Productivity

Online Appendix Table A.1.2: Experiment One: The Impact of Changes in Time-Series Length

		$T = 6$				$T = 18$			
	Estimator	Bias	SD	RMSE	Wald	Bias	SD	RMSE	Wald
$\beta = 0.8$	OLS	0.116	0.012	0.116	1.000	0.031	0.006	0.031	1.000
	FE	0.006	0.010	0.012	0.064	0.006	0.005	0.008	0.182
	FD-GMM	0.003	0.032	0.032	0.040	-0.003	0.013	0.013	0.058
	AS-GMM	-0.001	0.024	0.014	0.060	-0.004	0.012	0.008	0.058
	SYS-GMM	0.004	0.014	0.024	0.046	-0.003	0.007	0.013	0.009
	LD4	-0.624	0.691	0.930	0.850	-0.624	0.040	0.626	1.000
	LSDVC	0.001	0.010	0.010	0.164	0.001	0.005	0.005	0.188
	QML	0.000	0.010	0.010	0.024	0.000	0.005	0.005	0.052
$\beta = 0.5$	OLS	0.073	0.009	0.074	1.000	0.019	0.004	0.019	0.994
	FE	0.001	0.008	0.009	0.030	0.006	0.004	0.007	0.298
	FD-GMM	0.019	0.034	0.039	0.062	-0.002	0.010	0.010	0.058
	AS-GMM	-0.002	0.024	0.014	0.062	-0.003	0.010	0.007	0.050
	SYS-GMM	0.006	0.012	0.024	0.092	-0.003	0.006	0.010	0.074
	LD4	-0.289	0.217	0.361	0.926	-0.333	0.022	0.334	1.000
	LSDVC	0.003	0.009	0.009	0.172	0.001	0.004	0.004	0.190
	QML	0.000	0.009	0.009	0.026	0.001	0.004	0.004	0.048
$\beta = 0.2$	OLS	0.037	0.006	0.038	1.000	0.012	0.003	0.013	0.968
	FE	-0.010	0.007	0.012	0.268	0.004	0.003	0.005	0.208
	FD-GMM	0.036	0.034	0.049	0.196	0.001	0.008	0.008	0.054
	AS-GMM	-0.006	0.019	0.010	0.110	-0.001	0.007	0.005	0.054
	SYS-GMM	0.003	0.009	0.020	0.056	-0.002	0.005	0.007	0.074
	LD4	-0.109	0.052	0.121	0.992	-0.114	0.007	0.115	1.000
	LSDVC	0.001	0.007	0.007	0.164	0.001	0.003	0.003	0.174
	QML	-0.002	0.007	0.007	0.026	0.000	0.003	0.003	0.050

Fixed Parameters: $\lambda = 1 - \beta, \rho = 0.5, \zeta = 5$ & $\mu = 1$.

Notes: OLS and FE refer to the pooled OLS and within transformation estimators.FD, AS and SYS-GMM correspond to the two-step first-difference GMM estimators of Arellano and Bond (1991), the two-step first-difference non-linear instrument estimator of Ahn and Schmidt (1995) and the two-step system-GMM estimator of Blundell and Bond (1998). All GMM estimates adopt Windmeijer (2005) finite-sample corrected standard errors. LD4 is long difference estimator with the estimator set of Huang and Ritter (2009) with a distance of 4 lags. LSDVC is the least squares dummy variable correction estimator of Kiviet (1995) and Bruno (2005) and finally QML corresponds to the quasi-maximum likelihood estimator of Hsiao et al. (2002). Bias is the average difference between the estimated and true parameter value. SD is the standard deviation of the estimated parameter. RMSE is the root mean squared error. The wald rejection rate reports the percentage of simulations where the true parameter set in the data generating process falls outside the estimated 95% confidence interval. The parameter dimension $N = 500$ with a repetition rate of 500.

Online Appendix Table A.1.3: Experiment One: The Impact of Changes in Cross-sectional Size

	Estimator	$N = 100$				$N = 250$			
		Bias	SD	RMSE	Wald	Bias	SD	RMSE	Wald
$\beta = 0.8$	OLS	0.050	0.017	0.053	0.840	0.050	0.010	0.051	0.998
	FE	0.007	0.015	0.016	0.082	0.007	0.009	0.012	0.102
	FD-GMM	0.000	0.034	0.034	0.052	-0.002	0.025	0.025	0.058
	AS-GMM	-0.002	0.037	0.021	0.054	-0.005	0.025	0.014	0.076
	SYS-GMM	-0.005	0.020	0.037	0.056	-0.005	0.013	0.025	0.064
	LD4	-0.654	0.159	0.673	1.000	-0.631	0.088	0.637	1.000
	LSDVC	-0.001	0.015	0.015	0.190	0.000	0.009	0.009	0.154
	QML	-0.001	0.015	0.015	0.058	0.000	0.009	0.009	0.036
$\beta = 0.5$	OLS	0.031	0.013	0.034	0.682	0.032	0.008	0.032	0.974
	FE	0.007	0.012	0.014	0.104	0.007	0.007	0.010	0.144
	FD-GMM	0.004	0.028	0.029	0.052	0.001	0.021	0.021	0.072
	AS-GMM	-0.003	0.029	0.018	0.042	-0.003	0.020	0.012	0.078
	SYS-GMM	-0.003	0.017	0.029	0.062	-0.004	0.011	0.021	0.058
	LD4	-0.353	0.089	0.364	1.000	-0.340	0.053	0.344	1.000
	LSDVC	0.000	0.012	0.012	0.192	0.001	0.007	0.007	0.162
	QML	0.000	0.012	0.012	0.058	0.001	0.007	0.007	0.040
$\beta = 0.2$	OLS	0.018	0.010	0.021	0.492	0.019	0.006	0.019	0.880
	FE	0.002	0.010	0.010	0.076	0.002	0.006	0.006	0.052
	FD-GMM	0.012	0.022	0.025	0.074	0.008	0.017	0.018	0.106
	AS-GMM	0.001	0.021	0.014	0.043	-0.001	0.015	0.010	0.066
	SYS-GMM	-0.002	0.014	0.021	0.050	-0.003	0.009	0.015	0.060
	LD4	-0.123	0.035	0.128	1.000	-0.117	0.018	0.118	1.000
	LSDVC	0.001	0.010	0.010	0.198	0.001	0.006	0.006	0.166
	QML	-0.001	0.010	0.010	0.056	0.000	0.006	0.006	0.044

Fixed Parameters: $\lambda = 1 - \beta, \rho = 0.5, \zeta = 5 \& \mu = 1$.

Notes: OLS and FE refer to the pooled OLS and within transformation estimators. FD, AS and SYS-GMM correspond to the two-step first-difference GMM estimators of Arellano and Bond (1991), the two-step first-difference non-linear instrument estimator of Ahn and Schmidt (1995) and the two-step system-GMM estimator of Blundell and Bond (1998). All GMM estimates adopt Windmeijer (2005) finite-sample corrected standard errors. LD4 is long difference estimator with the estimator set of Huang and Ritter (2009) with a distance of 4 lags. LSDVC is the least squares dummy variable correction estimator of Kiviet (1995) and Bruno (2005) and finally QML corresponds to the quasi-maximum likelihood estimator of Hsiao et al. (2002). RMSE is the root mean squared error. The wald rejection rate reports the percentage of simulations where the true parameter set in the data generating process falls outside the estimated 95% confidence interval. Panel length is set to $T = 12$ with a repetition rate of 500.

Online Appendix Table A.1.4: Experiment Two: The Impact of The Time-Invariant Individual Effect

		$\mu = 1$				$\mu = 3$			
	Estimator	Bias	SD	RMSE	Wald	Bias	SD	RMSE	Wald
$\beta = 0.8$	OLS	-0.061	0.009	0.062	1.000	-0.016	0.010	0.019	0.358
	FE	0.007	0.006	0.010	0.186	0.007	0.006	0.010	0.188
	FD-GMM	-0.002	0.017	0.017	0.074	-0.002	0.017	0.017	0.046
	AS-GMM	-0.003	0.017	0.009	0.070	-0.005	0.017	0.010	0.070
	SYS-GMM	-0.004	0.009	0.017	0.078	-0.004	0.009	0.018	0.062
	LD4	-0.627	0.054	0.629	1.000	-0.702	0.218	0.735	0.998
	LSDVC	0.000	0.006	0.006	0.172	-0.001	0.007	0.007	0.150
	QML	0.000	0.006	0.006	0.050	0.000	0.007	0.007	0.036
$\beta = 0.5$	OLS	-0.027	0.006	0.028	0.996	0.006	0.007	0.009	0.142
	FE	0.007	0.005	0.009	0.252	0.007	0.005	0.009	0.254
	FD-GMM	0.001	0.014	0.014	0.066	-0.001	0.015	0.015	0.046
	AS-GMM	-0.001	0.014	0.008	0.080	-0.007	0.014	0.008	0.090
	SYS-GMM	-0.003	0.007	0.014	0.078	-0.002	0.008	0.016	0.056
	LD4	-0.332	0.030	0.334	1.000	-0.425	0.121	0.442	1.000
	LSDVC	0.001	0.005	0.005	0.176	0.001	0.005	0.006	0.140
	QML	0.001	0.005	0.005	0.046	0.001	0.005	0.005	0.042
$\beta = 0.2$	OLS	-0.005	0.004	0.006	0.244	0.017	0.005	0.018	0.972
	FE	0.002	0.004	0.005	0.062	0.002	0.004	0.005	0.088
	FD-GMM	0.003	0.010	0.010	0.070	0.003	0.013	0.013	0.062
	AS-GMM	0.001	0.010	0.006	0.058	-0.010	0.014	0.007	0.166
	SYS-GMM	-0.002	0.006	0.010	0.070	-0.001	0.007	0.017	0.062
	LD4	-0.114	0.009	0.114	1.000	-0.127	0.047	0.136	1.000
	LSDVC	0.000	0.004	0.004	0.174	0.003	0.004	0.005	0.224
	QML	0.000	0.004	0.004	0.052	0.000	0.004	0.004	0.040

Fixed Parameters: $\lambda = 1 - \beta, \rho = 0.5$ & $\zeta = 5$.

Notes: OLS and FE refer to the pooled OLS and within transformation estimators. FD, AS and SYS-GMM correspond to the two-step first-difference GMM estimators of Arellano and Bond (1991), the two-step first-difference non-linear instrument estimator of Ahn and Schmidt (1995) and the two-step system-GMM estimator of Blundell and Bond (1998). All GMM estimates adopt Windmeijer (2005) finite-sample corrected standard errors. LD4 is long difference estimator with the estimator set of Huang and Ritter (2009) with a distance of 4 lags. LSDVC is the least squares dummy variable correction estimator of Kiviet (1995) and Bruno (2005) and finally QML corresponds to the quasi-maximum likelihood estimator of Hsiao et al. (2002). Bias is the average difference between the estimated and true parameter value. SD is the standard deviation of Bias. RMSE is the root mean squared error. The wald rejection rate reports the percentage of simulations where the true parameter set in the data generating process falls outside the estimated 95% confidence interval. The panel dimensions are $T = 12$ and $N = 500$ with a repetition rate of $R = 500$.

Online Appendix Table A.1.5: Experiment Three: The Impact of Panel Unbalancedness

	Estimator	$\omega = 50\%$				$\omega = 90\%$			
		Bias	SD	RMSE	Wald	Bias	SD	RMSE	Wald
$\beta = 0.8$	OLS	0.044	0.010	0.045	0.986	0.051	0.008	0.052	1.000
	FE	0.009	0.010	0.014	0.174	0.008	0.006	0.010	0.216
	FD-GMM	0.003	0.027	0.027	0.054	-0.001	0.017	0.017	0.058
	AS-GMM	0.001	0.025	0.014	0.070	-0.003	0.016	0.009	0.066
	SYS-GMM	-0.003	0.014	0.025	0.060	-0.002	0.009	0.016	0.038
	LD4	-0.647	0.168	0.668	1.000	-0.633	0.063	0.636	1.000
	LSDVC	0.002	0.011	0.011	0.164	0.001	0.007	0.007	0.178
	QML	-0.002	0.011	0.011	0.052	0.000	0.007	0.007	0.044
$\beta = 0.5$	OLS	0.027	0.008	0.028	0.938	0.032	0.006	0.032	1.000
	FE	0.006	0.009	0.011	0.140	0.007	0.005	0.009	0.262
	FD-GMM	0.008	0.023	0.024	0.066	0.002	0.014	0.014	0.056
	AS-GMM	0.003	0.021	0.012	0.066	-0.002	0.013	0.008	0.054
	SYS-GMM	-0.002	0.012	0.021	0.054	-0.001	0.008	0.013	0.036
	LD4	-0.348	0.088	0.359	1.000	-0.343	0.036	0.345	1.000
	LSDVC	0.002	0.009	0.009	0.178	0.001	0.006	0.006	0.184
	QML	-0.004	0.009	0.010	0.062	0.000	0.006	0.006	0.044
$\beta = 0.2$	OLS	0.017	0.006	0.018	0.846	0.019	0.004	0.019	0.994
	FE	-0.002	0.007	0.007	0.084	0.002	0.004	0.005	0.076
	FD-GMM	0.014	0.018	0.023	0.152	0.006	0.011	0.013	0.080
	AS-GMM	0.005	0.015	0.010	0.086	0.000	0.010	0.006	0.050
	SYS-GMM	0.000	0.010	0.016	0.048	0.000	0.006	0.010	0.032
	LD4	-0.121	0.033	0.126	1.000	-0.118	0.014	0.119	1.000
	LSDVC	0.002	0.007	0.008	0.176	0.001	0.005	0.005	0.196
	QML	-0.007	0.007	0.010	0.166	0.000	0.005	0.005	0.044

Fixed Parameters: $\lambda = 1 - \beta, \rho = 0.5, \zeta = 5$ & $\mu = 1$.

Notes: OLS and FE refer to the pooled OLS and within transformation estimators. FD, AS and SYS-GMM correspond to the two-step first-difference GMM estimators of Arellano and Bond (1991), the two-step first-difference non-linear instrument estimator of Ahn and Schmidt (1995) and the two-step system-GMM estimator of Blundell and Bond (1998). All GMM estimates adopt Windmeijer (2005) finite-sample corrected standard errors. LD4 is long difference estimator with the estimator set of Huang and Ritter (2009) with a distance of 4 lags. LSDVC is the least squares dummy variable correction estimator of Kiviet (1995) and Bruno (2005) and finally QML corresponds to the quasi-maximum likelihood estimator of Hsiao et al. (2002). Bias is the average difference between the estimated and true parameter value. SD is the standard deviation Bias. RMSE is the root mean squared error. The wald rejection rate reports the percentage of simulations where the true parameter set in the data generating process falls outside the estimated 95% confidence interval. The parameter dimension $N = 500$ with a repetition rate of $R = 500$.

Online Appendix Table A.1.6: Experiment Four: The Impact of Changes in Signal Noise

		$\zeta = 2$				$\zeta = 8$			
	Estimator	Bias	SD	RMSE	Wald	Bias	SD	RMSE	Wald
$\beta = 0.8$	OLS	-0.061	0.009	0.062	1.000	-0.016	0.010	0.019	0.358
	FE	0.007	0.006	0.010	0.186	0.007	0.006	0.010	0.188
	FD-GMM	-0.002	0.017	0.017	0.054	-0.002	0.017	0.017	0.052
	AS-GMM	-0.003	0.017	0.009	0.070	-0.005	0.017	0.010	0.060
	SYS-GMM	-0.004	0.009	0.017	0.074	-0.004	0.009	0.018	0.064
	LD4	-0.627	0.054	0.629	1.000	-0.702	0.218	0.735	0.998
	LSDVC	0.000	0.006	0.006	0.172	-0.001	0.007	0.007	0.150
	QML	0.000	0.006	0.006	0.050	0.000	0.007	0.007	0.036
$\beta = 0.5$	OLS	-0.027	0.006	0.028	0.996	0.006	0.007	0.009	0.142
	FE	0.007	0.005	0.009	0.252	0.007	0.005	0.009	0.254
	FD-GMM	0.001	0.014	0.014	0.062	-0.001	0.015	0.015	0.064
	AS-GMM	-0.001	0.014	0.008	0.072	-0.007	0.014	0.008	0.064
	SYS-GMM	-0.003	0.007	0.014	0.074	-0.002	0.008	0.016	0.056
	LD4	-0.332	0.030	0.334	1.000	-0.425	0.121	0.442	1.000
	LSDVC	0.001	0.005	0.005	0.176	0.001	0.005	0.006	0.140
	QML	0.001	0.005	0.005	0.046	0.001	0.005	0.005	0.042
$\beta = 0.2$	OLS	-0.005	0.004	0.006	0.244	0.017	0.005	0.018	0.972
	FE	0.002	0.004	0.005	0.062	0.002	0.004	0.005	0.088
	FD-GMM	0.003	0.010	0.010	0.066	0.003	0.013	0.013	0.100
	AS-GMM	0.001	0.010	0.006	0.062	-0.010	0.014	0.007	0.068
	SYS-GMM	-0.002	0.006	0.010	0.070	-0.001	0.007	0.017	0.064
	LD4	-0.114	0.009	0.114	1.000	-0.127	0.047	0.136	1.000
	LSDVC	0.000	0.004	0.004	0.174	0.003	0.004	0.005	0.224
	QML	0.000	0.004	0.004	0.052	0.000	0.004	0.004	0.040

Fixed Parameters: $\lambda = 1 - \beta, \rho = 0.5$ & $\mu = 1$.

Notes: OLS and FE refer to the pooled OLS and within transformation estimators. FD, AS and SYS-GMM correspond to the two-step first-difference GMM estimators of Arellano and Bond (1991), the two-step first-difference non-linear instrument estimator of Ahn and Schmidt (1995) and the two-step system-GMM estimator of Blundell and Bond (1998). All GMM estimates adopt Windmeijer (2005) finite-sample corrected standard errors.LD4 is long difference estimator with the estimator set of Huang and Ritter (2009) with a distance of 4 lags. LSDVC is the least squares dummy variable correction estimator of Kiviet (1995) and Bruno (2005) and finally QML corresponds to the quasi-maximum likelihood estimator of Hsiao et al. (2002). Bias is the average difference between the estimated and true parameter value. SD is the standard deviation of Bias. RMSE is the root mean squared error. The wald rejection rate reports the percentage of simulations where the true parameter set in the data generating process falls outside the estimated 95% confidence interval. The parameter dimensions are set to $T = 12$ and $N = 500$ with a repetition rate of $R = 500$.

Online Appendix Table A.1.7: Experiment Five: The Impact of Cross-sectional and Time-series Heteroscedasticity

		$\sigma_i = U(0.5, 1.5)$				$\sigma_t = 0.95 - 0.05T + 0.1t$			
	Estimator	Bias	SD	RMSE	Wald	Bias	SD	RMSE	Wald
$\beta = 0.8$	OLS	0.192	0.008	0.192	1.000	0.051	0.008	0.051	1.000
	FE	-0.027	0.008	0.028	0.950	0.008	0.007	0.010	0.180
	FD-GMM	-0.001	0.016	0.016	0.044	-0.001	0.019	0.019	0.062
	AS-GMM	0.002	0.014	0.014	0.052	-0.003	0.019	0.010	0.056
	SYS-GMM	0.008	0.011	0.014	0.054	-0.002	0.009	0.019	0.056
	LD4	0.193	0.063	0.203	0.990	-0.634	0.058	0.637	1.000
	LSDVC	-0.004	0.008	0.009	0.248	0.000	0.007	0.007	0.164
	QML	-0.001	0.008	0.008	0.070	0.000	0.007	0.007	0.042
$\beta = 0.5$	OLS	0.033	0.006	0.034	1.000	0.031	0.006	0.032	0.998
	FE	0.008	0.006	0.010	0.266	0.007	0.006	0.009	0.222
	FD-GMM	0.001	0.014	0.014	0.048	0.004	0.016	0.017	0.066
	AS-GMM	-0.002	0.013	0.008	0.054	-0.001	0.015	0.008	0.062
	SYS-GMM	-0.002	0.007	0.013	0.050	-0.002	0.008	0.015	0.058
	LD4	-0.335	0.033	0.337	1.000	-0.343	0.038	0.345	1.000
	LSDVC	0.001	0.006	0.006	0.174	0.000	0.006	0.006	0.164
	QML	0.001	0.006	0.006	0.044	0.000	0.006	0.006	0.038
$\beta = 0.2$	OLS	0.019	0.004	0.020	0.998	0.017	0.005	0.018	0.966
	FE	0.003	0.005	0.005	0.092	0.002	0.005	0.005	0.074
	FD-GMM	0.006	0.011	0.013	0.080	0.008	0.014	0.016	0.088
	AS-GMM	0.000	0.010	0.006	0.050	-0.003	0.011	0.007	0.060
	SYS-GMM	-0.001	0.006	0.010	0.052	-0.002	0.007	0.011	0.060
	LD4	-0.116	0.012	0.117	1.000	-0.125	0.033	0.129	1.000
	LSDVC	0.001	0.004	0.005	0.184	0.001	0.005	0.005	0.160
	QML	0.000	0.004	0.004	0.046	-0.001	0.005	0.005	0.030

Fixed Parameters: $\lambda = 1 - \beta$, $\rho = 0.5$, $\zeta = 5$ and $\mu = 1$.

Notes: OLS and FE refer to the pooled OLS and within transformation estimators.FD, AS and SYS-GMM correspond to the two-step first-difference GMM estimators of Arellano and Bond (1991), the two-step first-difference non-linear instrument estimator of Ahn and Schmidt (1995) and the two-step system-GMM estimator of Blundell and Bond (1998). All GMM estimates adopt Windmeijer (2005) finite-sample corrected standard errors. LD4 is long difference estimator with the estimator set of Huang and Ritter (2009) with a distance of 4 lags. LSDVC is the least squares dummy variable correction estimator of Kiviet (1995) and Bruno (2005) and finally QML corresponds to the quasi-maximum likelihood estimator of Hsiao et al. (2002). Bias is the average difference between the estimated and true parameter value. SD is the standard deviation of the estimated parameter. RMSE is the root mean squared error. The wald rejection rate reports the percentage of simulations where the true parameter set in the data generating process falls outside the estimated 95% confidence interval. The parameter dimensions are set to $T = 12$ and $N = 500$ with a repetition rate of $R = 500$.

Online Appendix Table A.1.8: Experiment Six: The Impact of Predetermined and Endogenous Regressors ($x_{i,t}$)

	Estimator	$\tau = 0.0$ $\phi = 0.0$ $\delta = 0.05$				$\tau = 0.25$ $\phi = 0.10$ $\delta = 0.05$			
		Bias	SD	RMSE	Wald	Bias	SD	RMSE	Wald
$\beta = 0.8$	OLS	0.060	0.008	0.060	1.000	0.065	0.008	0.066	1.000
	FE	0.013	0.007	0.015	0.524	0.016	0.007	0.018	0.660
	FD-GMM	0.008	0.018	0.020	0.062	0.010	0.018	0.021	0.078
	AS-GMM	0.004	0.016	0.041	0.056	0.006	0.016	0.036	0.064
	SYS-GMM	-0.036	0.019	0.017	0.454	-0.031	0.019	0.018	0.372
	LD4	-0.722	0.069	0.726	1.000	-0.732	0.070	0.735	1.000
	LSDVC	0.007	0.007	0.010	0.318	0.010	0.007	0.012	0.452
	QML	0.007	0.007	0.010	0.198	0.010	0.007	0.012	0.350
$\beta = 0.5$	OLS	0.038	0.006	0.039	1.000	0.041	0.006	0.042	1.000
	FE	0.012	0.006	0.013	0.534	0.013	0.006	0.015	0.632
	FD-GMM	0.005	0.015	0.015	0.058	0.006	0.015	0.016	0.072
	AS-GMM	0.002	0.013	0.028	0.052	0.004	0.013	0.026	0.050
	SYS-GMM	-0.025	0.014	0.013	0.400	-0.021	0.014	0.014	0.324
	LD4	-0.365	0.038	0.367	1.000	-0.371	0.040	0.373	1.000
	LSDVC	0.005	0.006	0.008	0.310	0.007	0.006	0.009	0.382
	QML	0.005	0.006	0.008	0.170	0.007	0.006	0.009	0.272
$\beta = 0.2$	OLS	0.019	0.004	0.020	0.998	0.020	0.004	0.021	1.000
	FE	0.003	0.005	0.005	0.106	0.003	0.005	0.005	0.108
	FD-GMM	0.008	0.012	0.014	0.128	0.010	0.012	0.015	0.164
	AS-GMM	0.001	0.010	0.014	0.048	0.003	0.010	0.014	0.056
	SYS-GMM	-0.011	0.010	0.010	0.200	-0.010	0.010	0.010	0.156
	LD4	-0.119	0.012	0.119	1.000	-0.120	0.013	0.120	1.000
	LSDVC	0.001	0.004	0.005	0.188	0.001	0.004	0.005	0.200
	QML	0.000	0.004	0.004	0.038	0.001	0.004	0.004	0.048

Fixed Parameters: $\lambda = 1 - \beta$, $\rho = 0.5$, $\zeta = 5$, $\mu = 1$ & $\varrho = 0.5$.

Notes: OLS and FE refer to the pooled OLS and within transformation estimators.FD, AS and SYS-GMM correspond to the two-step first-difference GMM estimators of Arellano and Bond (1991), the two-step first-difference non-linear instrument estimator of Ahn and Schmidt (1995) and the two-step system-GMM estimator of Blundell and Bond (1998). All GMM estimates adopt Windmeijer (2005) finite-sample corrected standard errors. LD4 is long difference estimator with the estimator set of Huang and Ritter (2009) with a distance of 4 lags. LSDVC is the least squares dummy variable correction estimator of Kiviet (1995) and Bruno (2005) and finally QML corresponds to the quasi-maximum likelihood estimator of Hsiao et al. (2002). Bias is the average difference between the estimated and true parameter value. SD is the standard deviation of the estimated parameter. RMSE is the root mean squared error. The wald rejection rate reports the percentage of simulations where the true parameter set in the data generating process falls outside the estimated 95% confidence interval. The panel dimensions are set to $T = 12$ and $N = 500$ with a repetition rate of $R = 500$.

Online Appendix Table A.1.9: Experiment Six: The Impact of Predetermined and Endogenous Regressors ($z_{i,t}$)

		$\tau = 0.0$ $\phi = 0.0$ $\delta = 0.05$				$\tau = 0.25$ $\phi = 0.10$ $\delta = 0.05$			
	Estimator	Bias	SD	RMSE	Wald	Bias	SD	RMSE	Wald
$\beta = 0.8$	OLS	0.065	0.015	0.066	0.996	-0.010	0.015	0.018	0.996
	FE	0.041	0.014	0.043	0.830	-0.046	0.014	0.048	0.830
	FD-GMM	-0.080	0.029	0.085	0.738	-0.153	0.028	0.155	0.738
	AS-GMM	-0.081	0.028	0.104	0.790	-0.155	0.028	0.171	0.790
	SYS-GMM	-0.100	0.030	0.086	0.880	-0.169	0.030	0.157	0.880
	LD4	-0.902	0.077	0.906	1.000	-0.864	0.071	0.867	1.000
	LSDVC	0.034	0.014	0.036	0.682	-0.053	0.013	0.054	0.682
	QML	0.033	0.013	0.036	0.672	-0.053	0.013	0.055	0.672
$\beta = 0.5$	OLS	-0.019	0.013	0.023	0.280	-0.093	0.013	0.094	0.280
	FE	0.010	0.014	0.017	0.128	-0.076	0.014	0.077	0.128
	FD-GMM	-0.136	0.029	0.139	0.996	-0.208	0.028	0.210	0.996
	AS-GMM	-0.137	0.028	0.152	0.998	-0.209	0.027	0.218	0.998
	SYS-GMM	-0.149	0.029	0.139	0.998	-0.216	0.029	0.210	0.998
	LD4	-0.628	0.048	0.630	1.000	-0.605	0.042	0.607	1.000
	LSDVC	0.003	0.014	0.014	0.186	-0.082	0.014	0.083	0.186
	QML	0.001	0.014	0.014	0.048	-0.085	0.014	0.086	0.048
$\beta = 0.2$	OLS	-0.001	0.011	0.011	0.032	-0.074	0.011	0.075	0.032
	FE	0.037	0.014	0.040	0.782	-0.047	0.014	0.049	0.782
	FD-GMM	-0.078	0.028	0.083	0.780	-0.153	0.027	0.155	0.780
	AS-GMM	-0.087	0.027	0.107	0.892	-0.158	0.026	0.172	0.892
	SYS-GMM	-0.103	0.028	0.091	0.966	-0.169	0.028	0.161	0.966
	LD4	-0.288	0.025	0.289	1.000	-0.280	0.022	0.281	1.000
	LSDVC	0.035	0.013	0.037	0.714	-0.050	0.013	0.051	0.714
	QML	0.024	0.013	0.027	0.418	-0.060	0.013	0.061	0.418

Fixed Parameters: $\lambda = 1 - \beta$, $\rho = 0.5$, $\zeta = 5$, $\mu = 1$ & $\varrho = 0.5$.

Notes: OLS and FE refer to the pooled OLS and within transformation estimators.FD, AS and SYS-GMM correspond to the two-step first-difference GMM estimators of Arellano and Bond (1991), the two-step first-difference non-linear instrument estimator of Ahn and Schmidt (1995) and the two-step system-GMM estimator of Blundell and Bond (1998). All GMM estimates adopt Windmeijer (2005) finite-sample corrected standard errors. LD4 is long difference estimator with the estimator set of Huang and Ritter (2009) with a distance of 4 lags. LSDVC is the least squares dummy variable correction estimator of Kiviet (1995) and Bruno (2005) and finally QML corresponds to the quasi-maximum likelihood estimator of Hsiao et al. (2002). Bias is the average difference between the estimated and true parameter value. SD is the standard deviation of the estimated parameter. RMSE is the root mean squared error. The wald rejection rate reports the percentage of simulations where the true parameter set in the data generating process falls outside the estimated 95% confidence interval. The panel dimensions are set to $T = 12$ and $N = 500$ with a repetition rate of $R = 500$.

Online Appendix Table A.1.10: Experiment One: Implied Speed of Adjustment

	True SOA	OLS	FE	FD-GMM	AS-GMM	SYS-GMM	LD4	LSDVC	QML
$T = 6$	80%	55.7%	86.3%	80.7%	80.1%	76.6%	59.6%	80.6%	80.2%
	50%	32.9%	38.5%	44.0%	49.2%	40.0%	50.0%	49.6%	48.9%
	20%	12.9%	47.4%	44.9%	20.2%	12.0%	26.6%	23.2%	23.0%
$T = 18$	80%	64.3%	81.6%	80.0%	79.8%	79.5%	58.9%	80.2%	80.0%
	50%	37.9%	47.2%	49.6%	49.9%	49.3%	40.5%	49.6%	49.7%
	20%	14.4%	26.8%	21.8%	21.0%	18.6%	18.6%	20.7%	20.6%

Notes: OLS and FE refer to the pooled OLS and within transformation estimators. FD, AS and SYS-GMM correspond to the first-difference GMM estimators of Arellano and Bond (1991), the first-difference non-linear instrument estimator of Ahn and Schmidt (1995) and the system-GMM estimator of Blundell and Bond (1998). LD4 is long difference estimator with the estimator set of Huang and Ritter (2009) with a distance of 4 lags. LSDVC is the least squares dummy variable correction estimator of Kiviet (1995) and Bruno (2005) and finally QML corresponds to the quasi-maximum likelihood estimator of Hsiao et al. (2002). The implied speed of adjustment (SOA) is calculated as of one minus the average estimated coefficient of the dynamic parameter.

Online Appendix Table A.1.11: Experiment One: Implied Speed of Adjustment

	True SOA	OLS	FE	FD-GMM	AS-GMM	SYS-GMM	LD4	LSDVC	QML
$N = 100$	80%	60.7%	82.6%	80.8%	79.6%	78.8%	55.4%	80.2%	80.1%
	50%	35.7%	45.5%	47.7%	50.0%	48.2%	37.3%	49.5%	49.6%
	20%	13.6%	31.3%	29.1%	22.3%	18.5%	15.1%	20.9%	21.0%
$N = 250$	80%	60.7%	82.5%	80.2%	79.8%	79.0%	58.1%	80.3%	80.1%
	50%	35.6%	45.5%	48.6%	49.7%	48.0%	39.5%	49.4%	49.6%
	20%	13.6%	31.2%	26.1%	21.9%	16.8%	18.0%	21.0%	21.0%

Notes: OLS and FE refer to the pooled OLS and within transformation estimators. FD, AS and SYS-GMM correspond to the first-difference GMM estimators of Arellano and Bond (1991), the first-difference non-linear instrument estimator of Ahn and Schmidt (1995) and the system-GMM estimator of Blundell and Bond (1998). LD4 is long difference estimator with the estimator set of Huang and Ritter (2009) with a distance of 4 lags. LSDVC is the least squares dummy variable correction estimator of Kiviet (1995) and Bruno (2005) and finally QML corresponds to the quasi-maximum likelihood estimator of Hsiao et al. (2002). The implied speed of adjustment (SOA) is calculated as of one minus the average estimated coefficient of the dynamic parameter.

Online Appendix Table A.1.12: Experiment Two: Implied Speed of Adjustment

	True SOA	OLS	FE	FD-GMM	AS-GMM	SYS-GMM	LD4	LSDVC	QML
$\mu = 1$	80%	66.3%	82.6%	80.1%	80.0%	79.9%	58.8%	80.1%	80.1%
	50%	42.1%	45.5%	49.0%	49.3%	49.7%	41.0%	49.5%	49.5%
	20%	17.5%	31.3%	22.6%	22.0%	20.6%	19.6%	21.5%	21.0%
$\mu = 3$	80%	30.3%	82.6%	80.1%	79.5%	78.8%	50.1%	80.2%	80.1%
	50%	17.2%	45.5%	49.6%	48.9%	45.5%	25.7%	49.8%	49.5%
	20%	6.2%	31.3%	23.5%	15.5%	10.7%	13.7%	20.0%	21.1%

Notes: OLS and FE refer to the pooled OLS and within transformation estimators. FD, AS and SYS-GMM correspond to the first-difference GMM estimators of Arellano and Bond (1991), the first-difference non-linear instrument estimator of Ahn and Schmidt (1995) and the system-GMM estimator of Blundell and Bond (1998). LD4 is long difference estimator with the estimator set of Huang and Ritter (2009) with a distance of 4 lags. LSDVC is the least squares dummy variable correction estimator of Kiviet (1995) and Bruno (2005) and finally QML corresponds to the quasi-maximum likelihood estimator of Hsiao et al. (2002). The implied speed of adjustment (SOA) is calculated as of one minus the average estimated coefficient of the dynamic parameter.

Online Appendix Table A.1.13: Experiment Three: Implied Speed of Adjustment

	True SOA	OLS	FE	FD-GMM	AS-GMM	SYS-GMM	LD4	LSDVC	QML
$\omega = 50\%$	80%	60.1%	84.8%	80.5%	79.9%	79.7%	56.6%	80.6%	80.1%
	50%	35.0%	42.0%	48.2%	49.4%	49.3%	38.5%	49.0%	49.2%
	20%	13.1%	38.7%	27.4%	23.4%	18.6%	16.3%	22.6%	22.5%
$\omega = 90\%$	80%	60.6%	82.6%	80.1%	79.8%	79.6%	58.0%	80.4%	80.0%
	50%	35.5%	45.5%	49.1%	49.9%	48.8%	38.9%	49.3%	49.9%
	20%	13.5%	31.5%	24.2%	21.2%	16.7%	16.6%	21.3%	20.4%

Notes: OLS and FE refer to the pooled OLS and within transformation estimators. FD, AS and SYS-GMM correspond to the first-difference GMM estimators of Arellano and Bond (1991), the first-difference non-linear instrument estimator of Ahn and Schmidt (1995) and the system-GMM estimator of Blundell and Bond (1998). LD4 is long difference estimator with the estimator set of Huang and Ritter (2009) with a distance of 4 lags. LSDVC is the least squares dummy variable correction estimator of Kiviet (1995) and Bruno (2005) and finally QML corresponds to the quasi-maximum likelihood estimator of Hsiao et al. (2002). The implied speed of adjustment (SOA) is calculated as of one minus the average estimated coefficient of the dynamic parameter.

Online Appendix Table A.1.14: Experiment Four: Implied Speed of Adjustment

	True SOA	OLS	FE	FD-GMM	AS-GMM	SYS-GMM	LD4	LSDVC	QML
$\zeta = 2$	80%	64.1%	84.8%	80.2%	79.9%	79.1%	73.0%	80.6%	80.1%
	50%	38.7%	42.1%	49.0%	49.7%	48.4%	46.5%	49.2%	49.6%
	20%	18.6%	38.8%	21.5%	20.6%	19.7%	19.9%	22.2%	20.2%
$\zeta = 8$	80%	59.5%	81.8%	80.1%	79.9%	79.4%	33.9%	80.3%	80.1%
	50%	34.7%	46.7%	48.9%	49.5%	48.4%	33.0%	49.4%	49.5%
	20%	12.6%	28.3%	25.0%	21.6%	14.9%	15.9%	20.8%	21.2%

Notes: OLS and FE refer to the pooled OLS and within transformation estimators. FD, AS and SYS-GMM correspond to the first-difference GMM estimators of Arellano and Bond (1991), the first-difference non-linear instrument estimator of Ahn and Schmidt (1995) and the system-GMM estimator of Blundell and Bond (1998). LD4 is long difference estimator with the estimator set of Huang and Ritter (2009) with a distance of 4 lags. LSDVC is the least squares dummy variable correction estimator of Kiviet (1995) and Bruno (2005) and finally QML corresponds to the quasi-maximum likelihood estimator of Hsiao et al. (2002). The implied speed of adjustment (SOA) is calculated as of one minus the average estimated coefficient of the dynamic parameter.

Online Appendix Table A.1.15: Experiment Five: Implied Speed of Adjustment

	True SOA	OLS	FE	FD-GMM	AS-GMM	SYS-GMM	LD4	LSDVC	QML
$\sigma_i = U(0.5, 1.5)$	80%	60.8%	82.7%	80.1%	79.8%	79.2%	60.7%	80.4%	80.1%
	50%	35.8%	45.3%	49.1%	49.7%	48.1%	40.5%	49.3%	49.6%
	20%	13.7%	31.6%	24.6%	21.8%	16.4%	18.6%	21.1%	21.0%
$\sigma_t = 0.95 - 0.05T + 0.1t$	80%	60.6%	82.7%	80.3%	79.9%	79.1%	57.9%	80.1%	79.9%
	50%	35.4%	45.5%	48.1%	49.2%	47.7%	39.2%	50.0%	50.0%
	20%	13.1%	30.3%	27.5%	21.4%	15.7%	14.5%	18.6%	19.7%

Notes: OLS and FE refer to the pooled OLS and within transformation estimators. FD, AS and SYS-GMM correspond to the first-difference GMM estimators of Arellano and Bond (1991), the first-difference non-linear instrument estimator of Ahn and Schmidt (1995) and the system-GMM estimator of Blundell and Bond (1998). LD4 is long difference estimator with the estimator set of Huang and Ritter (2009) with a distance of 4 lags. LSDVC is the least squares dummy variable correction estimator of Kiviet (1995) and Bruno (2005) and finally QML corresponds to the quasi-maximum likelihood estimator of Hsiao et al. (2002). The implied speed of adjustment (SOA) is calculated as of one minus the average estimated coefficient of the dynamic parameter.

Online Appendix Table A.1.16: Experiment Six: Implied Speed of Adjustment

	True SOA	OLS	FE	FD-GMM	AS-GMM	SYS-GMM	LD4	LSDVC	QML
$\tau = 0.0$ $\phi = 0.0$ $\delta = 0.05$	80%	64.9%	84.7%	82.0%	81.1%	71.5%	47.9%	82.8%	82.5%
	50%	38.4%	42.8%	48.0%	48.9%	43.4%	35.5%	46.3%	46.7%
	20%	14.2%	32.4%	25.3%	21.8%	14.8%	17.4%	22.6%	22.5%
$\tau = 0.25$ $\phi = 0.10$ $\delta = 0.05$	80%	66.5%	85.7%	82.5%	81.7%	72.5%	46.8%	83.9%	83.6%
	50%	39.6%	41.7%	47.5%	48.3%	44.2%	34.6%	45.1%	45.4%
	20%	14.8%	33.3%	26.1%	22.5%	15.5%	17.0%	24.0%	23.9%

Notes: OLS and FE refer to the pooled OLS and within transformation estimators. FD, AS and SYS-GMM correspond to the first-difference GMM estimators of Arellano and Bond (1991), the first-difference non-linear instrument estimator of Ahn and Schmidt (1995) and the system-GMM estimator of Blundell and Bond (1998). LD4 is long difference estimator with the estimator set of Huang and Ritter (2009) with a distance of 4 lags. LSDVC is the least squares dummy variable correction estimator of Kiviet (1995) and Bruno (2005) and finally QML corresponds to the quasi-maximum likelihood estimator of Hsiao et al. (2002). The implied speed of adjustment (SOA) is calculated as of one minus the average estimated coefficient of the dynamic parameter.