Parameter heterogeneity in the market-accounting relation:

The need for dynamic firm-level modelling in capital market research[1]

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Abstract

In this paper firm parameter heterogeneity in cross section regression analysis in capital market research (CMR) is investigated. Using panel data for 30 large US firms over the period 1955 to 2004, a well-specified common form of dynamic model for each firm is identified. Average parameter estimates from these models are compared to average parameter estimates from 50 annual cross section models having the same functional form. The dynamic parameters are mostly stable over time but variation in individual firm parameters is apparent. Analysis shows that even well-specified annual cross section models using large samples of data cannot guarantee valid and reliable estimates of the parameters of interest. Firm-level dynamic analysis is necessary to avoid this problem.

We show how a fixed effects panel analysis of the sample data can be used to approximate the average data generating process of the firms in the sample. Although the impact of accounting variables is slight, compared to the autoregressive component in market value, it is systematic. There is weak evidence of cointegration between market and accounting data in most firms in the sample. Consequently, it is possible to construct the cross section analogue of the dynamic error correction model. Book value of net assets is used to illustrate the role of accounting variables. Other variables could be used, but single variable, multiplicative noise models perform best when judged by joint explanatory power and forecast ability criteria.

Keywords: *Cross section modelling*, *misspecification*, *heterogeneity*, *dynamic modelling*, *long-run effect*, *fundamentals*

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[1] Based on papers presented at the 2007 (July) Australasian Meeting of Econometrics Society, University of Queensland, Australia; the European Accounting Conference in Tampere, Finland, 2009 (May); the Quantitative Accounting Research Workshop at the University of Auckland in 2009 (June); and the seminar series at University of Technology, Sydney, 2009 (June).

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1. Introduction

Parameter constancy or its practical counterpart, parameter 'homogeneity', is assumed in most studies of fundamentals in CMR. By parameter homogeneity we mean that regression analysis can be pursued as though the parameters in the underlying data generating processes (DGPs) are constant. In cross section analysis it is understood that parameters probably do vary between firms but it is assumed that this variation is random so that large samples may provide a reliable average view of the population. This paper assesses the extent to which this belief is correct.

In Falta and Willett (2009) we show, for a panel of 30 of the largest US companies over a 50 year period, that a regression model of market on accounting values is not well-specified unless the variables are logged. This implies a multiplicative relation between the explanatory variables for market value and the error term, not the additive relation usually assumed in CMR formulations. When this holds true, additive models yield biased and inconsistent estimates. In this paper, the focus is on the use of well-specified models, save only that they may be heterogeneous with respect to the value of their parameters. Here, we use the same panel data as in the earlier paper but this time, we adopt a testing-down method to identify, on the basis of joint statistical and forecasting criteria, the best candidate for a common, well-specified functional form for the cross section market-accounting relation. As before, the dynamic and cross section results are compared and a combination of analysis and computational experiment is used to determine which modelling approaches provide valid and reliable estimates.

The results confirm that multiplicative models produce better specification statistics than additive models. On the model selection criteria, single variable models perform best, with single lags being required to provide a correct specification. The autoregressive component is easily the strongest component of these models with accounting values having a weak but systematic relation to market value in the majority of cases. A book value model is used to investigate the value of cross section analysis of the panel data. Comparison of the individual dynamic and annual cross section estimates shows that the former indicate relatively stable parameters within firms over time and a considerable degree of heterogeneity between firms, the latter indicating a fair degree of movement over time. Also, cross section models fail to provide reliable estimates of the average dynamic estimates when lagged variables are included. The static cross section, on the other hand, appears to be quite accurate.

Analysis, however, shows, even when parameters are homogeneous, the ability of the commonly used static cross section regression to recover the permanent or persistent long-run market-account effect, is dependent on the regressor having a unit root. This deficiency, which is more likely to affect returns than levels regressions, carries through to the case where parameters are heterogeneous. Analysis also shows that firm parameter heterogeneity in cross section models leads to the fallacious impression that dynamic parameters change with time. Unlike the case reported in Falta and Willett (2009), this has nothing to do with functional form misspecification. Computational experiments additionally show that firm parameter heterogeneity causes the pattern of misestimation observed in cross section models with lagged variables.

For these reasons, annual cross sections of levels and returns are unlikely to yield valid and reliable estimates of fundamental market-accounting relations, unless informed by dynamic analysis. Pesaran and Smith (1995) made this point in a broader econometric context several years ago,

> "*… when large T panels are available, the individual micro-relations should be estimated separately and the averages of the estimated micro-parameters and their standard error calculated explicitly. … .*" (pp. 102)

This argument has particular force in the context of the fundamental analysis of interpreting the market-accounting relation due to typical characteristics of the data used to model the relation. We suggest using a fixed effects panel analysis that implements, to a degree of approximation, their advice. Applying this estimation approach to our sample, we construct a cross section, error-correction model (ECM) analogue to the more familiar dynamic ECM used in econometric analysis and estimate that, on average, the approximate linear market-book ratio over the sample period is 3.76, compared to a simple average based on the panel data of 4.24. The estimated coefficient on the change in book value for raw returns is about 70% and imbalances in the long-run market-to-book relation most often take between four and eight years to work through to market value, although there is wide variation in this figure.

Sections 2 and 3 of the paper respectively review some relevant literature and the theory and methods used to support the arguments of the paper. Section 4 reports the empirical results of estimating the market-accounting relation using our sample of panel data. Section 5 analyses the reasons for the empirical results. Section 6 shows the results of modelling the data with a fixed effects panel analysis. Section 7 concludes by summarising the broader implications of the paper's findings and listing some of the new research questions highlighted by the results.

2. Prior Research

Most hypotheses and theory about the relationship between market and accounting values can be traced to dividend discounting theory and variations of it (e.g. as in Fisher, 1930). Generally it is believed that there must be some kind of long-run relationship between market values and variables reported in financial reports, such as the book values of net assets, earnings and dividends. This is assumed implicitly or explicitly in much economic theory (e.g. Modigliani & Miller, 1961). Falta and Willett (2009) show that, with the sample of large US long-lived firms that we continue to investigate in this paper, multiplicative models of the relationship with lags on the accounting variables provide better statistical descriptions of the data than do additive linear models.

Following Lev's (1989) critique and Penman's (1992) call for a return to fundamentals, research interest has focused on the relative explanatory power of different accounting variables such as book value of assets and earnings. In part this interest has been driven by implications for the market-accounting relationship suggested by the theories of Penman and Ohlson, where there are differing degrees of belief in the importance of these and other accounting variables. Fundamental theories, such as those of Ohlson (1995) are concerned with cause and effect in the market-accounting relation, which is essentially a dynamic issue. Despite this, most empirical modelling is cross sectional with inferences based on the assumption of well-specified models in general and homogeneous firm parameters in particular. For example, Collins et al. (1997) and Francis and Schipper (1999) infer value relevance changes in accounting variables based on variations in cross section statistics over time. In addition, most cross section modelling is based upon very large samples of firms on the basis that this improves precision of estimates. However, this also presumes that models are well-specified in all respects and therefore that estimates are at least asymptotically consistent with respect to the number of firms in the sample.

Dynamic analysis is less commonly used in CMR, relative to cross section modelling, though it is sometimes applied to derive estimates for use in the latter (e.g. Dechow et al., 1999; Choi et al., 2006). Examples of studies that have approached this issue from a time perspective are Campbell and Shiller (1987), Ely and Robinson (1997), Kothari and Shanken (1997), Callen and Morel (2001), Qi et al. (2000) and Bartholdy et al. (2003). In the time domain, more attention is devoted to issues of specification and its impact on inference, due to the possibility of integrated variables being a source of spurious regression (Granger & Newbold, 1974). Consequently, research that uses dynamic modelling as the main approach to investigating relationships between levels' variables, such as market and book values, adopts some kind of cointegration modelling technique. Qui et al. (2000) studied the extent of cointegration at the firm-level between market values and predictions based on the Ohlson model and found evidence of cointegration in only 20% of their sample. Bartholdy et al. (2003) used S&P index data over the period 1962 to 1997 to model the relationship between price and book value per share, also finding only weak evidence of cointegration. Cooke et al. (2009) examined five large Japanese firms over a 50 year period using error correction models in logs to assess the consistency, value relevance and sufficiency of accounting for market values, finding that four out of five of their sample firms show evidence of cointegration in the market-accounting relation. The approach to modelling in Cooke et al. (2009) is based on Alexander et al. (2009) and is the one we also follow in this paper.

The empirical findings from dynamic modelling in CMR can be summed up as consistently showing only a weak observable relationship between market and accounting data. This stands in contrast to the cross section evidence, which tends to appear inconsistent over time, sometimes indicating a strong relationship, sometimes a weak or non-existent one. It is therefore worthwhile considering in more detail how cross section and dynamic models relate to one another and why they may sometimes appear to give conflicting results.

In Section 4, as a starting point for this analysis, we follow the advice of Pesaran et al. (1995) modelling individual DGPs to estimate the long-run coefficients from market accounting relationships for each of the 30 firms in our sample. Next, in Section 3, we describe the econometric theory underlying our analysis and the method used to implement it.

3. Theory and method

In Falta and Willett (2009) we presented arguments and evidence from a sample of long-lived firms that support a multiplicative model of the market-accounting relation. We did not claim the results are necessarily generalisable, only that, if they apply to such a sample, it demonstrates that market-accounting data is not universally, accurately represented by additive models. Nothing is known about the impact on estimation when including subsamples of firms within larger samples of firms, some of which may have different forms of DGP. It is evident, therefore, that our earlier findings pose problems for the interpretation of cross section parameter estimates based on additive models.

More specifically, in the above paper we showed that multiplicative forms of autoregressive distributed lag models of the market-accounting models are well-specified in our sample. For convenience we reproduce the specification here:

$$M_{i,t} = k_{i,t} M_{i,t-1}^{\alpha_{i,t}} \prod_j \left(A_{i,j,t}^{\beta_{i,j,t}} A_{i,j,t-1}^{\beta_{i,j,t-1}} \right) \omega_{i,t} \tag{3.1}$$

where $M_{i,t}$ is market value of firm i at time t, $A_{i,j,t}$ represents a list of j=1,..,n accounting variables and $\omega_{i,t}$ represents independent residual effects centered on a median value of 1. Both $A_{i,j,t}$ and $\omega_{i,t}$ are lognormal and $k_{i,t}$, $\alpha_{i,t}$, $\beta_{i,j,t}$ and $\beta_{i,j,t-1}$ are parameters to be estimated. Expression (3.1) can be reformulated as an ECM:

$$\frac{M_{i,t}}{M_{i,t-1}} = \left(\frac{\kappa_{i,t} \prod_j A_{i,j,t-1}^{\varphi_{i,j,t-1}}}{M_{i,t-1}} \right)^{\lambda_{i,t}} \prod_j \left(\frac{A_{i,j,t}}{A_{i,j,t-1}} \right)^{\beta_{i,j,t}} \omega_{i,t}, \tag{3.2}$$

where the term in the first parentheses represents the imbalance in last year's long-run relationship between market and an accounting value that 'error corrects' the market value to its long-run equilibrium value $\kappa_{i,t} \prod_j A_{i,j,t-1}^{\varphi_{i,j,t-1}}$ at that date. The long-run parameters in (3.2) are defined by the original 'short-run' parameters in (3.1) as $\kappa_{i,t} = k_{i,t}^{(1-\alpha_{i,t})}$ and $\varphi_{i,j,t} = (\beta_{i,j,t} + \beta_{i,j,t-1})/(1-\alpha_{i,t})$.

Long-run parameters measure the persistent impact on market value of fluctuations in the accounting variable. Short-run parameters such as $\beta_{i,j,t}$ measure the effect of a contemporaneous change in the accounting variable j. If Expression (3.1) is statistically well-specified, ordinary least-squares (OLS), in logged data, return in a dynamic regression consistent estimates of their parameters with a bias in the estimate of the autoregressive term, reducing as the length of the sample period increases. In this case, dropping the lagged variables and running the 'static' form of

Expression (3.1) over time, holding the subscript *i* constant, gives consistent OLS estimates of the long-run parameters κ_i and $\varphi_{i,j}$.

If all firm DGPs in a sample have the form of Expression (3.1) with identical parameters, cross section forms of Expressions (3.1) and (3.2) return estimates of those parameters perturbed only by random variation. If the variation in DGP parameters across firms is sufficiently small, this result is presumed to continue to hold to an approximation, in that the estimates are then close to the average parameter value. This is the 'homogeneous parameter' case analysed in Falta and Willett (2009). In this case, it is possible to reliably assess the dynamics of the market-accounting value relationship by cross sectional means alone. However, we saw in that paper that parameter variability between firms cast doubt on that possibility. To our knowledge, there are no established statistical metrics for gauging the effect of firm-parameter variability on the ability of annual cross section models to provide reliable estimates of average parameter values.

In order to gauge the effect of firm-parameter heterogeneity on cross section estimation, therefore, in the following section we compare firm average parameter estimates from the statistically strongest, common form, dynamic models of our sample data with time averages produced by cross section models of the same functional form. The cross section modelling uses standard OLS estimation, inferential and diagnostic techniques, requiring no further discussion as to method. The dynamic modelling procedure adopts a simple testing down procedure, the details of which, applied to a single firm in the sample, are described in Alexander et al. (2009). The basis of the General-to-Specific (GETS) approach used is outlined in Table 1.[1] It stresses the importance of determining a statistically well-specified model of the data, prior to drawing conclusions about what relationships might exist between variables in the data. Models in this paper are estimated using *PcGive* (Hendry & Doornik, 2001).

[INSERT TABLE 1 ABOUT HERE]

[1] GETS estimation is argued by its proponents to have advantages over the more usually adopted 'specific-to-general' approach to econometric modelling usually taken in CMR in determining well-specified models (see Hendry, 1995).

The particular GETS approach adopted here is a form of the 'single equation conditional error correction approach to testing for cointegration' (Ericsson & MacKinnon, 1999). It relies on demonstrating the existence of a 'satisfactory' ECM to support claims of a long-run relationship between regressand and regressor. A number of criteria are used for judging if an ECM is a satisfactory model of market value. These are summarised in Table 2. The most important is forecasting performance relative to a random walk model in a ten year hold-out period. This is judged by comparing the root mean square error (RMSE) of the two models over the ten year period and their relative abilities to predict the one year ahead direction of change in raw returns (i.e., 'abnormal' returns). Interpretability of the model is also important. This is assessed by calculating the implied linear multiplier (ILM), as defined in Table 2. The ILM translates the estimated parameters to an approximate average multiple of the accounting variable over the sample period. For the model to be interpretable, the ILM must be of a sensible order.[2]

[INSERT TABLE 2 ABOUT HERE]

In the ECMs estimated in Section 4 all the contemporaneous change variables on the right hand side (RHS) of Expression (3.2) are eliminated to give a 'pure' ECM. In most instances, the coefficient estimates in the error correction term do not alter significantly from those in the full ECM, indicating that the error correction term is orthogonal to the omitted variables. If a statistically well-specified pure ECM forecasts convincing patterns in a hold out period and is interpretable in the sense defined above, it is taken as evidence of the existence of a long-run relationship between the variables in the error-correction part of the ECM. The original ADL form of the ECM is then re-estimated over the entire sample period and used to calculate the estimated long-run relationship between the market and accounting values.

[2] For example, the ILM is expected to be near to an average, simple book to market ratio for a book value ECM estimated over the sample period.

The firms in the sample are shown in Table 4. The logs of negative values are replaced by the number -10.[3]

[INSERT TABLES 3 AND 4 ABOUT HERE]

In Section 5, computer experiments based upon Monte Carlo simulations are used to identify the reasons or check explanations for the results reported in Section 4. The experiments have a simple structure. They generate a number of firm DGPs over a number of periods of time in years. The number of firms initially is set to 30 and the number of years is set to 50 in order to correspond to the sample data. The number of firms is then expanded to 3000 in order to check the likely asymptotic behaviour relative to the state or ensemble variable.

The general approach is to generate DGPs for market value, based on Expression (3.1), with accounting variables being generated as a simple autoregressive time series that may have a unit root. The elements of Expression (3.1) simulated by Monte Carlo methods are the starting values for the market and accounting variables, the parameters of the DGPs and the error term. All starting values are set equal to the mean values of the thirty firms in 1955. Heterogeneous parameters are created from a uniform distribution with endpoints set to the minimum and maximum of the thirty firm values for each of the model estimated parameters. The error term is sampled from a Normal distribution, centered on zero, with standard distribution equal to the mean of the standard error of the thirty, estimated regressions. In the case of the thirty firm samples, data is generated once for each of the thirty different sets of parameter values. In the case of the 3000 firm samples, data is generated 100 times for each set of parameter values. Cross section models are then estimated in each case, using OLS to see to what extent their coefficient estimates represent averages of the

[3] Of a total of five negative book values in the entire sample period from 1955 to 2004, only one is replaced for estimation purposes, the remainder falling into the 10 year hold-out period. In contrast, thirty of sixty negative earnings observations fall into the 40 year estimation period. This method of replacing negative earnings reduces the occurrence of earnings as an explanatory variable of choice in the logarithmic models. Other methods, such as the linear interpolation of profits from adjacent periods to replace negative earnings, increases the occurrence of earnings as a significant explanatory variable.

dynamic parameters for the thirty or 3000 firm DGPs. Estimates and a variety of inferential statistics are calculated.

4. Empirical Models of Firm DGPs

This section describes the results of regressing market on accounting values using the sample data of 30 firms over 50 years. First, the best statistical candidate for a common form of firm-level DGP within the sample is established and the extent of parameter homogeneity between firms is assessed. Second, long-run dynamic parameter estimates, averaged over all firms, are compared with parameters estimated from cross sections, averaged over the sample period.

Table 4 shows estimated ECMs constructed using the method and criteria described in Section 3, for each of the 30 firms in the sample. Once the data are transformed to logs, about two-thirds of the models are well-specified in the form of Expression (3.1) with only one, Gillette, not having a plausible interpretation, as indicated by the ILM in Column 3 of the Table. The ECMs are shown in the multiplicative and raw data form in Column 4 of the table. The source variables generally test as being *I(1)*. In 27, out of 30 firms, the error correction terms in the ECMs test as being stationary (Column 9). These are the best statistical models, based on the selection criteria stated and the initial data set used for testing down. Half of the models show varying degrees of misspecification but are much superior to linear additive models in the raw data in terms of diagnostics.[4] This is consistent with the misspecification test results reported in Falta and Willett (2009) in the case of two variable, book and earnings, models.

[INSERT TABLE 4 ABOUT HERE]

[4] In seven instances the added constant term outside the parentheses in the models in Table 4 is noticeably different from zero, indicating that in those cases the estimated error correction coefficient may be biased by the omission of the short-run variables from the model. However, only one of these models (Gillette) contains accounting data and, in this case, the appearance of the inflation index I_t may also affect the scale of k.

Recursive graphics showing the evolution of parameter estimates as the sample size increases through time, indicate that the dynamic parameters in these models are stable over time. The estimated error correction coefficient typically settles down within 15 years after the start of the sample period and, only rarely, after there is any visually discernable, significant change in the sample path evident. The associated *t*-statistic consistently tracks towards more and more significant values. Figure 1 illustrates a typical recursive graph for the estimated ECM. In this case the firm concerned is Bausch. This evidence is consistent with individual firm parameters being relatively constant over time.[5]

[INSERT FIGURE 1 ABOUT HERE]

The utility of the models in forecasting, relative to the random walk model, is evident from their ability to forecast abnormal returns (Column 8). On average, there is no significant reduction in the RMSE compared to a random walk model (Column 7). However, the likelihood of obtaining the predictions of change shown in Column 8 due to chance alone is extremely remote.[6] All but two of the models have only one regressor.[7] In ten models, non-accounting variables dominate accounting data as the explanatory variable. The market value of equities is the regressor in nine of these and real gross domestic product (GDP) is the regressor in another. Of the rest, six are earnings, nine are book value and five are dividend models, including one in real dividends (Corning). Alternative ECMs with accounting values as regressors exist but they are more marginal in terms of their explanatory power and usually inferior in forecasting performance.

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[5] Although we only show the recursive graphics for one company and one model, the patterns shown in the graphs of Figure 1 are representative for the great majority of the firms and (multiplicative) models discussed in this paper.

[6] This assessment is based on a sample size of 30 firms over nine years of data, sampling from a binomial distribution with a 50% probability of a score greater than 5. The models correctly predict the direction of one-year-ahead abnormal returns approximately 62% of the time in 270 hold-out periods over the 10 year hold-out period from 1995 to 2004 using data up to 1994. The probability that this is due to luck is not likely.

[7] In both of these exceptions, there are two regressors, the second being the price index. The sign and magnitude of the coefficients in each case suggests that the price index acts as a deflator on the other variable in the model (dividends in one case, GDP in the other).

The models in Table 4 are homogenous with respect to functional form but not with respect to regressors. The results indicate that functions of a variety of different variables, sometimes including non-accounting variables, can act as best ‘attractors’ to market value over time. Different firms appear to have different best attractors. In some, the book value of net assets is superior compared to earnings, whereas in others the situation is reversed. Also, there is usually too close a relationship between book value, earnings and dividends to be able to include more than one of these variables in firm-level dynamic models of market value.

A cross section model encompassing all the independent variables in the dynamic models shown in Table 4 would require the inclusion of six different regressors. To maintain efficiency of estimation with the small sample size and because the main issue is whether a common well-specified from of DGP exists, we estimate ECMs with the book value of net assets as the single explanatory variable. Book value has the advantage of only rarely being negative and thus minimizes the problems caused by missing values in log transformed data (see Footnote 3). Book value ECMs are frequently sub-optimal with respect to forecast ability, relative to the models shown in Table 4, but are still reasonably well-specified statistically and show, in about two-thirds of all firms, evidence of a consistent long-term relationship with market value. These results are consistent with those reported in Falta and Willett (2009). Details of the book value models for each firm are shown in Table 5.

[INSERT TABLE 5 ABOUT HERE]

Although the book value models in Table 5 are well-specified and have the same patterns of stability as shown in Figure 1, the individual firm-parameters of these models exhibit variability. This is indicated in the ILM, which now gives a rough indication of the simple, long-run linear multiplier on book value, equivalent to the long-run effect measured by the coefficients shown in Columns 3 to 4 of Table 5. The average of the ILMs is 3.76 with a standard deviation of 4.27.

Calculation of the ILM is dependent on the intercept term in the log-linear regression, and the standard error in that term produces volatility in the statistic. The maximum value observed is for Schering at 17.25 and the minimum is 0.07 for Gillette. However, this corresponds to variation in the simple market-to-book ratio over the entire period since the ILM only once, marginally, falls outside the range of the minimum and maximum market-to-book ratios observed by each firm. [8] Consequently, we take these patterns in the data to indicate variability in firm market-to-book parameters.

In Table 6, average dynamic and cross section estimates from book value, static regressions and ADLs underlying the book value ECMs are compared.[9] The average of the estimates from the cross section static model quite closely accords with the average of the theoretical long-run static estimates calculated using the dynamic models. However, this is not true of the coefficients in the ADL models. The average autoregressive coefficient in the cross section ADL is 0.94, while the average of the corresponding time-series coefficients is 0.81. Differences between the average cross section estimates on the regressors and the average of the corresponding time-series estimates are more noticeable, with an especially large increase in the average negative coefficient on the lagged regressor (-0.83 in the cross section, compared to a dynamic average of -0.38).

[INSERT TABLE 6 ABOUT HERE]

Estimating cross section models using time-averaged data, as assumed in the Pesaran et al. (1995) analysis, presents a similar picture (bottom row, Table 6). The cross section static models produce estimates that are similar to the average of the individual firm dynamic estimates (a = 1.62, b = 0.92). However, the cross section ADL estimates of the short-run coefficients based on time-averaged data are again quite different from the averaged individual firm parameter, i.e., they are k =

[8] Merck's highest market-to-book ratio is 14.56 observed in the year to 31 December 2000. The ILM is 14.7. The market-to-book ratio divided by the ILM is 1.38 with a standard deviation of 0.73.
[9] Parameters in these models are estimated over the full sample period 1955 to 2004. Tables A1 and A2 in the Appendices give details of the individual year and firm estimates.

0.07, α = 1.01, β_1 = 0.44 and β_2 = -0.46. Using the residuals from the relatively accurate cross section static model to produce a cross section version of the ECM in Expression (3.2) gives an estimate of the implied average error correction coefficient (λ = 1-α) close to zero. This is consistent with the cross section ADL estimate of α (i.e., λ =1-1.01= 0.01) but not with the average dynamic estimate of α (i.e., λ =1-0.81= 0.19), as it would be if the parameters of the individual firm DGPs were homogeneous.

Summarising the empirical results pertaining to our data, we find that a well-specified common functional from DGP of type (3.1) and (3.2) in book value exists, although it is not always statistical significant at 5% or 1% confidence levels. The autoregressive lag coefficient is the most significant aspect of the dynamics. The lagged regressor that is needed for stationarity of the dynamic model is often insignificant but its value relevance is demonstrated by the forecasting ability of the models in ten year hold out samples. The parameters in firm DGPs are stable over time but differ between firms. Static cross section models produce estimated coefficients quite close to the average of the implied long-run parameters across all firms. However, cross section forms of ADL and ECM do not yield estimates close to the average of estimates from their dynamic counterparts.

Most of these points are unsurprising: The existence of a well-specified common form DGP is necessary for cross section models to have a valid, averaging of parameters, interpretation. The weak evidence of cointegration is consistent with previous dynamic modelling studies in CMR (e.g., Qi et al., 2000). The multiplicative form of the models is consistent with the results in Falta and Willett (2009) using weighted averages of book values and earnings. Those static cross section levels regressions appear to give reasonably accurate estimates of average long-run effects in levels, which is consistent with Pesaran et al. (1995). However, the dissimilarity between the dynamic and cross section estimates in the case of the ADL and ECMs is important. We would expect consistency between cross section and dynamic models in well-specified, constant parameter models. Since we have checked all other aspects of model specification, we investigate the impact of parameter heterogeneity on cross section parameter estimation in the following section.

5. Implications of firm parameter heterogeneity for annual cross section analysis of the market-accounting relation

The implications of the empirical results in Section 4 for annual cross section modelling of data, with characteristics similar to those contained in the sample, are analysed in this section of the paper. It is sub-divided into two parts. First, the impact of non-stationary regressors in cross section static regressions, when parameters are homogeneous, is analysed. Second, the impact of firm-parameter heterogeneity on OLS estimates is discussed with the aid of computational experiments.

5.1 Sources of bias in static cross section regressions when parameters are homogeneous

The case of homogeneous parameters discussed in this sub-section refers to those situations where either firm DGP parameters are identical or they exhibit such little variation that for practical purposes their impact on estimation and inference can be ignored. This is the case that is often implicitly assumed in the annual cross section analysis of fundamentals (see Falta and Willett, 2009). When parameters in firm-level DGPs are homogeneous, ADL forms of cross section models provide reliable estimates of the implied long-run parameters based on annual data but static regressions may not.[10] Time-averaging of data is necessary to eliminate this bias. This problem and its solution came to light in running the experiments described in the following sub-section. We have not found any discussion of this point in the literature.

The need for time-averaging of data is illustrated here in the presence of a significant autoregressive coefficient in DGPs of type (3.1). Under these conditions, if the regressor is stationary,

[10] This phenomenon was first noticed when varying parameters in the experiments reported in the preceding section of the paper. To our knowledge, it has not been previously noted in the literature, neither in accounting nor elsewhere. The effect is not evident in the empirical data in Section 5 because the empirical parameters are heterogeneous and the regressors are close to having a unit root. Under these circumstances ADL forms exhibit bias but in static forms the bias is muted or absent.

annual cross section estimates of the long-run parameters derived using the static model are inconsistent, the bias being at a maximum when the DGP is white noise. In that case, the static model estimates give the short-run effect of the exogenous variable, not the long-run effect.[11]

Heuristically, the reason why this happens can be seen from considering the simple one variable static model when the firm DGPs for market value are homogeneous, containing a lagged dependent variable and no lags on the exogenous accounting variable, i.e. with DGPs of the form

$$M_{i,t} = \alpha_{i,1,t} M_{i,t-1} + \beta_{i,2,t} A_{i,t} + \varepsilon_t \tag{5.1}$$

Assuming a common zero intercept, the cross section estimate b_t is:

$$b_t = \frac{\sum_i A_{i,t} M_{i,t}}{\sum_i A_{i,t}^2} \tag{5.2}$$

Repeatedly substituting Expression (5.1) in Expression (5.2) yields, after n steps,

$$b_t = \alpha^n \sum_i M_{i,t-n} A_{i,t} + \alpha^{n-1} \beta \sum_i A_{i,t-n+1} A_{i,t} + \ldots + \alpha\beta \sum_i A_{i,t-1} A_{i,t} + \beta \sum_i A_t^2 \tag{5.3}$$

Consequently, assuming $A_{i,t}$ is stationary with autoregressive parameter γ, as $n \to \infty$, $i \to \infty$ and $\gamma \to 0$, $b_t \to \beta$ in probability (since $\Sigma A_{t-n}, A_t \to 0$). If, instead, $\gamma \to 1$, $b_t \to \beta/(1-\alpha)$ (since then $\Sigma A_{t-n}, A_t \to \Sigma A_t^2$). This problem continues to exist in the presence of heterogeneous parameters, which we consider next.

5.2 Heterogeneous parameters in firm DGPs

Two effects of parameter heterogeneity that are important in the context of interpreting cross section estimates of the long-run in CMR are discussed below. The first concerns their effect on the

[11] An implicit assumption made here is that the underlying DGPs have been in existence for a sufficiently long period to reach a representative dynamic state. If this assumption does not hold, a bias in estimates of the long-run, similar to the bias in dynamic models caused by finite sample periods, is introduced into static cross section models.

interpretation of variations in cross section parameter estimates over time, even if models are well-specified. Generally, variations in cross section parameter estimates over time should be interpreted with care as they may have nothing to do with variations in individual DGP parameters. The second effect of parameter heterogeneity concerns its impact on the ability of cross section models of levels and returns to accurately identify the average dynamics in the market-accounting relation for a sample of firms. Potential sources of bias in cross section estimates of long-run, persistent effects, may be created.

Cross section parameter variation over time. When parameters are heterogeneous, variation in cross section coefficient estimates over time, even if derived from well-specified models, can be caused by variations in factors other than changes in the systematic relationship between market and accounting values. In the simplest case, for example, where the individual firm-level DGPs for market value are described by a static regression on the single variable $A_{i,t}$, that is constant over time but where individual firm parameters differ, OLS yields the following estimated cross section slope coefficient for each t:

$$\hat{b}_t = \frac{\sum_i^n \alpha_i \sum_i^n A_{i,t} + \sum_i^m \beta_i A_{i,t} \sum_i^n A_{i,t} + \sum_i^n e_i A_{i,t} - n\left(\sum_i^n \alpha_i A_{i,t} + \beta_i A_{i,t}^2 + e_i A_{i,t}\right)}{\left(\sum_i^n A_i\right)^2 - n \sum_i^n A_i^2} \tag{5.4}$$

Unlike the situation where all the firm parameters are identical, neither the terms in α_i nor in X_{it} cancel and the OLS estimator of b_t is dependent on time, despite none of the individual firm coefficients varies through time. Expression (5.4) shows that the unconditional expectation of the estimated coefficient is equal to the population average of the firm's coefficients. However, it also shows that the expected value, conditional upon the sample, has a number of sources of variability, some of which could be large. In particular, the estimated cross section coefficient is not a simple average of individual firm parameters but is the outcome of a complicated weighting regime. In models containing more than one regressor, the complexity of the weights quickly explodes, making the interpretation of between-sample fluctuations in the estimated cross section coefficients difficult. It is possible that cross section coefficient variation over time reflects systematic changes in the market accounting relationship but parameter heterogeneity makes determining if this is the case problematic.

Effect of parameter heterogeneity on cross section estimates of average long-run effects. Pesaran et al. (2005) consider the consistency of estimates from static cross section models in random coefficient panel models. Interpreting this in the context of the market-accounting relationship, the DGP, for each firm *i*, is assumed to be:

$$M_{i,t} = \alpha_i M_{i,t-1} + \beta_i A_{i,t} + \varepsilon_{i,t}, \tag{5.5}$$

where the *i* subscript on the parameters indicates they may differ randomly between firms and $A_{i,t}$ is an exogenous accounting variable. The randomness in the coefficients is modeled as a parameter, perturbed by a white noise process. In one case, the exogenous variable is stationary and, in the other case, it is *I(1)* and cointegrated with the dependent variable. In both cases it is shown that heterogeneity of the parameters does not upset the consistency of estimates derived from static cross section models. The caveat, however, is that time averaging of the data for estimation is assumed in the proofs, implying that annual cross sections are inconsistent when this is not done.

The difficulty with applying this result in practice is that it depends upon asymptotic conditions and some regularity in parameter variation across firms that may not be observed. The impact of irregular parameter heterogeneity on static and ADL cross section estimates in finite sample sizes is illustrated through a Monte Carlo simulation experiment.

The experiment has two settings (cf. Table 7). The first illustrates the homogeneous case, the second the heterogeneous case. In both, micro data are generated using estimated parameters and starting values from the empirical, book value, dynamic ADLs, as reported in Section 4.

In Setting 1.1, 30 firm data are generated over 50 periods, using the average of the estimated, empirical mean values for each element in the ADL, producing homogeneous parameters for each firm. Only the error terms are random, with mean zero and standard deviation calibrated to the empirical, firm average, standard errors of 30 regressions. A larger sample of 3,000 firms is generated in Setting 1.2 by repeating the generation of firm data 100 times. The purpose of the latter setting is to illustrate what happens when the firm sample size is increased.

In Setting 2.1, simulated parameter values for 30 firms are generated by being set equal to the estimated mean value of their empirical counterpart firm, i.e., the parameter values are heterogeneous across firms, but constant over time. Parameters and starting values for a larger sample of 3,000 firms in Setting 2.2 are generated from a uniform distribution, using the minimum and maximum values of the thirty empirically estimated parameters as endpoints. Consequently there are 30 groups of 100 firms with parameters drawn from the same distributions within each group.

Setting 2.2, as with Setting 1.2, is designed to check on the state convergence properties of the estimates. Setting 2.1A, also shown in Table 7, creates data for 30 firms using the same method of generating data as in Setting 2.2. Its purpose is to link the results in Setting 2.1 with those from Setting 2.2. Both ADL and static forms of cross section models are estimated. Parameter estimates for the static cross section models for the last year in the simulation are calculated.

[INSERT TABLE 7 ABOUT HERE]

In Setting 1.*x*, all estimates are accurately recovered by the ADL cross section model as firm averages of the corresponding micro-level dynamic models. However, the annual parameter estimates from the cross section static form are biased due to the combined effect of the autoregressive coefficient and an exogenous regressor that is on average stationary (the autoregressive coefficient on the regressor DGP has an average value of 0.61). Extending the cross section to 3,000 firms, reduces the variance but does not eliminate this bias.[12]

[12] Averaging the variables over the 50 year period in the case of identical parameters almost eliminates the bias, with some residual effect of the relatively short time-series on the dynamic estimates of the slope coefficient.

Under Setting 2.1, the ADL model ceases to recover reliable estimates of the coefficients on book value. The autoregressive coefficient is close to 1 and the coefficients on book value take on nearly equal but opposite values, far from the true underlying parameter values (*k*: 0.05→0.33; *α*: 0.98→ 0.81; β_t : 0.04→0.55; β_{t-1} -0.2→-0.38). The R^2, however, approaches unity. This pattern repeats itself in the other settings. In Setting 2.1A, the resulting different parameter estimates (*k*: -0.13→1.13; *α*: 1.01→ 0.61; β_t : 0.99→0.94; β_{t-1} -0.99→-0.66) also test strongly (and wrongly) significant. When the sample size is increased in Setting 2.2, the same pattern persists (*k*: -0.22→1.13; *α*: 1.03→ 0.61; β_t : 0.96→0.94; β_{t-1} -0.98→-0.66). The R^2 in both of these experiments is virtually one. The annual estimates based on the static models under all three settings continue to show bias and test significant in large samples (e.g., *b*: 1.27 → 0.71 and *t(b)* = 10.78, with a between-sample standard deviation of 4.5 in Setting 2.2). However, the R^2 for the static model drops to 4%. The bias due to the process generating the regressor variable therefore does not mitigate significantly with increasing sample size. Using data averaged over 50 years reduces the bias in the static model under each setting (not shown in the table for reasons of space) but this is still noticeable at a firm sample size of 3,000 (*b* : 1.19→0.71, *t*(*b*) = 11.23).

It is clear from this experiment that the presence of parameter heterogeneity spoils the similarity between dynamic and cross section estimates. Further experiments show how extreme the effect of even a small amount of discontinuous heterogeneity can be in its effect on cross section estimation. For example, if the values of all parameters in 3,000 simulated firm DGPs are set to one, except for a constant autoregressive parameter of 0.8, both dynamic and cross section OLS estimates over 50 periods are accurate and virtually identical. If only a single DGP is introduced into the sample consisting of two independent unit root processes (i.e., no relationship between the dependent and independent variables exists), the ADL cross section model exhibits the pattern of estimated coefficients evident in the experiment described in the preceding paragraphs and in the empirical modelling of Section 4. The autoregressive coefficient approximates unity and the coefficients on the regressor and its lag are of approximately equal and opposite magnitude. Furthermore, again, the static regression again exhibits a bias even when time-averaged data are used, and does not appear to decrease as the sample size increases.

This ‘bad apple’ effect, of a single or few noisy observations spoiling the inferential properties of cross section models, is likely to be important in CMR. The empirical evidence relating to CMR data, such as that displayed by the sample data in Section 4, makes it very probable that some observations in any sample of firm market and accounting values will be closer to being independent *I(1)* processes than to being significantly cointegrated, thus upsetting parameter estimation.

The extent of inconsistency in cross section coefficient estimates thus varies with the magnitude of the autoregressive coefficients in the DGPs of both the dependent *and* the exogenous variables, directly in one case and inversely in the other. To achieve consistent estimates of long-run effects using static regressions then requires using time-averages of the data, based on time periods, commensurate with an extent that allows the long-run effect to work on the dependent variable (e.g., see Pesaran et al., 1995; Easton et al., 1992). Unfortunately, short of averaging across the entire sample period, this information is only available from knowledge of the average lag structure, which must be gleaned from an ADL type model. Parameter heterogeneity thus prevents dynamic information being recovered by cross section means alone. In the next section, as an alternative to annual cross section modelling, we implement the Pesaran et al. (1995) strategy by using a fixed effect panel analysis.

6. Fixed effects analysis

In our study, all the evidence indicates that, compared to the cross section firm parameters, estimates of the individual dynamic parameters of the simple models we study are relatively stable over fairly long periods of time. Within sample, instability tests of the dynamic parameters of the

ECMs in book value shown in Table 5, estimated over the entire period from 1955 to 2004, are negative at the 5% level in only one instance in a total of 60 tests.[13] Recursive graphs of parameter estimates, such as shown in Figure 1, invariably exhibit the same stable patterns. The stability of the models is what makes it possible to use ten year hold-out samples to test the robustness of the model specifications (see Table 4, Column 8). Figure 2 shows the forecast performance of Motorola's book value model and illustrates this point - see Tables 4 and 5, eight rows from the foot of each table. The direction of abnormal returns is correctly predicted eight times in the ten year hold-out period, based on a model estimated using data between 1955 to 1994 and regressor variables observed in the preceding period.

[INSERT FIGURE 2 ABOUT HERE]

The sample data suggest stable parameters over time for individual firms but idiosyncratic market-accounting relations, having varying parameter values between firms. In these circumstances, it is natural to use a fixed-effect panel analysis with individual intercepts *and* slope coefficients to estimate the average parameter values of the firm sample, assuming they have a common-form DGP.[14] This way of estimating the parameters returns the same estimates shown in earlier tables, since it is equivalent to running 30 separate dynamic regressions. Table 8 shows the fixed-effect estimates for the ECM of raw returns based on data from 1955 to 1994.

[INSERT TABLE 8 ABOUT HERE]

The average short-run coefficient on the proportional change in book value is 70% and the error correction coefficient averages to 25%. This implies that, on average for this sample, an imbalance between the expected long-run relationship between book and market value in any year is corrected over a period of four subsequent years. The average *t*-distribution probability in a two

[13] These tests are based on *PcGive* (Hendry et al., 2001).
[14] Most textbooks and software treat fixed effects panel analysis only in the context of varying intercepts due to a degrees of freedom problem. The length of our time period permits us to allow the slope parameters to vary also.

tailed test for the error correction coefficient is 10%.[15] The short-run coefficient *t* probability is lower at 30%. Five firms have weak error correction effects, indicating an adjustment period greater than ten years. Twenty five firms have error correction periods less than 10 years, 17 less than 5 years, 13 less than 4 years, six less than 3 years and three less than 2 years. These numbers shift towards a longer period of adaptation if the full sample, through to 2004, is used for estimation. Twenty three firms then have error correction periods of less than 10 years, seven less than 5 years, six less than 4 years, four less than 3 years and two less than 2 years.

The evident movement in the parameters of the ECM in the hold-out period does not markedly affect the overall stability of the model, however. Figure 3 compares the time sequences of the actual raw returns with the ECM predicted values, estimated on the basis of the shorter period (with a 10 year forecast period) and the longer period (with no hold-out period). There is very little apparent change in the time series behaviour of the model predictions, again illustrating the relative stability of the model.

[INSERT FIGURE 3 ABOUT HERE]

Reflecting the changes just noted, however, during the early 1990s, the average ECM loses touch with the raw returns series but appears to reacquire it in 2001. Together with the diminishing coefficients on the change in book value and the error correction term, this might be taken as implying that value relevance of book value diminished during the 1990s. Nevertheless, the fact that there is a discernable ability of the book-to-market ratio to forecast abnormal returns through the hold-out period, one year ahead in the average data, is consistent with the results reported in Section 4. Figure 4 exhibits the tracking of the actual average data series by the short and long-run components of the model separately. It shows how each component contributes to the overall explanatory and predictive power of the model in the average data. In the hold-out period from 1995

[15] The average t-statistic for this coefficient across the 30 firms is greater than this figure might suggest, having a value of -2.34.

to 2004, the short-run component predicts the direction of abnormal returns seven times out of ten and the error correction component six times out of ten. These proportions are like their individual firms counterparts based on the estimation period up to 1994 and, in the case of the market-book error correction term, data one year prior to the observed raw returns. Thus, although the error correction component in book value's ability in forecasting is marginal, it is systematic and representative of the overall ability of the pure error correction book models (cf. Table 5) to predict raw returns one year ahead.

[INSERT FIGURE 4 ABOUT HERE]

7. Discussion and conclusions

In Falta and Willett (2009) we showed that additive linear models of the sort usually used to model fundamental theories in CMR are misspecified when applied to our sample data. We proposed that multiplicative models of the market-accounting relation are more appropriate and showed that they provide better-specified models of our data. We analysed the consequences of using misspecified additive models and their derivative returns formulations. Our findings are that the usual inferential t and R^2 statistics can be misleading in these circumstances, and we showed that using larger samples makes the problem worse.

Our earlier paper focused on misspecification of the functional form of the market-accounting relation. In this paper, we showed how, even if all aspects of specification are satisfied, annual static cross section regressions may not provide reliable estimates of persistence due the dynamic properties of the regressor variables. More importantly, we show that if the only source of misspecification in a regression model is firm-parameter heterogeneity, it prevents the identification of short-run and long-run effects by cross section analysis alone. This applies particularly in the case of returns regressions, which have traditionally been investigated using the technique of deflation by opening market value.

The main empirical findings of interest in this paper are that a detailed investigation of the dynamics of each firm's DGP confirms that multiplicative models provide good candidates for a common functional form of regression model of the market-accounting relation, for all firm samples exhibiting similar patterns in variables. The individual DGPs all have a strong autoregressive element. However, the testing-down approach to model building, adopted in Section 4, indicates that simple, single variable regressions provide the best models of the market-accounting relation. In individual dynamic models, accounting variables with a single period lag show weak evidence, compared to the autoregressive component, of being 'value relevant', in the sense of being able to forecast raw returns, one year hence. The parameter estimates in these dynamic models appear to be relatively stable over time, compared to their values between firms. This permits the use of a fixed effects panel analysis of the firm parameters, holding the parameters constant over time. The fixed effects analysis allows recovery of estimates of average firm parameter values for a cross sectional equivalent of an ECM of the market-accounting relation. In our sample, the average implied long-run market-to-book value ratio is about 3.6 and the error correction term on the market-to-book ratio is about 20%, implying that it takes about five years on average to impound the long-run impact of a change in book value into market value.

The implications for CMR into fundamentals are that inferential statistics should not be trusted in the absence of a clear demonstration that a model is well-specified. There is no point in using large samples of data unless models are well-specified, as increasing the size of sample under those conditions will simply increase confidence in a wrong result. In particular, the common procedure of deflating market value by market value should not be adopted: It is unlikely to return valid estimates of the parameters of interest and, due to sample variability, can return indications of a significant relationship, when in fact there is none.

The book value of net assets or 'equity' was used in this paper to illustrate the thesis that, if cross section analysis is to be used, it must be possible to identify a common, well-specified form of firm-level DGP. There is probably no good reason for not using either earnings (as is done in Alexander et al. (2009)

or dividends instead, or as we did in Falta and Willett (2009), an empirically weighted average of two of these variables). However, the error correction treatment of the book value model does raise interesting questions as to the implications for regression analysis of the classic treatment of the market-to-book ratio as an indicator of 'risk' (Fama and French, 1992). The error correction interpretation of the market-to-book ratio implied in this paper is that if there is a long-run or persistent relationship between market and book value, the market value has to reflect corrections to the long-run value implied by the book series. This is a simple interpretation of the market-to-book ratio and is not necessarily inconsistent with the risk interpretation. However, it does raise the question of how return and risk might be identified as separate components in a regression analysis. Initially it might be supposed that the ECM is an explanation of returns but there is also a sense in which it is an explanation of risk. The further apart market and book become, the more likely they are to revert to the value of the other and the more likely the movement in market is to be larger. This poses something of a dilemma if it is proposed to try to reduce firm parameter heterogeneity by the addition of regressors that might be expected to factor out some of the variability from the returns parameters.

Another quite topical implication of this paper relates to the literature on 'scaling'. Scaling seems to be the cause of much confusion. There is a viewpoint that the way in which a regressor variable is scaled somehow causes misspecification in cross section studies. This is based on the presumption that firms in different size categories have different characteristics and this leads to 'bias' in estimation. It is a basic fact of regression modelling that differences in the scale of the regressor variables are usually a good thing, not a bad thing. It promotes greater precision in estimates if the explanatory variables possess variability. We suggest that the real cause of the problem of misspecification is heterogeneity in parameters, not scaling. The problem with different categories of firms in different size groups is that they have DGPs with substantially different parameters, not that the values of their accounting and market values are of a different scale.

The main limitations of our work are that it focuses on a particular estimation method (OLS) and a small subset of non-randomly selected firms to show, that certain things that traditionally have been claimed for cross section work in CMR, generally cannot be so claimed. It is an existential argument, not a universal one. We cannot draw any conclusion about loss-making firms from our analysis, for instance. However, the primary purpose of our work is to show that something is *not* universally the case rather than that certain things *are* generally true. It suggests the possibility of dealing with the problems that it identifies and points to various new research questions.

What we have suggested is that, once a thorough specification testing regime has identified a sensible statistical model, fixed effects panel data modelling that implements Pesaran et al.'s (1995) strategy should be used in the analysis of fundamentals, if sufficient time series observations are available to make this possible. If this is not possible, the likely dynamics of the firms in a sample should at least be considered, particularly to see if firm parameter heterogeneity is likely to be a problem. The degree of parameter heterogeneity at any size of firm sample can be checked using OLS by estimating the cross section form of ADL in Expression (3.1). The closer the distance of the estimate of the autoregressive coefficient from one, and the closer the regressors and their lags are to being equal and opposite in magnitude, the more is parameter heterogeneity likely to cause estimation problems.

The magnitude of the pervasive autoregressive coefficient in dynamic market-accounting regressions reflects the strength of the effect of accounting variable on market value and cannot be ignored simply by switching to a cross section analysis. In the absence of any regressors, market value typically follows a random walk and the autoregressive coefficient has a value of one. The distance of this coefficient from one (and of the error correction from zero) is therefore an index of the strength, or immediacy, of the effect of the accounting variable on market value. Unless a reliable estimate of the error correction coefficient can be obtained, an appreciation of the impact of accounting on market value cannot be gained. Static cross section regressions alone cannot provide the information required to measure the value relevance of accounting information.

Another limitation of our analysis, alluded to above, is that it does not investigate the potential for additional variables in the cross section models to cure the problem of parameter heterogeneity. For example, if a meaningful risk measure, uncorrelated with the returns variable in a model could be identified, this would presumably extract a potential source of heterogeneity in parameters on accounting variables. However, it seems to us progress is most likely to be made in finding practical ways to dealing with parameter heterogeneity, in the absence of long stable time series of data, by mixed analytical and computational methods, such as the simulated maximum likelihood approaches advocated by Greene (2008) and others.

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Table 1
Procedure used to derive empirical ECMs in Section 5.

Step 1:	Formulate an unrestricted ADL including all the variables in the data set as regressors. Use 2 lags on all variables. Include a constant and trend and use a hold out sample of ten periods. Estimate the model using OLS.
Step 2:	Test the model for correct functional form (Note 1) and the residuals for heteroskedasticity (Note 2), autocorrelation (Note 3), and Normality (Note 4).
Step 3:	Eliminate the trend term if its estimate proves statistically insignificant. Return to Step 2 and re-estimate the model if the trend is dropped.
Step 4:	Compute the long-run solution for the ADL and test the significance of lags (Note 5).
Step 5:	If the second lag length tests jointly insignificant for all variables and there is no evidence of significance in any variable at that lag length, eliminate that lag length (Note 6). Repeat from Step 4 until all such lags have been eliminated.
Step 6:	Eliminate insignificant explanatory variables one-by-one, starting with the least significant *t*-statistic in the long-run solution (Note 7). Repeat Steps 4 to 6 in each case. Repeat until all variables in the model test significant in the long-run dynamics at the adjusted significance level.
Step 7:	Calculate the equilibrium correction term (ECT) implied by the long-run solution at the completion of step 6, using the exact estimates computed for that solution. Note whether Augmented Dickey Fuller (ADF) unit root tests indicate that the ECT is stationary.
Step 8:	Reparameterise the ADL as an ECM, dropping all contemporaneous differenced variables. If necessary repeat Step 6 on the reparameterised model until all insignificant variables at the adjusted significance level have been eliminated. The resulting model is the statistical ECM for the chosen dependent variable, given the initial data set.
Step 9:	Compare the statistical ECM with other models based on criteria contained in Table 2.
Notes:	
1	RESET test (Ramsey, 1969).
2	Based on White (1980).
3	*F*-test form for unconditional autocorrelation (Harvey, 1990).
4	Doornik and Hansen (1994).
5	The critical value for a Type I error using *t*-statistics to assess the significance of the coefficients from the OLS and long-run estimates is computed as $1-(1-\alpha)n$, where α is the nominal significance level of 5% and n is the number of repetitions on the reduction procedure (Maddala, 1998, pp. 425). This is referred to as the 'adjusted' significance level. See Hendry et al. (2001, pp. 255-257) for details of how the long-run solution and lag coefficients are estimated.
6	Based upon the *t*-statistics for the OLS estimates and the tests described in Hendry and Doornik (2001, pp. 257, Sections 18.3.2.1, 18.3.2.2 and 18.3.3).
7	Using tests on the 'static long-run parameters' defined in Hendry and Doornik (2001, pp. 255-6, Section 18.3.1).

Table 2
Criteria used for judging the strength of an ECM as an explanation of market value.

Criterion	**Details of criterion**
Misspecification tests	The number of diagnostic tests showing significant model misspecification, as described in the Notes to Table 1. The fewer of these reported, the better the model.
t	The strength of significance of the standard t-statistic on model coefficient estimates. The higher the t-statistic, the better the model.
R^2	Standard R^2 statistic. Used as an indicator of goodness of fit of model in the estimation period.
Unit root test	Augmented Dickey Fuller test for the presence of a unit root in the ECT. Statistical significance of this test suggests the ECT is stationary and is evidence of a long-run-relationship between market value and the regressor variables.
Average forecasting performance: Reduction in RMSE of model forecasts over the ten year hold-out period compared to a random walk with drift model.	The difference in the hold-out period between the root mean square error of the ECM and the root mean square error of a simple random walk model. The strength of a model is directly related to the extent that the RMSE of the ECM is reduced relative to the random walk model.
Direction: Prediction of sign on abnormal returns relative to long-run average	The number of times the model correctly predicts the direction of change, one period ahead, in raw returns. A ‘value relevant’ ECM is expected to more often correctly predict the change of direction of raw returns than a random walk (i.e. five times out of ten, on average).
Interpretation: ILM	In the case of the variable in a multiplicative relationship of the type $M = \alpha A_t^{\beta}$, the number a such that $a = \alpha A_t^{*\,(\beta\text{-}1)}$, where A^* is the mean value of the time-series data in A_t. The ILM is expected to be of the same order as the linear multiplier defined by the long-run average ratio of M_t/A_t.

Table 3
Definitions and sources of data used in empirical models.

Data	Sources
Earnings, dividends and book value of net assets	As defined by Compustat annual data item numbers A172, A21 and A60 respectively. Sources: Compustat tapes: 1955-1998; Mergent Online 1999 -2002; Company website 2003.
Market value	Defined as share price at fiscal year-end (A199) multiplied by the number of shares outstanding. Sources: Compustat 1955 - 1998; Datastream 1999 - 2002; Company website 2003.
GDP	Source: US Bureau of Economic Analysis National Income Accounts, NIPA Tables. Series code: A191RL1. http://www.bea.doc.gov/bea/dn/nipaweb/DownSS2.asp). Files downloaded on 7/20/2004.
Interest rate	Prime rate of interest in money and capital markets for the twelve months ending December. Source: Board of Governors of Federal Reserve System. http://www.federalreserve.gov/releases/h15/data/a/prime.txt. Files downloaded 7/19/2004. 2003 data downloaded 2/9/2003.
CPI	U.S. city average consumer prices, all items. Series Id: CUUR0000SA0, CUUS0000SA0. Source: US Department of Labor, Bureau of Labor Statistics http://data.bls.gov/cgi-bin/surveymost. Files downloaded 7/19/2004.
Productivity index	Output per person. Source: US Department of Labor, Bureau of Labor Statistics. Series Id: PRS84006163. Sector: Business. http://data.bls.gov/servlet/SurveyOutputServlet. Files downloaded 7/19/2004.
Foreign exchange index	Foreign currency units per 1 U.S. Dollar, 1948-2003. 2004 data is an equally weighted average for 23 countries (excluding Indonesia) taken from the following source: Pacific Exchange Rate Service (University of British Columbia). http://fx.sauder.ubc.ca.
Credit supply	Total Credit Market Debt. Source: Flow of Finds Accounts of the Board of Governors of the Federal Reserve. Table L1 Page 50. Files downloaded 7/24/2004.
Value of US equities	Market value of corporate equities. Source: Flow of Funds Accounts of the Board of Governors of the Federal Reserve. Table L213 page 82. Files downloaded 7/24/2004.

Table 4
ECMs for 30 firms determined statistically by an empirical testing down procedure. Column 1: Firm name. Column 2: OLS estimates of parameters of model specification $\boldsymbol{M_t}/\boldsymbol{M_{t-1}} = k_i \left(\frac{\kappa_i(\boldsymbol{A_{i,t-1}})^{\varphi_i}}{\boldsymbol{M_{i,t-1}}}\right)^{\boldsymbol{\lambda_i}} \omega_{i,t}$. Notes apply. Column 3: ILM. Column 4: Misspecification tests significant at the 5% level or lower in tests defined in Table 1. Column 5: Probability p(λ) of λ being different from zero. Column 6: R^2. Column 7: Reduction in RMSE of one year ahead model forecasts compared to a random walk with drift model. Column 8: Number of times, out of ten, one year ahead direction of change in M_t/M_{t-1} correctly predicted. Column 9: Augmented Dickey-Fuller unit root tests of the error correction term significant at the 5% level or lower in at least one of zero, one or two lags, when a constant is included.

1	2	3	4	5	6	7	8	9
Abbott Laboratories	$1.05(27.4E_{t-1}^{0.98}/M_{t-1})^{0.32}$	24.03		0.0	0.19	0.04	7	*
Bausch and Lomb	$1.28(0.52B_{t-1}^{1.2}/M_{t-1})^{0.44}$	1.73	Normality; RESET	0.02	0.2	-0.01	7	*
Baxter International	$1.26(153.22D_{t-1}^{0.52}/M_{t-1})^{0.12}$	16.34		0.01	0.17	0.03	8	*
Bristol Myers	$1.25(74.14D_{t-1}^{0.78}/M_{t-1})^{0.20}$	18.33		0.01	0.15	0.04	7	*
Coca Cola	$1.13(33.1E_{t-1}^{0.92}/M_{t-1})^{0.12}$	18.88	Normality	0.24	0.04	0.03	5	
Colgate	$1.06(0.11V_{t-1}^{1.30}/M_{t-1})^{0.20}$	NA		0.05	0.1	0.02	5	*
Cooper	$1.14(1.19B_{t-1}^{1.06}/M_{t-1})^{0.80}$	1.8		0.0	0.36	0.01	5	*
Corning	$1158(0.98D_{t-1}^{1.78}/I_{t-1}^{1.35}M_{t-1})^{0.25}$	NA	Normality	0.15	0.05	0.07	8	*
Du Pont	$1.00(7.86D_{t-1}^{1.11}/M_{t-1})^{0.43}$	16.06		0.01	0.3	-0.01	6	*
Eaton	$1.06(1.04B_{t-1}^{1.08}/M_{t-1})^{0.18}$	1.78		0.12	0.06	-0.02	8	*
General Electric	$6.98(1.08V_{t-1}^{1.09}/M_{t-1})^{0.13}$	NA	Normality	0.37	0.02	0.0	6	*
General Motors	$1.0(20516E_{t-1}^{0.01}/M_{t-1})^{0.34}$	12.43	Autocorrelation	0.00	0.17	-0.03	7	*
Georgia Pacific	$1.07(17.62B_{t-1}^{0.7}/M_{t-1})^{0.31}$	1.88		0.0	0.23	0.04	9	*
Gillette	$1.04(3.47E_{t-1}^{1.67}/M_{t-1})^{0.05}$	165.34		0.34	0.024	0.01	6	*
Goodyear	$1.02(48.61B_{t-1}^{0.51}/M_{t-1})^{030}$	1.26	Normality	0.02	0.14	0.01	7	*
Hercules	$0.99(73.37B_{t-1}^{0.49}/M_{t-1})^{0.19}$	2.37		0.07	0.07	0.28	5	*
Ingersoll	$1.00(22.50B_{t-1}^{0.63}/M_{t-1})^{0.29}$	1.26		0.03	0.12	0.17	5	*
IBM	$1.05(661.80B_{t-1}^{0.43}/M_{t-1})^{0.35}$	2.71		0.00	0.23	0.16	8	*
International paper	$6.58(1.07V_{t-1}^{0.83}/M_{t-1})^{0.25}$	NA	Autocorrelation	0.04	0.11	-0.02	7	*
Johnson & Johnson	$0.87(1.05V_{t-11.60}/M_{t-1})^{0.13}$	NA		0.05	0.1	0.02	3	
Lilly	$0.63(1.04V_{t-1}^{1.27}/M_{t-1})^{0.20}$	NA		0.02	0.15	-0.03	5	*
Merck	$1.14(67.37E_{t-1}^{0.8}/M_{t-1})^{0.18}$	15.22		0.04	0.11	-0.02	6	*
Motorola	$1.26(2.58B_{t-1}^{0.94}/M_{t-1})^{0.36}$	1.6		0.02	0.14	-0.06	8	*
Pfizer	$0.12(1.07V_{t-1}^{1.45}/M_{t-1})^{0.37}$	NA	Normality	0.01	0.16	-0.04	6	*
Raytheon	$9.84(1.09V_{t-1}^{0.74}/M_{t-1})^{0.06}$	NA		0.27	0.1	-0.01	7	*
Rohm	$2.05(1.08V_{t-1}^{0.86}/M_{t-1})^{0.21}$	NA		0.09	0.07	-0.01	8	
Schering	$1.13(56.17D_{t-1}^{0.76}/M_{t-1})^{0.06}$	13.45		0.49	0.01	-0.01	8	*
Tektronix	$0.01(0.99G_{t-1}^{6.0}/I_{t-1}^{7.34}M_{t-1})^{0.12}$	NA		0.36	0.02	0.0	6	*
UST	$0.14(1.08V_{t-1}^{1.30}/M_{t-1})^{0.05}$	NA		0.62	0.01	-0.01	8	*
United Technologies	$1.20(10.61E_{t-1}^{1.03}/M_{t-1})^{0.53}$	12.43		0.00	0.26	0.04	6	*

Note: The model specification is shown in its accounting to market value ratio form, which gives a positive sign of the error correction term λ_i, and contains an additional constant term k. The additional constant is included to check the orthogonality of the short and long-run variables in the model. If the additional constant term k is not close to unity it indicates the estimates of the parameters of the model may be biased.

Table 5

Book value ECMs. Results for model ${M_t}/{M_{t-1}} = \boldsymbol{k_i}\left(\frac{\kappa_i(B_{i,t-1})^{\varphi_i}}{M_{i,t-1}}\right)^{\lambda_i}\omega_{i,t}$. Column 1: Firm name. Columns 2-5: Coefficients (2: *k*; 3: κ; 4: φ; 5: λ). Columns 6-8: Long-run solution (6: standard error of φ; 7: ILM; 8: Augmented Dickey-Fuller unit root tests significant at the 5% level or lower). Columns 9-13: ECM (9: Probability $p(\lambda)$ of λ being different from zero; 10: R^2; 11: Misspecification tests significant at the 5% level or lower in tests defined in Table 1; 12: Reduction in RMSE of one year ahead model forecasts compared to a random walk with drift model; 13: Number of times, out of then, one year ahead direction of change in M_t/M_{t-1}correctly predicted).

	Coefficients				Long-run solution			ECM				
1	2	3	4	5	6	7	8	9	10	11	12	13
Abbott	1.06	1.24	1.23	0.32	0.08	7.27		0	0.21		0.0	7
Bausch	1.28	0.52	1.20	0.44	0.10	1.75	**	0.02	0.20	Normality, RESET	0.01	7
Baxter	1.21	10.11	0.77	0.20	0.11	1.53	**	0.02	0.15		-0.01	5
Bristol	1.27	5.26	0.89	0.16	0.15	2.12		0.01	0.13		-0.03	7
Coca Cola	1.08	2.47	1.22	0.06	0.59	14.38		0.39	0.02	Normality	-0.01	2
Colgate	1.08	2.20	1.11	0.04	0.62	4.67		0.69	0.0		-0.01	6
Cooper	1.08	1.19	1.06	0.80	0.03	1.75	**	0	0.36		-0.01	5
Corning	1.08	38.68	0.58	0.13	0.36	1.90	*	0.15	0.06	Normality	-0.01	7
DuPont	1.01	2.05	1.03	0.16	0.44	2.77		0.01	0.19		0.03	7
Eaton	1.06	1.04	1.08	0.18	0.22	1.78	*	0.12	0.06		0.02	8
General Electric	1.10	6.40	0.90	0.26	0.19	2.41		0.02	0.15	Normality	0.10	6
General Motors	1.0	112184.5	-0.19	0.30	0.22	1.25	**	0.01	0.16		0.02	8
Georgia Pacific	1.07	17.62	0.70	0.31	0.17	1.88	**	0.0	0.23		-0.04	9
Gillette	0.94	0.38	0.58	0.03	2.47	0.02	**	0.24	0.04		0.01	6
Goodyear	1.02	48.61	0.51	0.30	0.32	1.26	*	0.02	0.14	Normality	0.01	7
Hercules	0.99	73.37	0.49	0.19	0.24	2.37	**	0.07	0.07		0.28	5
Ingersoll	1.0	22.50	0.63	0.29	0.16	1.60		0.03	0.12		0.17	5
IBM	1.05	661.80	0.43	0.33	0.12	2.71	**	0.0	0.23		0.16	8
International Paper	1.02	0.34	1.12	0.10	0.11	0.95		0.14	0.46		0.02	8
Johnson & Johnson	1.10	10.88	0.91	0.09	0.27	5.12	**	0.20	0.05		0.02	7
Lilly	1.12	20.39	0.75	0.11	0.18	2.84		0.14	0.06		0.01	7
Merck	1.01	108.02	0.76	0.09	0.36	14.70		0.14	0.06		-0.03	5
Motorola	1.26	2.58	0.94	0.37	0.07	1.60	**	0.02	0.14		-0.06	8
Pfizer	0.99	10.45	0.90	0.26	0.11	4.27	*	0.01	0.15		0.20	7
Raytheon	1.27	0.80	1.09	0.38	0.06	1.55	**	0.02	0.13	Autocorrelation, Normality	0.10	7
Rohm	1.06	2.33	0.99	0.11	0.45	2.14	*	0.14	0.06		0.01	6
Schering	1.02	197.89	0.67	0.05	0.81	17.25		0.42	0.02		-0.01	8
Tektronix	1.03	4.31	0.87	0.22	0.19	1.71	**	0.04	0.11		0.02	7
UST	1.08	0.71	1.09	0.25	0.13	1.40		0.04	0.11		0.16	8
United Technologies	1.0	0.26	1.60	0.34	0.12	5.93		0.0	0.27		0.45	2

Table 6
Comparison of average dynamic and average cross section coefficient estimates of ADL and static forms of the market-accounting relationship for 30 firms over the period 1955 to 2004.

	ADL								**Static regression**			
	$M_{i,t} = k + \alpha M_{i,t-1} + \beta_1 B_{i,t} + \beta_2 B_{i,t-1} + \upsilon_i$, for each year t								$M_{i,t} = a + bB_{i,t} + \varepsilon_i$, for each year t			
	k	$p(k)^1$	α	$p(\alpha)^1$	β_1	$p\beta_1)^1$	β_2	$p\beta_2)^1$	a	$p(a)^1$	b	$p(b)^1$
Dynamic models												
Average (across firms) [2]	0.33	0.34	0.81	0.00	0.55	0.26	-0.38	0.33	1.83	0.14	0.89	0.03
Average standard deviation [2]	0.59	0.29	0.17	0.02	0.55	0.28	0.46	0.31	2.74	0.24	0.40	0.13
Cross section models												
Average (over time) [3]	0.12	0.35	0.94	0.00	0.87	0.23	-0.83	0.20	1.88	0.18	0.91	0.00
Average standard deviation [3]	0.43	0.30	0.18	0.00	0.84	0.29	0.78	0.26	2.05	0.20	0.24	0.01
Using time averaged data[4]	0.07	0.01	1.01	0.00	0.44	0.07	-0.46	0.07	1.62	0.61	0.92	0.09

Notes

1. $p(x)$ denotes the p value associated with the estimate x.

2. Average (across firms) is the average of the dynamic estimates and statistics over the 30 firms. The Average standard deviation in this case is the average standard deviation of the dynamic estimates and statistics over the 30 firms.

3. Average (over time) is the average of the cross section coefficient estimates and statistics over the 50 year time period. The Average standard deviation in this case is the average standard deviation of the cross section estimates and statistics over the 50 year time period.

4. Using time averaged data: Estimates are calculated for each model using data averaged over the period 1955-2004.

Table 7
Experiment to illustrate the impact of parameter heterogeneity in data generating processes on cross section model estimates and inferential statistics. Shown are Average estimates and inferential statistics under four different degrees of heterogeneity. For the DGPs, data are generated across all *t* for each *i*. The cross section models are estimated across all *i* for each *t*.

Dynamic DGP and cross section models		ADL: $M_{i,t} = \alpha + kM_{i,t-1} + \beta_1 B_{i,t} + \beta_2 B_{i,t-1} + \upsilon_{i,t}$					Static Model: $M_{i,t} = a + bB_{i,t} + \varepsilon_{i,t}$		
Setting	Parameters	k $t(k)$	α $t(\alpha)$	β_1 $t(\beta_1)$	β_2 $t(\beta_2)$	R^2	a $t(a)$	b $t(b)$	R^2
1.1	30 Firms;50 Years; 1000 repetitions								
	Average firm dynamic parameters (Note 1)	0.33 n/a	0.81 n/a	0.55 n/a	-0.38 n/a		1.77 n/a	0.92 n/a	
	Average cross section estimates	0.32 1.77	0.82 8.22	0.55 5.2	-0.38 -2.94	0.91	2.8 4.35	0.76 8.46	0.71
	Monte-Carlo standard deviation (Note 2)	3.59 1.12	0.11 2.0	0.12 1.43	0.14 1.23	0.03	0.68 1.32	0.1 1.92	0.09
1.2	3000 Firms;50 Years; 200 repetitions								
	Average firm dynamic parameters (Note 1)	0.33 n/a	0.81 n/a	0.55 n/a	-0.38 n/a		1.77 n/a	0.92 n/a	
	Average cross section estimates	0.33 7.21	0.82 84.13	0.55 53.03	-0.38 -29.6	0.91	2.9 44.95	0.77 85.1	0.7
	Monte Carlo standard deviation (Note 2)	0.05 1.03	0.01 1.72	0.01 1.33	0.01 1.09	0	0.07 1.28	0.01 1.89	0.01
2.1	30 Firms;50 Years; 1000 repetitions								
	Average firm dynamic parameters (Note 1)	0.33 n/a	0.81 n/a	0.55 n/a	-0.38 n/a		1.77 n/a	0.92 n/a	
	Average cross section estimates	0.05 0.15	0.98 21.26	0.04 0.6	-0.02 -0.35	0.97	5.37 5.16	0.54 4.53	0.42
	Monte Carlo standard deviation (Note 2)	0.38 1.05	0.05 5.69	0.09 1.14	0.09 1.14	0.01	1.84 2.11	0.2 1.93	0.18
2.1A	30 Firms;50 Years; 1000 repetitions								
	Average firm dynamic parameters (Note 1)	1.13 n/a	0.61 n/a	0.94 n/a	-0.66 n/a		2.89 n/a	0.71 n/a	
	Average cross section estimates	-0.13 -0.14	1.01 427.62	0.99 6.43	-0.99 -6.38	1	8.28 0.2	1.31 0.18	0.03
	Monte Carlo standard deviation (Note 2)	1.73 2.13	0.01 215.6	0.57 4.48	0.58 4.53	0	57.91 0.93	6.91 0.98	0.05
2.2	3000 Firms;50 Years; 200 repetitions								
	Average firm dynamic parameters (Note 1)	1.13 n/a	0.61 n/a	0.94 n/a	-0.66 n/a		2.89 n/a	0.71 n/a	
	Average cross section estimates	-0.22 -3.49	1.03 4363.2	0.96 31.22	-0.98 -31.3	1	9.25 1.98	1.27 10.8	0.04
	Monte Carlo standard deviation (Note 2)	0.09 1.19	0 370.9	0.04 4.14	0.04 4.07	0	7.27 1.5	0.6 4.5	0.03
Notes	1. Average firm dynamic parameters: Theoretical parameters used to generate data 2. Monte Carlo standard deviation: Between-sample standard deviation based on Monte Carlo experiments. The standard errors of the average values are approximately one-thirtieth and one-fourteenth of the size of the standard deviations, for the 30 firm and 3000 firm experiments respectively, based upon the number of repetitions of the experiment.								

Table 8
Fixed effects coefficients for full error correction model estimated on period 1955 to 1994. Note that $\beta_{i,1}$ is the coefficient on the proportional change in book value; λ is the error correction coefficient. Probability is the t probability in a two tailed test.

Firm	$\boldsymbol{\beta_{i,1}}$	**Prob($\boldsymbol{\beta_{i,1}}$)**	$\boldsymbol{\lambda}$	**Prob($\boldsymbol{\lambda}$)**
Abbott	0.30	0.77	-0.30	0.05
Bausch	2.75	0.01	-0.48	0.00
Baxter	1.16	0.25	-0.20	0.00
Bristol	1.74	0.09	-0.14	0.08
Coca Cola	0.74	0.46	-0.07	0.30
Colgate	0.61	0.55	-0.08	0.38
Cooper	1.05	0.30	-0.84	0.00
Corning	0.93	0.36	-0.14	0.08
Du Pont	0.11	0.91	-0.15	0.03
Eaton	0.60	0.55	-0.22	0.05
General Electric	1.09	0.28	-0.19	0.19
General Motors	-0.08	0.93	-0.30	0.01
Georgia Pacific	0.65	0.52	-0.24	0.03
Gillette	0.09	0.93	0.02	0.67
Goodyear	0.43	0.67	-0.29	0.00
Hercules	-0.28	0.78	-0.21	0.11
Ingersoll	0.04	0.97	-0.30	0.04
IBM	0.48	0.63	-0.33	0.00
International Paper	0.43	0.67	-0.28	0.05
Johnson & Johnson	0.72	0.48	-0.12	0.13
Lilly	1.17	0.25	-0.16	0.08
Merck	0.03	0.98	-0.09	0.22
Motorola	2.07	0.04	-0.52	0.00
Pfizer	-0.27	0.79	-0.28	0.04
Raytheon	2.40	0.02	-0.52	0.00
Rohm	0.69	0.50	-0.14	0.10
Schering	0.28	0.78	-0.05	0.42
Textronix	0.23	0.82	-0.22	0.01
UST	0.92	0.36	-0.31	0.01
United Technologies	0.03	0.97	-0.33	0.02
Average	**0.70**	**0.55**	**-0.25**	**0.10**
Standard Deviation	**0.75**	**0.31**	**0.17**	**0.16**

Figure 1:
Illustration of the stability of the estimated error correction term at firm level.

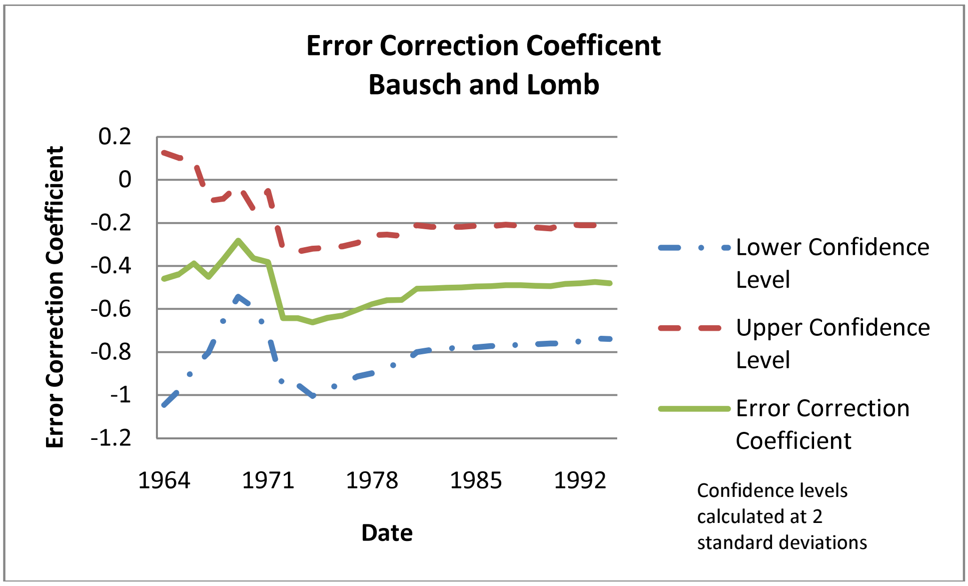


Figure 2
Illustration of ability of book value ECM to predict abnormal returns at firm level.

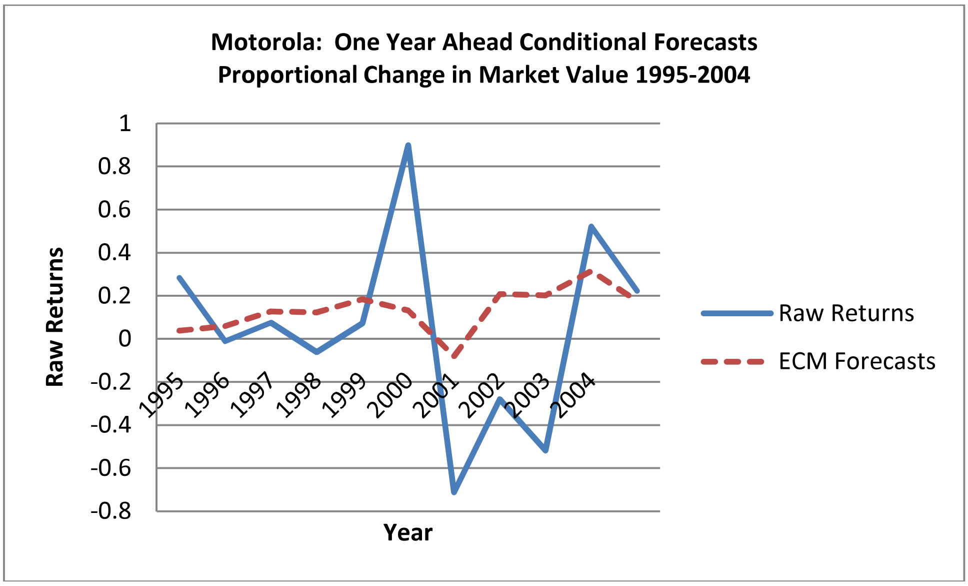


Figure 3
Illustration of similarity of ECM time series predictions using estimation periods 1956 to 1994 and 1956 to 2004 (models based on average of firm coefficients).

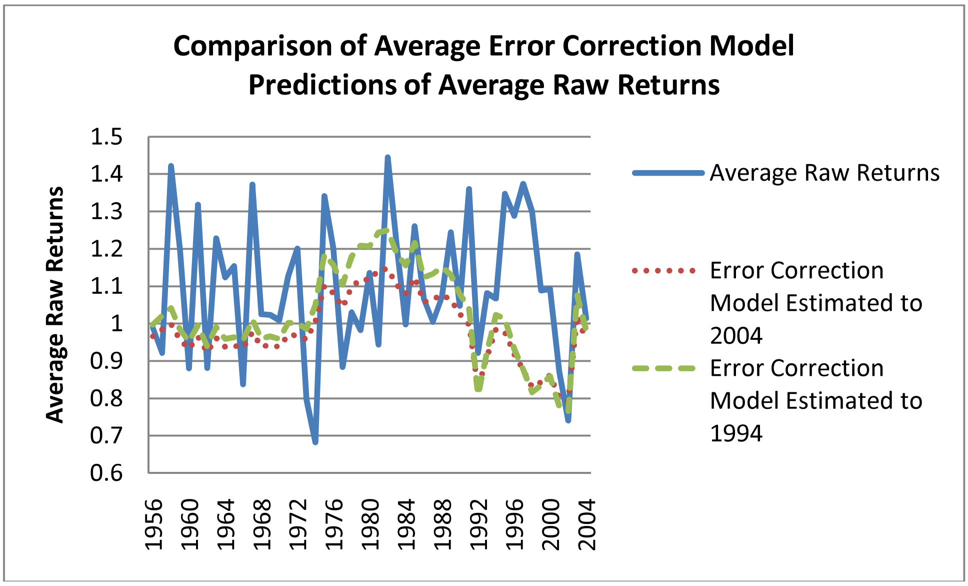
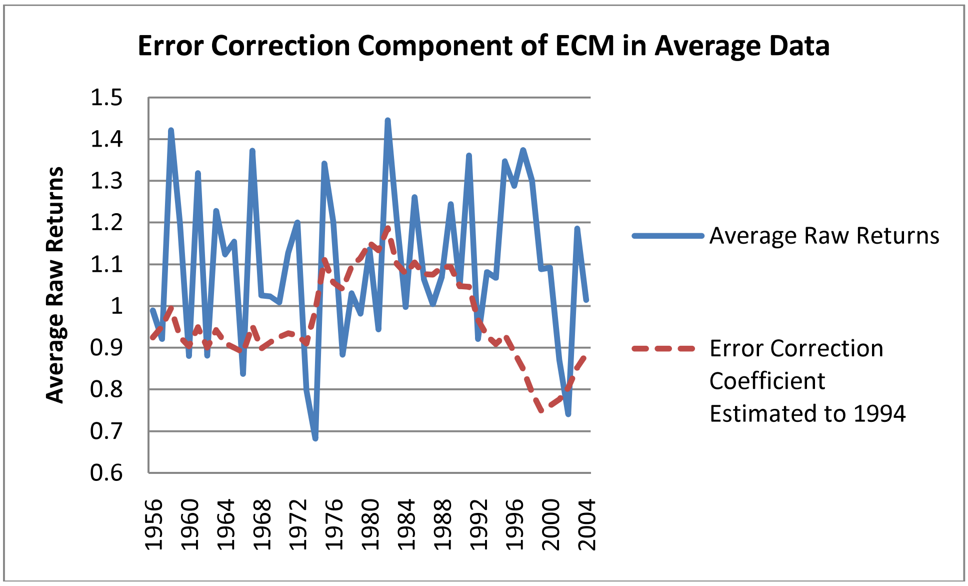
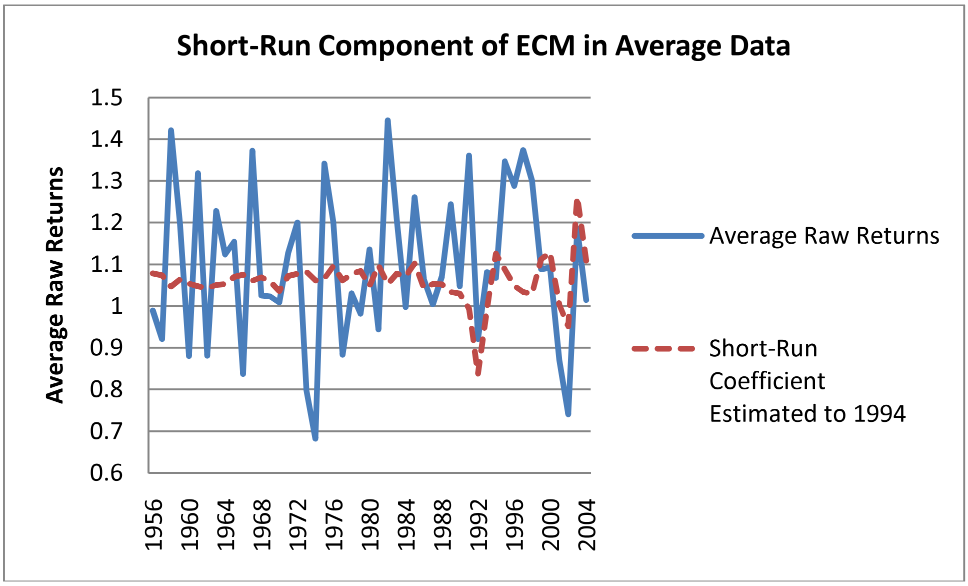


Figure 4
Illustration of model predictions split between short-run and error correction components, based on estimation period 1955 to 1994 (models based on average of firm coefficients).

Panel 1:



Panel 2:



APPENDIX

Table A1
Dynamic autoregressive distributed lag and static models: Estimated coefficients and inferential statistics for 30 firms. $p(x)$ denotes the p-value associated with the estimate x.

Firm	**ADL**								**Static regression**					
	$M_{i,t} = k + \alpha M_{i,t-1} + \beta_1 B_{i,t} + \beta_2 B_{i,t-1} + \upsilon_{i,}$ for each firm i.								$M_{i,t} = a + bB_{i,t} + \varepsilon_i$, for each firm i.					
	k	$p(k)$	α	$p(\alpha)$	β_1	$p(\beta_1)$	β_2	$p(\beta_2)$	a	$p(a)$	b	$p(b)$	$LR(a)$	$LR(b)$
Abbott	0.10	0.43	0.72	0.00	-0.08	0.87	0.42	0.40	-.06	.74	1.22	.00	0.35	1.23
Bausch	-0.23	0.28	0.52	0.00	1.96	0.00	-1.38	0.01	-.55	.02	1.23	.00	-0.47	1.19
Baxter	0.38	0.02	0.87	0.00	0.77	0.00	-0.66	0.01	1.40	.00	.98	.00	2.81	0.81
Bristol	0.07	0.69	0.89	0.00	1.85	0.00	-1.74	0.00	.84	.01	1.11	.00	0.69	1.03
Coca Cola	0.21	0.35	0.94	0.00	0.49	0.35	-0.43	0.40	-.28	.60	1.28	.00	3.41	0.92
Colgate	-0.08	0.77	0.96	0.00	0.22	0.13	-0.15	0.31	-2.35	.04	1.53	.00	-2.14	1.89
Cooper	0.09	0.52	0.21	0.14	0.83	0.00	0.02	0.94	-.04	.78	1.10	.00	0.12	1.08
Corning	0.67	0.14	0.82	0.00	0.64	0.01	-0.52	0.02	3.10	.00	.71	.00	3.62	0.65
DuPont	-0.22	0.56	0.90	0.00	0.19	0.33	-0.04	0.82	3.12	.00	.75	.00	-2.16	1.39
Eaton	-0.15	0.53	0.80	0.00	0.65	0.03	-0.41	0.15	-.68	.05	1.17	.00	-0.76	1.22
General Electric	0.01	0.96	0.88	0.00	0.71	0.26	-0.57	0.38	.98	.04	1.03	.00	0.09	1.15
General Motors	2.59	0.01	0.79	0.00	-0.03	0.65	-0.02	0.73	8.98	.00	.10	.16	12.44	-0.20
Georgia Pacific	0.80	0.01	0.69	0.00	0.69	0.02	-0.46	0.11	1.74	.00	.85	.00	2.56	0.74
Gillette	0.02	0.96	1.02	0.00	0.01	0.58	-0.02	0.24	6.57	.00	.24	.00	-19.04	1.63
Goodyear	1.55	0.01	0.82	0.00	0.01	0.64	-0.03	0.21	7.21	.00	.07	.07	8.51	-0.10
Hercules	0.79	0.05	0.89	0.00	0.02	0.35	-0.01	0.41	6.65	.00	.08	.04	7.35	0.02
Ingersoll	0.15	0.59	0.85	0.00	0.38	0.38	-0.23	0.57	1.67	.00	.85	.00	1.00	0.99
IBM	1.18	0.01	0.86	0.00	0.27	0.38	-0.23	0.42	4.28	.00	.69	.00	8.30	0.30
Int. Paper	-0.11	0.67	0.82	0.00	0.46	0.16	-0.25	0.46	.59	.16	.96	.00	-0.61	1.14
Johnson	0.18	0.19	0.88	0.00	0.87	0.03	-0.75	0.05	.24	.38	1.16	.00	1.50	1.04
Lilly	0.30	0.11	0.93	0.00	-0.08	0.83	0.15	0.69	.65	.13	1.13	.00	4.02	0.88
Merck	0.47	0.01	0.88	0.00	0.06	0.84	0.04	0.88	1.30	.00	1.07	.00	3.88	0.84
Motorola	0.32	0.15	0.49	0.00	1.59	0.00	-1.08	0.02	.73	.00	1.02	.00	0.62	1.02
Pfizer	0.18	0.30	0.94	0.00	0.55	0.01	-0.49	0.03	.24	.50	1.15	.00	2.96	0.92
Raytheon	0.24	0.20	0.60	0.00	1.24	0.00	-0.84	0.01	.49	.02	1.01	.00	0.59	0.99
Rohm	0.01	0.98	0.88	0.00	0.69	0.01	-0.55	0.03	1.61	.00	.87	.00	0.05	1.13
Schering	0.26	0.18	0.96	0.00	0.39	0.25	-0.37	0.23	1.09	.01	1.07	.00	6.72	0.48
Tektronix	0.18	0.44	0.81	0.00	0.23	0.52	-0.05	0.89	.20	.58	1.03	.00	0.97	0.98
UST	-0.32	0.19	0.85	0.00	0.83	0.02	-0.62	0.05	-1.00	.02	1.20	.00	-2.14	1.38
United Tech.	0.12	0.32	1.00	0.00	0.01	0.28	-0.01	0.44	6.05	.00	.04	.70	24.82	0.87
Average	0.33	0.34	0.81	0.00	0.55	0.26	-0.38	0.33	1.83	.14	0.89	0.03	2.34	0.92
SD	0.59	0.29	0.17	0.02	0.54	0.28	0.46	0.31	2.74	.24	0.4	0.1	6.72	0.47
Long-run estimates of market-to-book relationship based on average of ADL coefficients													1.77	0.89

Table A2
Cross section ADL and static models: Estimated coefficients and inferential statistics. $p(x)$ denotes the p-value associated with the estimate x. Average (time) and SD (time) are the average and standard deviation of the cross section coefficient estimates and statistics over time. Average (firm) and SD (firm) are the average and standard deviation of the dynamic estimates and statistics over the 30 firms.

Year	**ADL**								**Static regression**			
	$M_{i,t} = k + \alpha M_{i,t-1} + \beta_1 B_{i,t} + \beta_2 B_{i,t-1} + \upsilon_{i}$, for each year t								$M_{i,t} = a + bB_{i,t} + \varepsilon_i$, for each year t			
	k	$p(k)$	α	$p(\alpha)$	β_1	$p(\beta_1)$	β_2	$p(\beta_2)$	a	$p(a)$	b	$p(b)$
1955									-0.14	0.71	1.21	0.00
1956	0.03	0.89	0.94	0.00	0.84	0.08	-0.77	0.09	-0.18	0.63	1.20	0.00
1957	0.18	0.36	0.96	0.00	0.72	0.15	-0.73	0.11	-0.12	0.76	1.17	0.00
1958	0.40	0.02	0.88	0.00	1.84	0.00	-1.73	0.00	0.42	0.29	1.12	0.00
1959	0.11	0.65	0.95	0.00	1.83	0.02	-1.79	0.02	0.63	0.15	1.10	0.00
1960	0.24	0.25	1.14	0.00	0.21	0.78	-0.43	0.55	0.80	0.13	1.04	0.00
1961	0.07	0.61	0.95	0.00	1.55	0.05	-1.48	0.05	0.81	0.13	1.07	0.00
1962	-0.32	0.02	0.88	0.00	0.50	0.33	-0.33	0.50	0.30	0.53	1.12	0.00
1963	0.07	0.59	1.02	0.00	0.83	0.01	-0.84	0.01	0.34	0.51	1.13	0.00
1964	0.13	0.17	0.93	0.00	0.44	0.11	-0.36	0.18	0.36	0.46	1.14	0.00
1965	0.28	0.11	0.89	0.00	2.98	0.00	-2.91	0.00	0.87	0.08	1.07	0.00
1966	0.33	0.21	0.99	0.00	1.46	0.01	-1.54	0.01	1.29	0.02	0.97	0.00
1967	0.60	0.02	0.98	0.00	0.19	0.82	-0.22	0.77	1.64	0.01	0.95	0.00
1968	0.22	0.18	0.80	0.00	2.00	0.00	-1.81	0.00	1.62	0.00	0.95	0.00
1969	-0.53	0.09	1.22	0.00	0.99	0.09	-1.19	0.03	1.33	0.06	0.98	0.00
1970	-0.27	0.16	0.81	0.00	1.68	0.00	-1.43	0.00	0.85	0.20	1.04	0.00
1971	0.46	0.11	0.82	0.00	2.79	0.00	-2.66	0.00	1.25	0.08	0.99	0.00
1972	-0.23	0.52	0.86	0.00	2.41	0.01	-2.22	0.01	0.99	0.18	1.04	0.00
1973	0.07	0.84	1.03	0.00	0.80	0.53	-0.89	0.46	0.94	0.25	1.00	0.00
1974	-0.21	0.61	0.86	0.00	1.24	0.32	-1.12	0.34	0.58	0.46	0.99	0.00
1975	0.14	0.46	0.69	0.00	1.38	0.00	-1.05	0.01	0.54	0.37	1.03	0.00
1976	-0.03	0.85	0.69	0.00	1.88	0.00	-1.54	0.00	0.42	0.37	1.05	0.00
1977	-0.11	0.70	1.00	0.00	1.76	0.03	-1.80	0.02	0.47	0.40	1.00	0.00
1978	0.09	0.62	1.09	0.00	0.36	0.24	-0.46	0.12	0.47	0.45	0.99	0.00
1979	0.58	0.02	0.96	0.00	0.82	0.01	-0.86	0.01	0.95	0.16	0.92	0.00
1980	-0.13	0.58	0.96	0.00	2.39	0.00	-2.34	0.00	1.18	0.12	0.90	0.00
1981	0.40	0.13	0.87	0.00	0.61	0.02	-0.53	0.04	1.38	0.05	0.86	0.00
1982	-0.18	0.61	0.81	0.00	1.98	0.00	-1.74	0.00	0.81	0.25	0.96	0.00
1983	0.54	0.01	0.77	0.00	1.60	0.00	-1.42	0.00	1.08	0.08	0.94	0.00
1984	0.01	0.95	0.96	0.00	0.67	0.13	-0.63	0.14	0.99	0.11	0.94	0.00
1985	0.32	0.23	1.02	0.00	0.55	0.02	-0.58	0.02	1.28	0.06	0.92	0.00
1986	0.62	0.02	1.02	0.00	-0.03	0.86	-0.04	0.85	2.09	0.01	0.84	0.00
1987	0.22	0.48	1.01	0.00	0.07	0.79	-0.10	0.70	2.31	0.01	0.80	0.00
1988	0.21	0.41	1.00	0.00	0.01	0.49	-0.03	0.64	7.91	0.00	0.11	0.05
1989	0.29	0.41	1.17	0.00	-0.22	0.03	0.03	0.21	4.18	0.00	0.60	0.00
1990	-0.48	0.14	1.16	0.00	-0.01	0.98	-0.12	0.51	3.26	0.01	0.71	0.00
1991	1.30	0.00	0.98	0.00	0.19	0.29	-0.28	0.06	3.46	0.01	0.72	0.00
1992	0.33	0.00	0.05	0.00	0.08	0.48	0.06	0.26	3.28	0.01	0.75	0.00
1993	0.54	0.21	0.89	0.00	0.11	0.61	-0.04	0.85	3.40	0.00	0.75	0.00
1994	-0.86	0.01	1.07	0.00	-0.07	0.48	0.10	0.25	2.22	0.04	0.88	0.00
1995	-0.21	0.47	1.10	0.00	0.12	0.38	-0.18	0.25	2.75	0.02	0.84	0.00
1996	-0.37	0.22	1.02	0.00	0.23	0.13	-0.19	0.21	2.47	0.03	0.89	0.00
1997	-0.34	0.32	1.09	0.00	0.14	0.45	-0.19	0.30	1.92	0.12	0.97	0.00
1998	-0.67	0.08	1.06	0.00	0.72	0.02	-0.69	0.02	1.08	0.39	1.09	0.00
1999	0.05	0.94	0.93	0.00	0.53	0.04	-0.46	0.13	1.77	0.20	0.99	0.00
2000	-0.31	0.51	1.15	0.00	0.28	0.11	-0.42	0.02	1.82	0.24	0.97	0.00
2001	-0.18	0.68	0.89	0.00	0.95	0.00	-0.81	0.00	0.81	0.58	1.07	0.00
2002	0.17	0.75	1.00	0.00	0.00	0.89	-0.05	0.62	8.63	0.00	0.16	0.00
2003	1.30	0.00	0.87	0.00	0.02	0.08	0.01	0.59	8.78	0.00	0.17	0.00
2004	0.82	0.00	0.89	0.00	0.07	0.15	-0.03	0.06	5.69	0.00	0.53	0.00
Average (time)	0.12	0.35	0.94	0.00	0.87	0.23	-0.83	0.20	1.88	0.18	0.91	0.00
SD (time)	0.43	0.30	0.18	0.00	0.84	0.29	0.78	0.26	2.05	0.20	0.24	0.01
Average (firm)	0.33	0.34	0.81	0.00	0.55	0.26	-0.38	0.33	1.83	0.14	0.89	0.03
SD (firm)	0.59	0.29	0.17	0.02	0.55	0.28	0.46	0.31	2.74	0.24	0.40	0.13