Corporate Investment and the Role of Expected Profitability: A Re-Examination

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Abstract

In the first chapter, we extend the empirical analysis in Cummins et al. (2006) to consider the significance of lagged cash flow in explaining the investment behaviour of the publicly-traded US companies, using their sample for years between 1982 and 1999. We find significant evidence of excess sensitivity of corporate investment to lagged cash flow, even controlling for their preferred measure of Tobin's Q. This new measure uses securities analysts' earnings forecasts rather than stock market valuations to capture the influence of expected future profitability on current investment decisions. Our results do suggest that capital market imperfections should not be dismissed on the basis that corporate investment displays no sensitivity to indicators of the availability of internal funds.

The second chapter further explores the robustness of the Cummins et al. (2006) results by examining their subsamples of firms with and without bond ratings. We expand on the subsample results presented in Cummins et al. (2006) by introducing a lagged cash flow measure in both static and dynamic model specifications. As in the full sample, we find excess sensitivity to lagged cash flow for the rated firms subsample. These results are further strengthened once we use the two-step GMM estimators, with standard errors calculated using the finite sample correction proposed by Windmeijer (2005). We also provide evidence that selective reporting bias may be a source of the high predictive power of the alternative measure of Tobin's Q in the results presented in Cummins et al. (2006).

In the third chapter, we review the roles of expected profitability and cash flow in explaining investment rates for around 700 publicly-traded UK firms between the years 1987 and 2000. We do so by revisiting the dataset of Bond et al. (2004). We find that their main results, which are similar in spirit to those of Cummins et al. (2006), are not robust once we use additional valid instruments to estimate their models, and we use two-step GMM estimators with appropriate standard errors. We conclude that cash flow sensitivity, for this particular sample, cannot be dismissed, even when controlling for the novel measures of expected profitability, based on analysts' earning forecasts, suggested by Bond et al. (2004).

In the fourth chapter, we follow closely the methods described in Bond et al. (2004) to recreate a dataset for publicly-traded UK firms covering the period 1987 to 2000, using sources of data which are currently available. In particular, we use company accounts data from Worldscope,

which provides less detail (although wider coverage of firms) than the older Datastream source used by Bond et al. (2004). Consequently our new dataset is not an exact replica of that constructed by Bond et al. (2004). A particular concern could be that we cannot replicate their measure of the level of investment, which used information on the increase in net fixed assets due to acquisitions which is not available from Worldscope. Nevertheless, after dropping observations on firms which were not covered by Datastream, we show that both descriptive statistics and the results of econometric models of investment are broadly comparable using the two datasets. These results provide a bridge to the analysis in the final chapter, which studies the investment behaviour of publicly-traded UK firms in more recent years, using data obtained from the same currently available sources.

In the last chapter, we extend our dataset for publicly traded UK firms through to 2016. We first confirm, using a larger sample of firms covered by Worldscope, that while the Bond et al. (2004) measure of expected profitability is an informative explanatory variable for corporate investment rates, it does not eliminate the sensitivity of investment to cash flow over the time period 1987-2000. We then explore how the excess sensitivity of investment to cash flow evolved over time for our full sample of UK firms. We present evidence that cash flow sensitivity has diminished for this sample, and we find no significant cash flow sensitivity for sample periods after the 2008 financial crisis. These findings echo similar results found previously for publicly-traded US firms. However, we also find interesting heterogeneity in the disappearance of cash flow sensitivity. We consider subsamples of firms which had relatively high and relatively low share price volatility over our sample period. We find significant and interesting differences between the results for these two subsamples. In particular, the decline in the sensitivity of investment to cash flow over this period reflects the behaviour of firms with less volatile stock market valuations. For the subsample of firms with more volatile stock market valuations, we find no significant excess sensitivity of investment to cash flow in any sub-period. For the subsample of firms with less volatile stock market valuations, we find significant cash flow sensitivity for periods up to 2007, but no significant cash flow sensitivity for periods after the 2008 financial crisis.

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Introduction

Following the seminal paper by Fazzari et al. (1988), there has been considerable interest in the sensitivity of corporate investment to indicators of the availability of internal funds, such as cash flow, after controlling for the determinants of investment in an environment characterized by perfect capital markets. This interest reflects the potential importance of the financial accelerator in the propagation of business cycle shocks, and the role of the credit and net worth channels in the transmission of monetary policy, in an environment with a cost premium for external sources of finance, or other forms of capital market imperfections.[1]

Stein (2003) shows that financing frictions and their impact on real investment is a central matter in contemporary finance. This is no surprise given that the relationship between investment and financing frictions is used to study issues which affect optimal hedging and cash policies (Almeida et al. (2004); and Froot et al. (1993)) or firm organizational design (Stein (1997); Gertner et al. (1994)). Moreover, the presence of significant financial constraints has important implications for our understanding of business cycles, monetary policy, and tax policy, as well as corporate mergers and acquisitions (Bond and Söderbom (2013); Almeida and Campello (2007)).

The excess sensitivity test, pioneered by Fazzari et al. (1988), is based on the relationship between investment rates and Tobin's Q under perfect capital markets derived by Hayashi (1982). Motivated by the importance of internally generated

[1] See, for example, Bernanke and Gertler (1995) and Bernanke et al. (1996).

funds as a determinant of investment spending for firms which face a significant cost premium for external finance, Fazzari et al. (1988) suggested the inclusion of cash flow terms as additional explanatory variables in this econometric model. They found positive and significant coefficients on these additional cash flow variables, a finding which has since been replicated using many different datasets. The significance of these coefficients is a joint test of all the assumptions required to derive a simple linear relationship between investment rates and Tobin's Q, and not simply a test of the perfect capital markets assumption.[2]

In an important recent contribution, Cummins et al. (2006) investigated the importance of measurement error in Tobin's Q in contributing to the significance of these cash flow coefficients. The usual measure of Tobin's Q is constructed using the firm's stock market valuation as a measure of the present discounted value of expected future net payouts to shareholders. Intuitively, share prices contain information about current expectations of future profitability which are relevant for explaining current investment decisions in the presence of adjustment costs for capital. However, if stock market valuations deviate from these fundamental or intrinsic values, then other variables which are informative about expected future profitability may also help to explain corporate investment, even under perfect capital markets. The resulting measurement error in Tobin's Q will be difficult to deal with using econometric procedures if share prices contain a highly persistent bubble component, particularly if the evolution of the bubble is not independent of the intrinsic value of the firm.[3]

The measurement error hypothesis, unlike the other reasons for the failure of

[2]There has been controversy both about the power of this test to detect capital market imperfections, and whether the magnitude of the coefficient on cash flow should increase monotonically with the external finance premium. Using simulated data from an otherwise standard Q model with costly external finance, Bond and Söderbom (2013) showed that the estimated coefficient on the cash flow term is positive in the excess sensitivity specification suggested by Fazzari et al. (1988), and also that this coefficient increases monotonically with the external finance premium.

[3]Bond and Cummins (2001) showed that the baseline Q model is not identified if the innovation to the bubble component of the stock market valuation is itself correlated with relevant news about the intrinsic value of the firm.

the basic neoclassical investment model, seems an appealing explanation as it could explain all of Q theory's empirical shortcomings. Erickson and Whited (2000) explain why this might be the case. Nevertheless, most papers which have attempted to address this issue still find significant coefficients on measures of internal finance (Erickson and Whited (2000)). An exception is Cummins et al. (2006), who proposed using a novel measure of Tobin's Q in which the firm's stock market value is replaced by an estimate of its intrinsic value constructed using securities analysts' forecasts of its future earnings. Using this new measure of Tobin's Q, they show that the sensitivity of investment to current cash flow is eliminated.

This thesis aims to contribute to this literature by further exploring excess cash flow sensitivity and the role of measures of expected future profitability in models of corporate investment. It is important to study the evolution of the roles of expected profitability, standard measures of Tobin's Q and cash flow terms over time in general, and how these relationships may have changed before and after the 2008 financial crisis, in particular. This is especially true given the wide use of Tobin's Q-type models in understanding corporate investment and financing constraints or in building models to account for risk management in Finance (see, for example, Bolton et al. (2011)).

The thesis is organised as follows. The first two chapters review the work of Cummins et al. (2006) and find, in contrast to the original results presented by the authors, evidence of the (excess) sensitivity of investment to lagged cash flow in both their full sample of US firms, and in the subsample of firms with bond ratings. Given our findings in the first two chapters, we look next at the study by Bond et al. (2004), a similar study to Cummins et al. (2006), which uses data for UK firms and supports the view that measurement error in the standard measure of Tobin's Q explains the apparent importance of cash flow variables in standard Tobin's Q models. Using additional valid instruments and a two-step GMM estimator, we again find that cash flow sensitivity is not eliminated by the inclusion of their proposed measures of

expected profitability, which are again constructed from analysts' earnings forecasts.

Chapter Four studies the differences between the dataset used by Bond et al. (2004) and a dataset that we construct for UK firms over the same time period from currently available sources. Despite some unavoidable differences, which particularly affect the measure of investment, we find that the results of estimating econometric investment models using the two datasets are broadly comparable. This finding provides a bridge to the analysis in the final chapter, which studies the investment behaviour of publicly traded UK firms in more recent years, using data obtained from the same currently available sources.

In the last chapter, we confirm that while the Bond et al. (2004) measure of expected profitability is an informative explanatory variable for corporate investment, during their sample period, its inclusion does not always eliminate the explanatory power of a lagged cash flow variable. We further present evidence that cash flow sensitivity has diminished for UK firms in more recent sample periods, echoing similar results found previously for US firms. However, we find interesting heterogeneity in this disappearance of cash flow sensitivity. We consider subsamples of firms with relatively high and relatively low share price volatility during our sample period. We present evidence that the overall decline in cash flow sensitivity for UK firms reflects a change in the investment behaviour of firms with more volatile stock market valuations.

Chapter 1

Cash Flow, Earnings Expectations and Corporate Investment: New Evidence

By Stephen R. Bond, Revi Panidha, and Jing Xing[1]

Abstract

We extend the empirical analysis in Cummins et al. (2006) to consider the significance of lagged cash flow in explaining the investment behaviour of the publicly-traded US companies in their sample. We find significant evidence of excess sensitivity of corporate investment to lagged cash flow, even controlling for their preferred measure of Tobin's Q. This new measure uses securities analysts' earnings forecasts rather than stock market valuations to capture the influence of expected future profitability on current investment decisions. Our results do not establish the importance

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of a cost premium for external sources of finance, or other financing frictions. They do suggest that capital market imperfections should not be dismissed on the basis that corporate investment displays no sensitivity to indicators of the availability of internal funds.

Following the seminal paper by Fazzari et al. (1988), there has been considerable interest in the sensitivity of corporate investment to indicators of the availability of internal funds, such as cash flow, after controlling for the determinants of investment in an environment characterized by perfect capital markets. This interest reflects the potential importance of the financial accelerator in the propagation of business cycle shocks, and the role of the credit and net worth channels in the transmission of monetary policy, in an environment with a cost premium for external sources of finance, or other forms of capital market imperfections.[2] The excess sensitivity test, pioneered by Fazzari et al. (1988), is based on the relationship between investment rates and Tobin's Q under perfect capital markets derived by Hayashi (1982). Motivated by the importance of internally generated funds as a determinant of investment spending for firms which face a significant cost premium for external finance, Fazzari et al. (1988) suggested the inclusion of cash flow terms as additional explanatory variables in this econometric model. They found positive and significant coefficients on these additional cash flow variables, a finding which has since been replicated using many different datasets. The significance of these coefficients is a joint test of all the assumptions required to derive a simple linear relationship between investment rates and Tobin's Q, and not simply a test of the perfect capital markets assumption.[3]

In an important recent contribution, Cummins et al. (2006) investigated the importance of measurement error in Tobin's Q in contributing to the significance of these cash flow coefficients. The usual measure of Tobin's Q is constructed using the firm's stock market valuation as a measure of the present discounted value of expected future net payouts to shareholders. Intuitively, share prices contain in-

[2]See, for example, Bernanke and Gertler (1995) and Bernanke et al. (1996).

[3]There has been controversy both about the power of this test to detect capital market imperfections, and whether the magnitude of the coefficient on cash flow should increase monotonically with the external finance premium. Using simulated data from an otherwise standard Q model with costly external finance, Bond and Söderbom (2013) showed that the estimated coefficient on the cash flow term is positive in the excess sensitivity specification suggested by Fazzari et al. (1988), and also that this coefficient increases monotonically with the external finance premium.

formation about current expectations of future profitability which are relevant for explaining current investment decisions in the presence of adjustment costs for capital. However, if stock market valuations deviate from these fundamental or intrinsic values, then other variables which are informative about expected future profitability may also help to explain corporate investment, even under perfect capital markets. The resulting measurement error in Tobin's Q will be difficult to deal with using econometric procedures if share prices contain a highly persistent bubble component, particularly if the evolution of the bubble is not independent of the intrinsic value of the firm.[4]

To investigate this, Cummins et al. (2006) constructed an alternative measure of Tobin's Q in which the firm's stock market valuation was replaced by an estimate of the firm's intrinsic value, which they constructed by discounting the forecasts of the firm's future earnings made by professional securities analysts. In all other respects, the usual measure, which they termed the market-based measure of Q (Q^E), and the new measure, which they termed the analysts-based measure of Q ($\widehat{Q}$), were identical. As they noted, there are good reasons why their analysts-based estimate will also measure the firm's intrinsic value with error. These include the need to specify a discount factor, the fact that analysts forecast earnings rather than payouts to shareholders, and the fact that analysts only provide forecasts for a limited number of future years. Nevertheless, these sources of measurement error are different from the presence of a bubble component in stock market valuations, and may be less difficult to address using econometric methods. Certainly the empirical results found in specifications which use the new analysts-based measure of Q are strikingly different from those found in specifications which use the standard market-based measure of Q. While there is strong evidence of excess sensitivity of investment to cash flow using the standard specification, the estimated coefficient

[4]Bond and Cummins (2001) showed that the baseline Q model is not identified if the innovation to the bubble component of the stock market valuation is itself correlated with relevant news about the intrinsic value of the firm.

on the cash flow term becomes both small and insignificantly different from zero when the standard measure of Q is replaced by the new analysts-based measure. Moreover, the estimated coefficient on the standard measure of Q is also insignificantly different from zero when the analysts-based measure of Q is also included in the specification. Not only is there no excess sensitivity to cash flow, but also the theoretical prediction that Tobin's Q provides a sufficient statistic for investment rates is not rejected when using their new measure of Tobin's Q.

Cummins et al. (2006) present an impressive array of alternative specifications to establish the robustness of these key findings. Similar results are obtained using static and dynamic specifications of the baseline Q model, using subsamples of publicly-traded firms with and without bond ratings, using different estimates of the firm's intrinsic value, and using different instrument sets. However, one variation which they do not consider relates to the timing of the cash flow variable which is included in the investment model. This is somewhat surprising, since they use data from annual company accounts in which both investment spending and cash flow are flow measures cumulated over the twelve month period covered by the accounts. While it is clearly possible for investment spending in the second half of the year to be financed out of cash flow generated during the first half of the year, it is not possible for investment spending in the first half of the year to be financed out of cash flow generated during the second half of the same year. It is quite possible for such investment to be financed out of cash flow generated during the second half of the previous year. Thus it seems worth investigating whether there is any additional information in last year's cash flow which helps to explain this year's investment, after controlling for the most informative measure of Tobin's Q. Moreover, there are precedents for this specification in the literature. While Fazzari et al. (1988) found a relationship between current investment and current cash flow for publicly-traded US firms, Blundell et al. (1992) found a relationship between current investment and lagged cash flow for publicly-traded UK firms. In this paper we therefore extend the

empirical analysis presented in Cummins et al. (2006) to consider the role of lagged cash flow variables.

The differences in the empirical results produced by this rather modest change in the specification of the investment model are striking. Using exactly the same dataset as Cummins et al. (2006), conveniently posted on the American Economic Review web site, we have no difficultly in exactly replicating the results presented in their paper. However, we find significant evidence of excess sensitivity of corporate investment to *lagged* cash flow, even using their analysts-based measure of Tobin's Q. This evidence is also present in both static and dynamic specifications, and using different instrument sets. We remain agnostic about whether this excess sensitivity indicates the presence of a significant cost premium for external finance, or the failure of one of the other assumptions needed to derive a simple linear relationship between investment rates and Tobin's Q. We simply note the fragility of the conclusion of Cummins et al. (2006) that "using our preferred measure of fundamentals, we find no evidence that investment is sensitive to cash flow for U.S. companies that are covered by securities analysts" (p.809).

The remainder of this paper is organized as follows. Section 1.1 describes the econometric specifications and estimation methods used by Cummins et al. (2006). Section 1.2 presents the empirical results, first using their specification, then replacing their current cash flow term by its first lag. Section 1.3 concludes.

1.1 Econometric Models and Estimation

A. Models

Cummins et al. (2006) estimate investment models of the form

$$\left(\frac{I}{K}\right)_{i,t} = a + \frac{1}{b}Q_{i,t} + \gamma\left(\frac{CF}{K}\right)_{i,t} + \varepsilon_{i,t} \tag{1.1}$$

in which $I_{i,t}$ is gross investment of firm i in year t, $K_{i,t}$ is the replacement cost value of the firm's stock of capital (net of accumulated depreciation) at the end of year t, $Q_{i,t}$ is a measure of Tobin's (average) Q at the beginning of year t, and $CF_{i,t}$ is the firm's cash flow in year t. More precisely

$$Q_{i,t} = \left(\frac{V_{i,t}}{p_t^k (1-\delta) K_{i,t-1}} - 1 \right) \frac{p_t^k}{p_t}$$

and

$$V_{i,t} = E_t \left[\sum_{s=0}^{\infty} \beta_{t+s}^t \Pi_{i,t+s} \right],$$

where p_t is the price of output, p_t^k is the price of capital goods, δ is the constant, geometric, annual depreciation rate for capital goods, $\Pi_{i,t+s}$ is the net payout to shareholders in year $t+s$, β_{t+s}^t is the discount factor used in year t to value payouts in year $t+s$, and $E_t[.]$ denotes an expected value conditional on information available in year t, so that $V_{i,t}$ is the fundamental or intrinsic value of firm i at the beginning of year t.[5]

With γ set to be zero, equation 1.1 is a version of the simple linear relationship between investment rates and Tobin's Q derived by Hayashi (1982) as a representation of the first-order conditions for optimal investment in a model in which investment is chosen to maximize the intrinsic value of the firm. The model assumes that investment may be positive or negative (no irreversibility), and that any level of investment expenditure can be financed from either internal or external sources at a given required rate of return, which is reflected in the discount factor β_{t+s}^t (no cost premium for external finance). Other key assumptions are that there is a single capital input a firm can invest in, investment is subject to strictly convex adjustment costs which are symmetric and quadratic around a given investment rate a, with the magnitude of these adjustment costs reflected in the parameter b, and the error term

[5]The empirical measures of $Q_{i,t}$ used by Cummins et al. (2006) further allow for the presence of debt and taxes. Here we abstract from debt and taxes and follow the simpler exposition of the model in Section I of their paper.

$\varepsilon_{i,t}$ introduced as an unobserved shock to marginal adjustment costs. Furthermore, the production technology and these capital adjustment costs both satisfy constant returns to scale; all other inputs can be adjusted costlessly; and the firm is a price taker in both output and input markets. Other details of the specification considered here, which are likely to be less important, include that production in year t depends on the stock of capital $K_{i,t}$ which evolves as follows: $K_{i,t} = (1 - \delta)K_{i,t-1} + I_{i,t}$, so that current investment is productive immediately, and that adjustment costs take the form of foregone production.

With γ unrestricted, equation 1.1 is the excess sensitivity test specification suggested by Fazzari et al. (1988). The null hypothesis of interest is that $\gamma = 0$. While the inclusion of the cash flow term is motivated by the observation that, if external finance is more costly than internal finance, investment will depend to some extent on the availability of low cost internal funds, it has long been recognized that this is a joint test of all the assumptions required to derive the linear relationship between investment rates and Tobin's Q summarized by equation (1.1) with $\gamma = 0$.[6] We extend the empirical analysis of Cummins et al. (2006) by additionally considering lagged values of this cash flow term. In a discrete time setting, the inclusion of lagged cash flow could be motivated by introducing a one-period cash in advance requirement for investment spending. In practice, investment spending may occur at any point during the year covered by the firm's annual accounts, and it is less clear whether current or lagged cash flow would be the more significant influence on current investment spending.

Cummins et al. (2006) take seriously the fact that the intrinsic value of the

[6]It is worth emphasizing that equation 1.1 is not a structural model of investment under the alternative hypothesis that external finance is more costly than internal finance. Recently, both Hennessy et al. (2007) and Bond and Söderbom (2013) have derived structural investment equations from an otherwise standard Q model of investment with costly external finance. These structural models feature an additional interaction term between Tobin's Q and a measure of the costly external finance used by the firm in year t, in addition to the standard linear Tobin's Q term. Bond and Söderbom (2013) further show that this omitted interaction term is correlated with the cash flow term in equation 1.1, which provides a formal justification for the excess sensitivity test considered by Fazzari et al. (1988) and Cummins et al. (2006).

firm $V_{i,t}$ needed for the construction of $Q_{i,t}$ cannot be directly and accurately measured.[7] They construct two empirical measures of Tobin's Q. The standard measure uses the firm's stock market valuation at the start of year t ($V_{i,t}^E$) to construct the market-based measure ($Q_{i,t}^E$). The novel measure uses an estimate of the firm's intrinsic value ($\widehat{V}_{i,t}$) to construct the analyst-based measure ($\widehat{Q}_{i,t}$). This estimate of the firm's intrinsic value is based on consensus forecasts of the firm's current and future earnings provided by accredited securities analysts to I/B/E/S International Inc. near the beginning of year t.[8] In both cases, the replacement of the unobserved $Q_{i,t}$ by its measured counterpart ($Q_{i,t}^E$ or $\widehat{Q}_{i,t}$) introduces a further measurement error component into the error term of the empirical version of equation 1.1. For example, replacing $Q_{i,t}$ by the standard market-based measure $Q_{i,t}^E$ results in the empirical specification

$$\left(\frac{I}{K}\right)_{i,t} = a + \frac{1}{b}Q_{i,t}^E + \gamma\left(\frac{CF}{K}\right)_{i,t} + \left(\varepsilon_{i,t} - \frac{\mu_{i,t}}{b}\right) \tag{1.2}$$

in which $\mu_{i,t} = Q_{i,t}^E - Q_{i,t}$ is the measurement error introduced by using $Q_{i,t}^E$ as the measure of $Q_{i,t}$. In this case, consistent estimation of the parameters $\frac{1}{b}$ and γ relies on the availability of instrumental variables which are uncorrelated with this measurement error $\mu_{i,t}$, as well as with the adjustment cost shock $\varepsilon_{i,t}$. The main motivation for considering the analyst-based measure $\widehat{Q}_{i,t}$ is the likely difficulty of finding valid instruments in equation 1.2, if stock market valuations ($V_{i,t}^E$) deviate from intrinsic values ($V_{i,t}$) by a highly persistent bubble component which may be correlated with lagged values of observed 'fundamental' variables such as investment rates and cash flow variables.[9] Simply replacing $Q_{i,t}^E$ by the analysts-based measure

[7] They were not the first or only researchers to take this measurement issue seriously. See Erickson and Whited (2000) for a different approach using higher-order moment conditions.

[8] Further details of the construction of the estimated intrinsic values $\widehat{V}_{i,t}$ can be found in Appendix B of Cummins et al. (2006).

[9] See Bond and Cummins (2001) for further discussion.

$\widehat{Q}_{i,t}$ gives the alternative empirical specification

$$\left(\frac{I}{K}\right)_{i,t} = a + \frac{1}{b}\widehat{Q}_{i,t} + \gamma\left(\frac{CF}{K}\right)_{i,t} + \left(\varepsilon_{i,t} - \frac{\nu_{i,t}}{b}\right) \tag{1.3}$$

in which $\nu_{i,t} = \widehat{Q}_{i,t} - Q_{i,t}$ is the measurement error introduced by using $\widehat{Q}_{i,t}$ as the measure of $Q_{i,t}$. This does not eliminate the potential concern about measurement error, but the conjecture is that the measurement error component $\nu_{i,t}$ of the error term in equation 1.3 may more plausibly be uncorrelated with candidate instruments such as lagged investment rates and cash flow terms.

B. Estimation

To estimate equations 1.2 and 1.3 using panel data for publicly traded US firms that are tracked by securities analysts, Cummins et al. (2006) assume that the adjustment cost shock $\varepsilon_{i,t}$ is the sum of three mean zero components

$$\varepsilon_{i,t} = \xi_i + \eta_t + \omega_{i,t}$$

where ξ_i allows for time-invariant unobserved factors specific to firm i, η_t allows for time-varying unobserved factors that are common to all firms, and $\omega_{i,t}$ is the residual component which is assumed to be independent across firms but which may be serially correlated for a given firm. The time-specific component η_t is accounted for by the inclusion of time dummies (i.e. time-specific intercepts), and the firm-specific component ξ_i is eliminated by first-differencing. For their preferred empirical specification 1.3, this gives the equations used for estimation as

$$\Delta\left(\frac{I}{K}\right)_{i,t} = c_t + \frac{1}{b}\Delta\widehat{Q}_{i,t} + \gamma\Delta\left(\frac{CF}{K}\right)_{i,t} + \left(\Delta\omega_{i,t} - \frac{\Delta\nu_{i,t}}{b}\right) \tag{1.4}$$

where $c_t = \Delta\eta_t = \eta_t - \eta_{t-1}$. In their main results, the lagged variables $[(I/K)_{i,t-3}$, $(I/K)_{i,t-4}$, $(CF/K)_{i,t-3}$, $(CF/K)_{i,t-4}]$ as well as time dummies are used as the instruments to estimate the parameters $(c_t, \frac{1}{b}, \gamma)$ in these first-differenced equations.

The same instruments are also used to estimate the first-differenced counterpart of equation 1.2. Cummins et al. (2006) present evidence that these instruments are informative for the endogenous explanatory variables in these first-differenced equations. They report one-step GMM estimates using the weight matrix for first-differenced specifications suggested by Arellano and Bond (1991), with standard errors that are asymptotically robust to heteroskedasticity and arbitrary forms of serial correlation in the error term $\left(\Delta\omega_{i,t} - \frac{\Delta\nu_{i,t}}{b}\right)$.[10] The validity of the instruments is tested using the test of overidentifying restrictions proposed by Hansen (1982), and by the test of no second-order serial correlation in the first-differenced residuals proposed by Arellano and Bond (1991), both of which are also asymptotically robust to heteroskedasticity and autocorrelation. The omission of instruments dated $t-2$ is motivated by the rejection of their validity by one or both of these tests. Formally this allows for either $\omega_{i,t}$ or $\nu_{i,t}$ to have a first-order moving average component.

To allow for more persistent autocorrelation, Cummins et al. (2006) also report estimates from a dynamic specification which allows $\omega_{i,t}$ to have the first-order autoregressive form

$$\omega_{i,t} = \rho\omega_{i,t-1} + \varphi_{i,t}$$

in which $\varphi_{i,t}$ is assumed to be serially uncorrelated. The quasi-differencing of equation 1.4 gives the restricted dynamic specification

$$\begin{aligned}\Delta\left(\frac{I}{K}\right)_{i,t} &= c_t^* + \rho\Delta\left(\frac{I}{K}\right)_{i,t-1} + \frac{1}{b}\Delta\widehat{Q}_{i,t} - \frac{\rho}{b}\Delta\widehat{Q}_{i,t-1} \\ &\quad +\gamma\Delta\left(\frac{CF}{K}\right)_{i,t} - \rho\gamma\Delta\left(\frac{CF}{K}\right)_{i,t-1} + \left(\Delta\varphi_{i,t} - \frac{\Delta\nu_{i,t}}{b} + \frac{\rho\Delta\nu_{i,t-1}}{b}\right)\end{aligned} \tag{1.5}$$

where $c_t^* = c_t - \rho c_{t-1}$ and $\Delta\varphi_{i,t} = \Delta\omega_{i,t} - \rho\Delta\omega_{i,t-1}$. As suggested by Blundell et al. (1992), this model can be estimated by first estimating the unrestricted dynamic

[10] The finite sample correction proposed by Windmeijer (2005) to the standard errors for two-step GMM estimators in this context was not widely implemented at the time that Cummins et al. (2006) were computing their results. For consistency with their paper, we also report one-step GMM estimates in Section 2 below. Very similar results were obtained using the two-step version of the GMM estimator with the Windmeijer correction for the standard errors.

specification

$$\Delta\left(\frac{I}{K}\right)_{i,t} = c_t^* + \pi\Delta\left(\frac{I}{K}\right)_{i,t-1} + \beta_0\Delta\widehat{Q}_{i,t} + \beta_1\Delta\widehat{Q}_{i,t-1} \quad (1.6)$$
$$+\gamma_0\Delta\left(\frac{CF}{K}\right)_{i,t} + \gamma_1\Delta\left(\frac{CF}{K}\right)_{i,t-1} + \left(\Delta\varphi_{i,t} - \frac{\Delta\nu_{i,t}}{b} + \frac{\rho\Delta\nu_{i,t-1}}{b}\right)$$

and then imposing the non-linear 'common factor' restrictions $\beta_1 = -\pi\beta_0$ and $\gamma_1 = -\pi\gamma_0$ using minimum distance. Cummins et al. (2006) use the lagged variables $[(I/K)_{i,t-3},\ (I/K)_{i,t-4},\ (CF/K)_{i,t-3},\ (CF/K)_{i,t-4}]$ as well as time dummies as instruments to estimate the unrestricted parameters $(c_t^*, \pi, \beta_0, \beta_1, \gamma_0, \gamma_1)$ in equation (1.6).[11] They report the corresponding estimates of the restricted parameters $(\rho, \frac{1}{b}, \gamma)$ in equation (1.5), but not the underlying estimates of the coefficients on the current and lagged cash flow (and the current and lagged $\widehat{Q}$) terms in equation (1.6). This omission has some significance in our discussion of the results of our extended analysis in Section 1.2 below.

1.2 Empirical Results

Table 1.1 summarizes the key results presented in Cummins et al. (2006) based on static specifications like equation 1.4 for their full sample of publicly traded US corporations covered by securities analysts during the period 1982-99. We were able to replicate these results exactly using their dataset. Column (1) reports typical findings when the standard market-based measure of Tobin's Q is used; the coefficient on the current cash flow term is positive and significantly different from zero, after controlling for this measure of Tobin's Q. This specification is also strongly rejected

[11] It may appear that the four instruments listed here are insufficient to identify the five slope parameters in equation (1.6). In fact, following Arellano and Bond (1991), the estimation procedure used by Cummins et al. (2006) allows separate first-stage projections for each of the available first-differenced equations, so that they use a total of $4T$ instruments (in addition to the time dummies), where T is the number of first-differenced equations.

by the test of overidentifying restrictions. For the same sample, column (2) shows very different results when the analyst-based measure of Tobin's Q is used instead. Here the estimated coefficient on the current cash flow term is much smaller and insignificantly different from zero. This specification is also not rejected by the test of overidentifying restrictions, and the reported pattern of serial correlation in the first-differenced residuals is consistent with the validity of instruments lagged three or more periods.[12] Column (3) confirms that both the market-based measure of Tobin's Q and the current cash flow term are uninformative after controlling for the analyst-based measure of Tobin's Q, which summarizes information about expected future earnings.

[12]Using the xtabond2 command in Stata developed by Roodman (2009), we can report the Arellano-Bond test of no third-order serial correlation in the first-differenced residuals, which is more appropriate for assessing the validity of these instruments than the corresponding test of no second-order serial correlation reported by Cummins et al. (2006).

Table 1.1: GMM Estimates for First-Differenced Investment Equations

	(1)	(2)	(3)
$Q^E_{i,t}$	0.039		0.011
	(0.008)		(0.008)
	[5.078]		[1.295]
$\hat{Q}_{i,t}$		0.139	0.127
		(0.019)	(0.020)
		[7.458]	[6.329]
$\frac{CF}{K}_{i,t}$	0.314	0.044	0.054
	(0.102)	(0.108)	(0.107)
	[3.087]	[0.409]	[0.507]
Hansen p-value	0.000	0.304	0.311
m_2 p-value	0.002	0.002	0.005
m_3 p-value	0.232	0.501	0.493

Notes: The dependent variable is the first-difference of the ratio investment to capital $(I/K)_{i,t}$. Although not reported, each specification includes a full set of year dummies. Robust standard errors are in parentheses, whereas t-statistics are reported in square brackets. The sample contains 7,167 firm-year observations between 1987 and 1999. The instrumental variables are period $t-3$, and $t-4$ values of I/K and CF/K, as well as year dummy variables. The Hansen test of overidentifying restrictions is asymptotically distributed $(\chi)^2_{n-p}$ under the null of valid instruments, where n is the number of instruments and p is the number of parameters. The m_2 test for no second order serial correlation in the first-differenced residuals is asymptotically distributed N(0,1) under the null of no serial correlation. The m_3 test is the corresponding test for no third-order serial correlation in the first-differenced residuals.

Table 1.2 summarizes our findings when the current cash flow term is replaced by its first lag $(CF/K)_{i,t-1}$. Note that we use exactly the same sample and instrument set here as in Table 1.1. The coefficient on the lagged cash flow term is both larger and more significant in column (1) than the corresponding coefficient on the current cash flow term in column (1) of Table 1.1. However the more important differences are found in columns (2) and (3), where the analyst-based measure of Tobin's Q is included in the specifications. In both cases the coefficient on the lagged cash flow term is around four times larger than the corresponding coefficients on the

current cash flow terms in the same columns of Table 1.1. The null hypothesis that the coefficient on the lagged cash flow variable is zero is marginally rejected here, respectively at the 12% significance level in column (2) and at the 10% significance level in column (3). Lagged cash flow is thus found to be markedly more informative about corporate investment rates than the current cash flow variable considered by Cummins et al. (2006).

Table 1.2: GMM Estimates for First-Differenced Investment Equations

	(1)	(2)	(3)
$Q^E_{i,t}$	0.036		0.013
	(0.007)		(0.008)
	[4.963]		[1.618]
$\hat{Q}_{i,t}$		0.123	0.107
		(0.021)	(0.023)
		[5.966]	[4.738]
$\frac{CF}{K}_{i,t-1}$	0.404	0.182	0.199
	(0.096)	(0.117)	(0.121)
	[4.215]	[1.554]	[1.642]
Hansen p-value	0.034	0.483	0.524
m_2 p-value	0.004	0.002	0.005
m_3 p-value	0.410	0.499	0.501

Notes: The dependent variable is the first-difference of the ratio investment to capital $(I/K)_{i,t}$. Although not reported, each specification includes a full set of year dummies. Robust standard errors are in parentheses, whereas t-statistics are reported in square brackets. The sample contains 7,167 firm-year observations between 1987 and 1999. The instrumental variables are period $t-3$, and $t-4$ values of I/K and CF/K, as well as year dummy variables. The Hansen test of overidentifying restrictions is asymptotically distributed $(\chi)^2_{n-p}$ under the null of valid instruments, where n is the number of instruments and p is the number of parameters. The m_2 test for no second order serial correlation in the first-differenced residuals is asymptotically distributed N(0,1) under the null of no serial correlation. The m_3 test is the corresponding test for no third-order serial correlation in the first-differenced residuals.

To investigate this further, we consider dynamic specifications of the form shown

in equations (1.5) and (1.6). Column (1) of Table 1.3 reports the estimated coefficients from the unrestricted dynamic specification (i.e. equation (1.6)). We use exactly the same sample and instrument set as in Cummins et al. (2006). In this specification, we estimate positive and significant coefficients on both $\widehat{Q}_{i,t}$ and the lagged investment rate $(I/K)_{i,t-1}$. It is evident that the lagged cash flow term is more informative than the current cash flow term; in this case the marginal significance level of the coefficient on lagged cash flow is 11%.

Cummins et al. (2006) impose the non-linear common factor restrictions shown in equation (1.5). Imposing these restrictions here, using the minimum distance procedure suggested by Blundell et al. (1992), we reproduce exactly the results reported in column (1) of Table 3 (p.806) in Cummins et al. (2006). These results are shown in column (2) of Table 1.3 for comparison.[13] As in the results for the corresponding static specification, shown in column (2) of Table 1.1, the coefficient on the current cash flow term is small and insignificantly different from zero. Cummins et al. (2006) report a test of the validity of the restrictions imposed here, suggested by Blundell et al. (1992) and based on the criterion function for the minimum distance estimator, which does not reject their validity (p-value = 0.347). Other tests are less convincing. A standard Wald test of the two non-linear restrictions has a p-value of 0.04.[14] Moreover there are other valid restrictions that can be imposed on the dynamic model reported in column (1). In column (3), we impose the restrictions that $\beta_1 = \gamma_0 = 0$, and omit the insignificant $Q^E_{i,t}$ and $(CF/K)_{i,t}$ terms from the specification. A standard Wald test does not reject these restrictions (p-value = 0.85). The remaining coefficients are all at least marginally significant, with the coefficient on the lagged cash flow term significantly different from zero at the 12% level. These findings are strengthened by the use of additional instruments.

[13]Note that in column (2), the coefficients reported in the rows labelled $\widehat{Q}_{i,t}$, $(CF/K)_{i,t}$ and $(I/K)_{i,t-1}$ are respectively the restricted estimates of the parameters $(\frac{1}{b})$, γ and ρ in equation (1.5).

[14]This test is computed using the testnl post-estimation command in Stata, after using xtabond2 to estimate the unrestricted model reported in column (1).

Table 1.3: GMM Estimates for First-Differenced Investment Equations: Dynamic Models

	(1)	(2)	(3)
$\hat{Q}_{i,t}$	0.094 (0.022) [4.285]	0.101 (0.021) [4.810]	0.099 (0.020) [4.988]
$\hat{Q}_{i,t-1}$	0.010 (0.020) [0.52]		
$\frac{CF}{K}_{i,t}$	0.023 (0.093) [0.242]	-0.001 (0.089) [-0.011]	
$\frac{CF}{K}_{i,t-1}$	0.157 (0.103) [1.52]		0.162 (0.103) [1.567]
$\frac{I}{K}_{i,t-1}$	0.161 (0.078) [2.069]	0.254 (0.044) [5.773]	0.186 (0.066) [2.838]
Hansen p-value	0.639		0.706
m_2 p-value	0.580		0.736
m_3 p-value	0.688		0.736

Notes: The dependent variable is the first-difference of the ratio investment to capital $(I/K)_{i,t}$. Although not reported, each specification includes a full set of year dummies. Robust standard errors are in parentheses, whereas t-statistics are reported in square brackets. The sample contains 7,167 firm-year observations between 1987 and 1999. The instrumental variables are period $t-3$, and $t-4$ values of I/K and CF/K, as well as year dummy variables. The Hansen test of overidentifying restrictions is asymptotically distributed $\chi^2_{(n-p)}$ under the null of valid instruments, where n is the number of instruments and p is the number of parameters. The m_2 test for no second order serial correlation in the first-differenced residuals is asymptotically distributed N(0,1) under the null of no serial correlation. The m_3 test is the corresponding test for no third-order serial correlation in the first-differenced residuals. The results reported in column (2) impose the two non-linear "common factor" restrictions described in equation (1.6) on the dynamic specification in column (1). The results reported in column (3) omit the $\hat{Q}_{i,t-1}$ and $(\text{CF/K})_{i,t}$ terms from the dynamic specification in column (1).

In Table 1.4, we repeat the three specifications considered in Table 1.3, but

adding the third and fourth lags of the market-based measure of Tobin's Q to the set of instruments.[15] Importantly, the validity of this instrument set is not rejected by the reported Hansen test of overidentifying conditions, and the validity of the additional lagged Q^E instruments is not rejected by a Difference-Hansen test (p-value = 0.65 for the unrestricted specification in column (1)). There are two important changes to the results of Table 1.3. First, the validity of the two non-linear restrictions imposed in column (2), corresponding to the restricted dynamic specification shown in equation (1.5), is now strongly rejected by the standard Wald test (p-value = 0.008), while the p-value of the validity of these restrictions using the minimum distance procedure is 0.14. Second, the coefficients on the three terms included in our preferred specification reported in column (3) are now all highly significant, with the coefficient on the lagged cash flow term now significantly different from zero at the 1% level. The omission of the $\hat{Q}_{i,t-1}$ and $(CF/K)_{i,t}$ terms from the specification reported in column (1) is not rejected by a standard Wald test (p-value = 0.44). The significance of the lagged cash flow term can also be seen in the unrestricted dynamic specification reported in column (1). Hence, we find very clear evidence that corporate investment displays excess sensitivity to lagged cash flow, even controlling for the information in analysts' earnings forecasts, summarized in the analyst-based measure of Tobin's Q.

[15] Very similar results were found when adding either the second lag of the cash flow term or adding the second lag of Q^E to either the instrument set used in Table 1.3, or to the instrument set used in Table 1.4. Very similar results were also found with additional Q^E terms included in the model. These results are available on request.

Table 1.4: GMM Estimates for First-Differenced Investment Equations: Dynamic Models Using Additional Instruments

	(1)	(2)	(3)
$\hat{Q}_{i,t}$	0.070 (0.017) [4.172]	0.078 (0.016) [4.875]	0.073 (0.015) [5.016]
$\hat{Q}_{i,t-1}$	-0.004 (0.014) [-0.255]		
$\frac{CF}{K}_{i,t}$	0.083 (0.069) [1.211]	0.062 (0.068) [0.912]	
$\frac{CF}{K}_{i,t-1}$	0.217 (0.081) [2.694]		0.223 (0.084) [2.66]
$\frac{I}{K}_{i,t-1}$	0.200 (0.070) [2.875]	0.306 (0.043) [7.116]	0.188 (0.060) [3.116]
Hansen p-value	0.644		0.563
m_2 p-value	0.734		0.757
m_3 p-value	0.819		0.732

Notes: The dependent variable is the first-difference of the ratio investment to capital $(I/K)_{i,t}$. Although not reported, each specification includes a full set of year dummies. Robust standard errors are in parentheses, whereas t-statistics are reported in square brackets. The sample contains 7,167 firm-year observations between 1987 and 1999. The instrumental variables are period $t-3$, and $t-4$ values of I/K, CF/K and Q^E as well as year dummy variables. The Hansen test of overidentifying restrictions is asymptotically distributed $\chi^2_{(n-p)}$ under the null of valid instruments, where n is the number of instruments and p is the number of parameters. The m_2 test for no second order serial correlation in the first-differenced residuals is asymptotically distributed N(0,1) under the null of no serial correlation. The m_3 test is the corresponding test for no third-order serial correlation in the first-differenced residuals. The results reported in column (2) impose the two non-linear "common factor" restrictions described in equation (1.6) on the dynamic specification in column (1). The p-value associated with the test of these common factor restrictions is 0.140. The results reported in column (3) omit the $\hat{Q}_{i,t-1}$ and $(\text{CF/K})_{i,t}$ terms from the dynamic specification in column (1).

1.3 Conclusion

We extend the empirical analysis reported in Cummins et al. (2006) to consider the significance of a lagged cash flow term in explaining the investment behaviour of the publicly-traded US companies included in their sample. We confirm that their novel measure of Tobin's Q, using an estimate of the firm's intrinsic value based on securities analysts earnings forecasts, is highly informative for explaining the investment rates of these firms. Nevertheless, we also find that lagged cash flow helps to explain the investment behaviour of these firms, even when controlling for this analyst-based measure of Tobin's Q. This result is particularly clear in dynamic specifications which further allow for persistence in investment rates that is not accounted for by the preferred measure of Tobin's Q, and using additional instruments which are found to be valid in these dynamic specifications.

Our results thus reject the predictions of the Tobin-Hayashi Q model of investment, derived under the assumption of perfect capital markets. This should not be surprising. There is, for example, already strong evidence against the assumption that capital stock adjustment costs take the simple quadratic form needed to derive a linear relationship between investment rates and Tobin's Q.[16] Our results do not establish the importance of a cost premium for external finance, or other financing frictions. They do however suggest that capital market imperfections should not be dismissed on the basis that corporate investment displays no sensitivity to indicators of the availability of internal funds.

[16] See, for example, Doms et al. (1998), Cooper and Haltiwanger (2006) and Bloom (2009).

Chapter 2

The Relationship between Internal Funds, Observable Expectations, and Corporate Investment: Further Evidence

By Revi Panidha[1]

Abstract

This chapter further explores the robustness of the Cummins et al. (2006) results by examining their rated and unrated samples. We expand on the Cummins et al. (2006) subsample results by introducing a lagged cash flow measure in both static and dynamic model specifications. In addition to the full sample, we find excess sensitivity to lagged cash flow for the rated sample. These results are further strengthened once we use the two-step GMM estimators whose standard errors are calculated using the finite sample correction proposed by Windmeijer (2005). We finally provide evidence

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that reporting bias is a possible source of the high predictive power of the alternative measure of Tobin's Q in the results of Cummins et al. (2006).

2.1 Motivation and Brief Literature Review

Stein (2003) shows that financing frictions and their impact on real investment is a central matter in contemporary finance. This is no surprise given that the relationship between investment and financing frictions is used to study issues which affect optimal hedging and cash policies (Almeida et al. (2004); and Froot et al. (1993)) or firm organizational design (Stein (1997); Gertner et al. (1994)). Moreover, the presence of significant financial constraints has important implications for our understanding of business cycles, monetary policy, tax policy, takeovers etc. (Bond and Söderbom (2013); Almeida and Campello (2007)).

Fazzari et al. (1988) were the first to provide evidence of underinvestment when external finance is more costly than internal finance. In their seminal paper, Fazzari et al. (1988) find that, controlling for investment opportunities, firms that are more financially constrained have higher investment-cash flow sensitivity. Fazzari et al. (1988) empirically find that investment sensitivity to wealth shocks is greater in the relatively more financially constrained firms than in the less financially constrained firms (monotonicity hypothesis). A decade later, Hubbard (1998) surveyed many studies that have confirmed Fazzari et al.'s main result.

However, there are shortcomings to Fazzari et al. (1988). They use dividend policy as a proxy for the presence or severity of a financial constraint, which can be unreliable as it is not clear why firms pay dividends. Moreover, dividend payment is an endogenous variable. Indeed, Kaplan and Zingales (1997) find the contrary: investment-cash flow sensitivity decreases with a different proxy for the severity of the financial constraint. The key to these differences is the proxy used to classify firms as constrained or not. An alternative proxy is whether a firm has an industrial group membership (Hoshi et al. (1991)). Although results are not very precise, they go in the same direction as Fazzari et al. (1988).

Large informational asymmetries or poor collateral (e.g., the human capital of

a start-up software company) are the main reasons that might lead to financing constraints. Unfortunately, identifying financing-investment interactions in the data is not an easy task, because the notional demand of firms for external finance cannot be observed (Hajivassiliou and Savignac (2008)). Theoretically, cash flow sensitivities do not necessarily indicate financial constraints (Kaplan and Zingales (2000); Gomes (2001); Alti (2003)). Profits or cash flow may be correlated with investment even in perfect capital markets.

Lamont (1997) conducted important research where he tried to separate cash flow and investment profitability by looking at large segmented firms. The two segments are oil and non-oil. He finds that the non-oil segments of multi-segment firms reduce investments in response to exogenous negative cash flow shocks to the oil segment. This paper also raises interesting questions on internal capital allocation.

Different authors have used different proxies to classify firms as constrained. Moyen (2004) constructs a simulated panel with an equal number of unconstrained and constrained firms. She applies five different criteria to classify firms and carries out investment-cash flow regressions. Her ingenious paper provides an explanation for the previous mixed results in the literature and clearly shows that the financial constraints classification changes entirely the results of the regressions.

The literature so far has also presented various alternative reasons for the failure of the basic neoclassical investment model. The reasons include simultaneity bias, asymmetric information, fixed adjustment costs, wrong econometric assumptions and measurement error in the fundamentals. The measurement error hypothesis, unlike the other options, seems an appealing explanation as it might explain all of Q theory's empirical shortcomings. Erickson and Whited (2000) gave a satisfactory explanation as to why this might be the case. Nevertheless, most papers that have attempted to address this issue still find significant coefficients on measures of internal finance (Erickson and Whited (2000)). An exception is Cummins et al. (2006), which after correcting for measurement error in the fundamentals, shows that the

sensitivity of investment to current cash flow disappears. However, after a careful review of the work of Cummins et al. (2006) we find, on the contrary, evidence of the sensitivity of investment to lagged cash flow in both their full and rated samples.

2.2 Description of the Data

In this section, we review the data sources used to construct the Cummins et al. (2006) dataset. The two main sources of firm-level data are the Compustat and I/B/E/S databases. The samples are unbalanced panels that begin in fiscal year 1982 and end in fiscal year 1999. Care has been taken to delete any outliers that can seriously distort empirical results. Deletion rules have led to no significant data loss, usually less than a percentile, and are discussed in detail in their paper. The full sample contains over 11,000 firm-year observations. The subsamples are comprised of firms with and without bond ratings (i.e. rated and unrated firms). The analyst-based measure of average Q, denoted by $\hat{Q}$, is constructed using expected earnings from I/B/E/S while the data on capital stock, investment, Q^E, cash flow and the variables used to split the sample are from Compustat.[2] The final variables in each sample are Q^E, $\hat{Q}$, I/K, CF/K and year.[3] The median of these variables in the sample are not too far off the Compustat medians for all publicly-traded firms, irrespective of their availability in the I/B/E/S dataset. This argument makes it defensible that selection bias might not be a major concern.[4]

The I/B/E/S earning forecasts provide valuable information about the expected returns to investment. This claim is the working assumption of the authors which

[2]See Section 1.1 for further details on the construction of Q^E and $\hat{Q}$.

[3]For a replication of the descriptive statistics for the variables in the full sample and the comparison with the Compustat averages, refer to Table 1 of the original paper.

[4]Further details on the data construction are included in Appendix B of Cummins et al. (2006) Online Appendix. The Online Appendix can be found at https://www.aeaweb.org/articles?id=10.1257/aer.96.3.796 under the Additional Material section. There you will also find the appendices referenced in their paper as well as their original data.

they believe is supported by their data. Moreover, they recognize that while analysts' forecasts might not be fully rational or might have predictable forecast errors (Brown (1996)), they are useful for studying investment behaviour, as long as they provide a good proxy for the fundamentals that drive investment. The main hypothesised benefit of using an analyst-based measure of Q instead of Q^E is that it addresses problems related to measurement errors introduced by equating stock market values with fundamental values. Cutler et al. (1988) shows that measurement errors in average Tobin's Q can lead to spurious correlations between investment and cash flow. Cummins et al. (2006) believe that Q^E has a persistent measurement error correlated with the intrinsic value of the firm. Hence, when Q^E is used in investment-Q regressions this type of measurement error would invalidate instrumental variables that are also correlated with the intrinsic value of the firm. Consequently, GMM estimators that use lags of cash flow or lags of investment as instruments would be inconsistent. The main hypothesis of Cummins et al. (2006) is that the failings of investment-Q regressions could be explained by such measurement error in Q^E.[5]

[5]See Section 1.1 for further details on the measurement error issue.

2.3 Empirical Results

We first re-estimate the main results from Cummins et al. (2006) across all subsamples and summarize their main findings.[6] The authors use period $t-3$ and $t-4$ values of I/K and CF/K, as well as year dummies as their instrument set to obtain first-differenced GMM estimates of a static specification. They check that the F-statistics from the first-stage regressions exceeded 10, the rule of thumb suggested by Staiger and Stock (1997), and conclude that weak instruments are not a concern. We replicate the authors' main results in Table 2.1.[7]

When controlling for fundamentals using Q^E, the authors find that both Q^E and $\frac{CF}{K}_{i,t}$ in the full sample are statistically significant at 1% (estimation (1) in Table 2.1). These results are in line with typical findings in previous studies. The Hansen J-test of the model's overidentifying restrictions decisively rejects the validity of these instruments in two out of the three samples (i.e. estimations (1) and (2)).[8] The authors use this as evidence for their initial claim that models using Q^E would be misspecified due to measurement error.

The next set of specifications use $\hat{Q}$ instead of Q^E. In estimations (4)-(6) the presence of $\hat{Q}$ makes the current cash flow term insignificant while the effect of $\hat{Q}$ is both large, relative to the effect of Q^E in the previous specifications, and highly significant. In particular, the estimated coefficients on $\hat{Q}$ range from three to five times larger compared to their counterpart estimates for Q^E. Finally, the authors estimate their main model where both Q^E and $\hat{Q}$ are included. In this model, as they expect, both Q^E and current cash flow become insignificant while the coefficient on $\hat{Q}$ is still large and highly statistically significantly different from zero with t-statistics ranging from 3.6 to 6.3 . The authors use the Hansen J-test's high p-values in defense of the claim that models with $\hat{Q}$ are well specified (see estimation (4)-(9) in Table

[6] See Section 1.1 for further details of the regression models.

[7] m_3 and m_4 tests were not performed in the original paper.

[8] The Hansen J-test is referred to as the Sargan test in the tables produced in Cummins et al. (2006). Hence, Sargan p value or Hansen p we often used interchangeably.

2.1). However, the m_2 p-values are low (e.g., 0.002 in estimation (4)) in all but the rated sample which indicate that a dynamic model might be better suited to correct for serial correlation in the error term. The authors recognize this and also consider a dynamic specification which allows for an AR(1) error component (see section 1.2). After imposing the common factor restrictions, they find that while the lagged I/K is highly significant, their results do not change both in terms of the significance level and magnitude.[9] They conclude that correcting for serial correlation does not materially affect the results.

[9] "...the common factor restriction arises from the assumption that the disturbance term [...] follows a first-order autoregressive process. Under that assumption, the first lag of each right-hand-side variable enters the regression with a coefficient that is constrained to equal the coefficient on the contemporaneous term for that variable times the coefficient on the lagged dependent variable, multiplied by negative one." (Cummins et al. (2006) p. 805)

Table 2.1: GMM Estimates of First-Differenced Investment Equations

Dependent Variable: $\frac{I}{K}_{i,t}$

Variable	Full Sample (1)	Rated Sample (2)	Unrated Sample (3)	Full Sample (4)	Rated Sample (5)	Unrated Sample (6)	Full Sample (7)	Rated Sample (8)	Unrated Sample (9)
$Q^E_{i,t}$	0.039	0.027	0.013				0.010	-0.022	0.005
	(0.008)	(0.014)	(0.008)				(0.008)	(0.018)	(0.008)
	[5.078]	[1.997]	[1.667]				[1.295]	[-1.200]	[0.607]
$\frac{CF}{K}_{i,t}$	0.314	0.110	0.205	0.044	-0.007	0.105	0.054	-0.020	0.092
	(0.102)	(0.070)	(0.105)	(0.108)	(0.069)	(0.113)	(0.107)	(0.069)	(0.112)
	[3.087]	[1.569]	[1.959]	[0.409]	[-0.095]	[0.925]	[0.507]	[-0.284]	[0.8210]
$\hat{Q}_{i,t}$				0.139	0.144	0.071	0.127	0.172	0.068
				(0.019)	(0.030)	(0.019)	(0.020)	(0.033)	(0.019)
				[7.458]	[4.875]	[3.777]	[6.329]	[5.155]	[3.566]
Hansen $p-$value	0.000	0.000	0.105	0.304	0.213	0.259	0.311	0.272	0.236
Sargan df	51	51	51	51	51	51	50	50	50
m_1 test statistic	-9.01	-3.59	-6.44	-7.90	-4.00	-6.32	-7.37	-4.23	-5.97
m_2 $p-$value	0.002	0.105	0.003	0.002	0.240	0.013	0.005	0.173	0.020
m_3 $p-$value	0.232	0.441	0.864	0.501	0.621	0.924	0.493	0.571	0.953
m_4 $p-$value	0.955	0.994	0.572	0.561	0.408	0.599	0.571	0.431	0.513

IVs: $\frac{CF}{K}$: $t-3$, $t-4$; $\frac{I}{K}$: $t-3$, $t-4$

See Table 2.2 for further notes.

The authors then continue with further robustness checks by constructing an alternative $\hat{Q}$ that addresses potential concerns about the fact that different firms could have different discount factors in the calculation of $\hat{Q}$.[10] In particular, they switch to a discount rate that differs both across time and firms based on the Capital Asset Pricing Model. Their initial results do not change when performing a static GMM first-difference estimation.

The authors further experiment with alternative instrument sets by including 3^{rd} and 4^{th} lags of $\hat{Q}$ in the static model but these instruments are rejected by the Hansen J-test. This could possibly be, the authors claim, due to the measurement error in $\hat{Q}$ being serially correlated. Finally, the authors provide, in the online appendix, additional robustness tests which include the use of 1) different instrument sets; 2) the use of forward mean-differencing; and 3) different rules for deleting outliers. The authors then conclude that "none of these variations affected the two key features of our results - that $\hat{Q}$ is a highly significant determinant of investment and that cash-flow effects become insignificant in the presence of $\hat{Q}$" (p. 807). The authors conclude their paper with a recommendation against using market-based average Q as a control for fundamentals in such investment regressions to test for the presence of financing constraints.

In Table 2.2 we present the re-estimation of Columns (7)-(9) of Table 2.1 having now included lagged cash flow in all the specifications.[11] One can see that, using the same estimation technique with the original instrument set, lagged cash flow is much more informative than current cash flow in both the full sample and the rated sample. For example, in the full sample, the estimated lagged cash flow coefficient is around 20 times larger than the current cash flow coefficient and the lagged cash

[10] More information on how the discount factor enters the construction of $\hat{Q}$ can be found in Appendix B of the original paper.

[11] Stata codes and datasets used for all the presented results can be found in the online Appendix. The online Appendix of this chapter can be accessed via the following link http://bit.ly/3aUkfcN. The Hansen p-values and degrees of freedom for Tables 2.1 to 2.4 were manually adjusted and included in these tables due to the miscalculation by the xtabond2 command when *if* statements are used.

flow term is only marginally insignificantly different from zero at around the 10% significance level. In the rated sample, the lagged cash flow coefficient is around 4 times as large and statistically different from zero at the 10% significance level. These results are further strengthened in Table 2.3 once we present the two-step GMM estimates with the Windmeijer correction for standard errors, which was not widely available at the time Cummins et al. (2006) were completing their study.

Table 2.2: **One-step GMM Estimates of First-Differenced Investment Equations with Lagged Cash Flow**

Dependent Variable: $\frac{I}{K}_{i,t}$

(Comparison across samples - Cummins et al. data)

Variable	Full Sample	Rated Sample	Unrated Sample
$\hat{Q}_{i,t}$	0.112	0.113	0.055
	(0.025)	(0.044)	(0.021)
	[4.419]	[2.540]	[2.703]
$Q^E_{i,t}$	0.009	0.000	0.005
	(0.009)	(0.018)	(0.008)
	[0.993]	[0.002]	[0.577]
$\frac{CF}{K}_{i,t}$	0.010	0.072	0.092
	(0.103)	(0.089)	(0.109)
	[0.101]	[0.807]	[0.845]
$\frac{CF}{K}_{i,t-1}$	0.195	0.271	0.093
	(0.119)	(0.153)	(0.086)
	[1.639]	[1.774]	[1.081]
Hansen p-value	0.653	0.363	0.253
Sargan df	52	52	52
Sargan test statistic	47.45	38.36	58.38
m_1 test statistic	-7.04	-3.58	-5.97
m_2 p-value	0.004	0.092	0.014
m_3 p-value	0.400	0.972	0.574
m_4 p-value	0.826	0.713	0.19
Firms	1060	429	603
Observations	6904	2552	2722

IVs: $\frac{CF}{K}$: $t-3$, $t-4$; $\frac{I}{K}$: $t-3$, $t-4$

Notes to all Tables:
Time dummies are included as regressors and instruments. Asymptotic standard errors are reported in parentheses, while t-statistics are reported in square brackets. Standard errors are robust to general time-series and cross-section heteroskedasticity. m_1 and $m_2 - m_4$ are tests for first, second-order and higher-order serial correlation, asymptotically distributed as N(0,1) under the null of no serial correlation. The Hansen/Sargan test of overidentifying restrictions is asymptotically distributed $(\chi)^2_{n-p}$ under the null of valid instruments, where n is the number of instruments and p is the number of parameters. The p-value of this test is reported.

From Table 2.3 we can see that the estimated lagged cash flow coefficients in both the full sample and the rated sample are large, 0.248 and 0.234 respectively, and statistically significantly different from zero at the 1% and 5% levels respectively. Neither of the cash flow coefficients is statistically significantly different from zero for the unrated sample. This pattern may suggest that the significance of (lagged) cash flow reflects something other than financing constraints, if one is willing to accept the rating of a firm as a good proxy for the presence or severity of financing constraints. Devereux and Schiantarelli (1990) find that cash flow appears to play a more important role for large firms than for small firms. While this may be surprising at first sight, there are several reasons why this might be the case. For example, it may reflect the fact that large firms tend to have a lower relative cash flow[12] or it may reflect the possibility that large firms have a more diverse ownership structure, which tends to increase agency costs.[13] The insignificance of Q^E remains unchanged from the results of the Cummins et al. (2006) study. While still highly significant, the estimated coefficients on $\hat{Q}$ are now smaller and have significantly lower t-statistics as compared to the main results presented in columns (7) to (9) of Table 2.1. In particular, the t-statistics of $\hat{Q}$ in the Cummins et al. (2006) main results are 6.33, 5.16 and 3.57 for the full, rated, and unrated samples respectively. In Table 2.3 the analogous values are 4.41, 3.25, and 2.26. Even when estimating a static model which uses the authors' proposed instrument set but applying a two-step estimation procedure with the Windmeijer correction for standard errors, we see that lagged cash flow is a significant predictor of investment for the full and rated samples, even after controlling for investment opportunities as captured by

[12]Cummins et al. (2006) do report a median (mean) of 0.138 (0.157) for the cash flow of rated firms versus 0.206 (0.231) for the cash flow of unrated firms (See Table 1, p.801).

[13]We were not able to find formal evidence, however, that the estimated coefficients on lagged cash flow were statistically different in the rated and unrated samples. This could happen, for example, if in the rated sample we observe lots of variation in lagged cash flow (so that we can estimate its effect precisely), but we observe much less variation in the lagged cash flow in the unrated sample. In this case, we may not be able to reject either the null hypothesis that the coefficient on lagged cash flow is zero or the null hypothesis that it is the same as the one in the rated sample. See Section 2 of the online appendix of this chapter for the results of formal tests.

either $\hat{Q}$ or Q^E.

Table 2.3: **Two-step GMM Estimates of First-Differenced Investment Equations with Lagged Cash Flow**

Dependent Variable: $\frac{I}{K}_{i,t}$
(Comparison across samples - Cummins et al. data)

Variable	Full Sample	Rated Sample	Unrated Sample
$\hat{Q}_{i,t}$	0.100	0.103	0.050
	(0.023)	(0.032)	(0.022)
	[4.414]	[3.245]	[2.256]
$Q^E_{i,t}$	0.005	0.001	0.005
	(0.008)	(0.015)	(0.009)
	[0.596]	[0.045]	[0.600]
$\frac{CF}{K}_{i,t}$	-0.036	0.050	0.088
	(0.105)	(0.078)	(0.108)
	[-0.344]	[0.640]	[0.813]
$\frac{CF}{K}_{i,t-1}$	0.248	0.234	0.102
	(0.093)	(0.116)	(0.077)
	[2.651]	[2.019]	[1.325]
Hansen p-value	0.653	0.363	0.253
Sargan df	52	52	52
Sargan test statistic	470.45	380.36	580.38
m_1 test statistic	-70.94	-30.60	-50.82
m_2 p-value	0.005	0.092	0.014
m_3 p-value	0.380	0.998	0.545
m_4 p-value	0.940	0.770	0.187
Firms	1060	429	603
Observations	6904	2552	2722

IVs: $\frac{CF}{K}$: $t-3$, $t-4$; $\frac{I}{K}$: $t-3$, $t-4$

See Table 2.2 for further notes.

We next present the dynamic model by adding lagged investment and reporting the two-step GMM estimates with the Windmeijer correction for standard errors.[14]

[14]The corresponding one-step estimates are included in Section 4 of the online appendix.

One can see once again that the coefficient on the lagged cash flow term is statistically significantly different from zero at the 1% level in the full sample and significantly different from zero in the rated sample at the 10% significance level. This main result on the significance of the lagged cash flow term in the full sample (and the rated sample) is further confirmed when using alternative instruments. We provide some of these alternative estimations in the online appendix.[15] We highlight that the estimated coefficients on $\hat{Q}$ become even smaller in magnitude and statistically insignificant for the unrated sample. The t-statistics of the estimated coefficients on $\hat{Q}$ in estimations (7)-(9) of Table 2.1 have now been approximately halved given the modest modifications we had to make to produce the results in Table 2.4. We will come back to this observation in the final section of this paper.

[15]See Section 1 of the online Appendix. The online Appendix of this chapter can be accessed via the following link http://bit.ly/3aUkfcN.

Table 2.4: **Two-step GMM Estimates of First-Differenced Investment Equations with Lagged Cash Flow**

Dependent Variable: $\frac{I}{K}_{i,t}$

(Comparison across samples - Cummins et al. data)

Variable	Full Sample	Rated Sample	Unrated Sample
$\hat{Q}_{i,t}$	0.078	0.087	0.044
	(0.024)	(0.031)	(0.029)
	[3.221]	[2.843]	[1.525]
$Q^E_{i,t}$	0.004	0.002	0.005
	(0.008)	(0.013)	(0.009)
	[0.484]	[0.159]	[0.538]
$\frac{CF}{K}_{i,t}$	0.026	0.063	0.108
	(0.105)	(0.072)	(0.121)
	[0.251]	[0.869]	[0.895]
$\frac{CF}{K}_{i,t-1}$	0.250	0.201	0.100
	(0.089)	(0.105)	(0.075)
	[2.816]	[1.914]	[1.331]
$\frac{I}{K}_{i,t-1}$	0.147	0.197	0.037
	(0.069)	(0.095)	(0.108)
	[2.135]	[2.061]	[0.341]
Hansen p-value	0.761	0.541	0.268
Sargan df	51	51	51
Sargan test statistic	43.56	33.49	56.78
m_1 test statistic	-5.50	-3.22	-2.89
m_2 p-value	0.529	0.854	0.208
m_3 p-value	0.555	0.995	0.617
m_4 p-value	0.655	0.918	0.195
Firms	1060	429	603
Observations	6904	2552	2722

IVs: $\frac{CF}{K}$: $t-3$, $t-4$; $\frac{I}{K}$: $t-3$, $t-4$

See Table 2.2 for further notes.

2.4 Reporting Bias

The estimates reported in the Cummins et al. (2006) paper seem to be quite fragile in light of minor changes to the sample, specification or functional form. What might explain this? One simple answer is that the published estimates may not be representative of the larger universe of estimates. In other words, published work might suffer from selection bias.[16]

> "Reporting bias" refers to the possibility that published results are an unrepresentative sample. There are several reasons why this might occur. The "file drawer problem" refers to the tendency of researchers not to report on approaches that "didn't work out," in the sense of not yielding statistically significant estimates. Alternatively, "publication bias" arises when journals only publish estimates that meet standard tests of statistical significance. "Data mining" or "specification search" may also occur if career-driven or ideologically motivated researchers face incentives to report specifications that yield statistically significant evidence or estimates in favor of their preferred position. That said, it is worth emphasizing that reporting bias may occur without any of the authors being aware of it: they might simply want to report useful findings, and evidence falsifying a null hypothesis is typically regarded as more valuable (Donohue and Wolfers, 2006, p.42).

Reassuringly, one can test for the presence of reporting bias.[17] The intuition is that different estimation specifications should be more or less similar, assuming the existence of a single true parameter of interest. Some approaches might lead to estimates with smaller standard errors and others might lead to estimates with larger standard errors. For example, controlling for more relevant and exogenous

[16] This section was inspired by the excellent paper of Donohue and Wolfers (2006)'.
[17] See Ashenfelter et al. (1999).

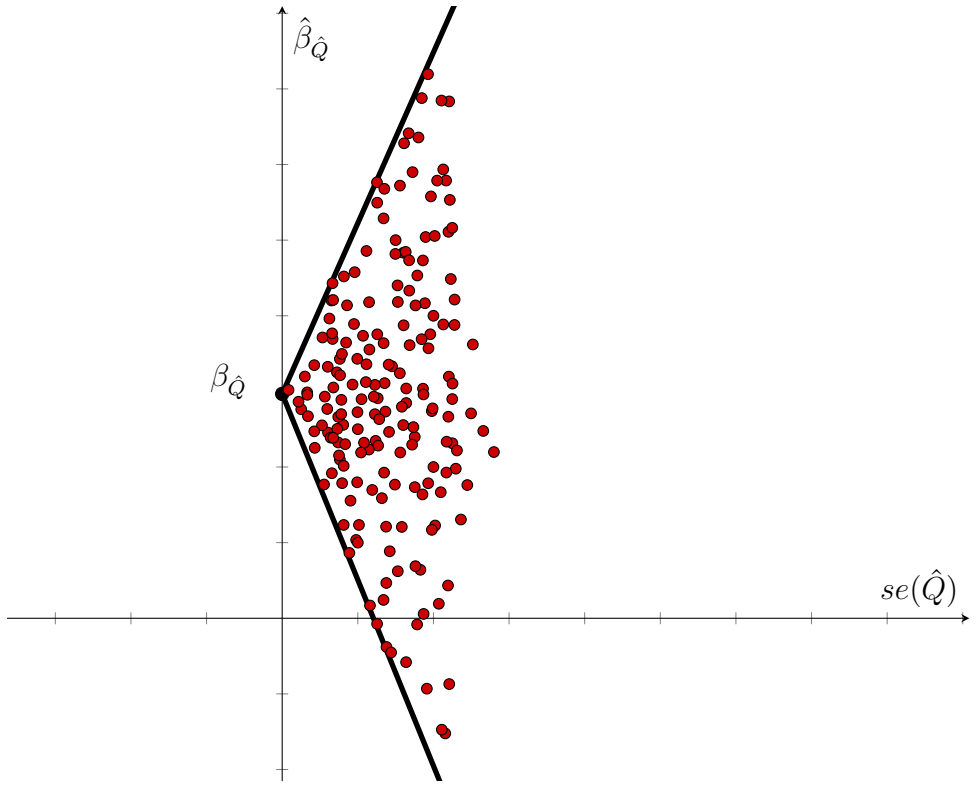


Figure 2.1: Expected patterns of coefficient and standard error estimates in the absence of reporting bias

variables should reduce the standard error associated with the estimate. Another example is the addition of further valid instruments. Thus, while it is likely that the size of the standard error will be related to the variability of the estimate, in expectation there should be no correlation between the estimated coefficients and the standard errors. Figure 2.1 illustrates this situation.

Hence, if we observe a correlation between the estimated coefficients and their standard error, this would suggest that the reported estimates are unrepresentative of the sample. As researchers might be more likely to report estimates which are significant, they would report large standard errors if the estimated effect is also large. In these situations we would expect a positive correlation in the reported sample. We are particularly interested in the estimated coefficients of $\hat{Q}$ in the Cummins et al. dataset. Following Donohue and Wolfers (2006), we plot the standard errors associated with each estimated $\hat{Q}$ to detect whether any correlation exists. Given

that the variability of estimates rises in a linear relationship with the standard error, we expect this correlation to be zero in the absence of any publication bias. In Figure 2.2 we plot the estimated coefficients on $\hat{Q}$ and their respective standard errors found both in the main paper and in the Appendix C that the authors provide. Out of 73 coefficients, 28 are found in the main paper and the remaining 45 coefficients are coming from Appendix C. The estimated coefficient on $se(\hat{Q})$ is 2.89 which is both large and statistically significant with a t-statistic of 5.90.[18] While it is worth emphasising that the authors have probably not been aware of this, Figure 2.2 provides some evidence that reporting bias might, at least in part, explain the higher significance of $\hat{Q}$ in their reported results and why, with minor modifications, we estimate much smaller t statistics.[19]



Figure 2.2: Illustration of publication bias using reported estimates from Cummins et al. (2006)

[18]We removed one outlier from the scatter plot that did not change our regression results but changed the scaling of the graph and hence its readability. We also ran separate regressions for the full sample estimates, the rated sample estimates and the unrated sample estimates. In all these three cases the coefficients were positive and statistically significant with t-statistics of 4.83, 6.09, 2.40 respectively. These results can be found in the online Appendix of this chapter which can be accessed via the following link http://bit.ly/3aUkfcN.

[19]This reporting bias does not alter the principal conclusions that $\hat{Q}$ is an informative explanatory variable for investment rates, that $\hat{Q}$ is considerably more informative than Q^E, and that current cash flow is insignificant when we control for fundamentals using $\hat{Q}$. Nevertheless, quantitatively speaking, the change in reported the t-statistic, for $\hat{Q}$ from 6.3 in the full sample in the original results presented in Table 2.1 to a corresponding t-statistic of 3.2 in Table 2.4 is a significant change.

2.5 Conclusion

This paper adds to the growing literature that has studied the effects of cash flow on investment and whether the coefficients on cash flow provide useful information about investment behaviour beyond measures of average Q. Cummins et al. (2006) claim that the sensitivity of investment to cash flow might be an artifact of the measurement error that might be present in the market-based measure of fundamentals, particularly if share prices are subject to bubbles. On the contrary, we provide new and robust evidence that correcting for measurement error in the fundamentals using the novel approach of Cummins et al. (2006) does not dismiss the effects of lagged cash flow on investment. The remaining cash-flow effects need not be due to the presence of financing constraints. Cash-flow effects can arise even in perfect capital markets when average Q does not equal marginal Q. In these settings, average Q is no longer a sufficient statistic, and additional explanatory variables such as cash flow might provide information about the profitability of investments (see Cooper and Ejarque (2001); Cooper and Ejarque (2003); Gomes (2001)). Finally, the very high significance of $\hat{Q}$ in the reported results of Cummins et al. (2006) might be, at least in part, due to reporting bias for which we provide evidence.

Chapter 3

The Roles of Expected Profitability, Tobin's Q and Cash Flow in Econometric Models of Company Investment: Further Evidence

By Revi Panidha[1]

Abstract

In this paper we review the role of expected profitability for around 700 UK publicly-traded firms between the years 1987 and 2000. We do so by revisiting Bond et al. (2004)'s dataset. We find that their main results, which are similar in spirit to Cummins et al. (2006), are not robust once we use two-step GMM estimators, whose standard errors are calculated using the finite sample correction proposed by Wind-

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meijer (2005), with additional valid instruments. We conclude that cash flow sensitivity, for this particular sample, cannot be dismissed when controlling for the novel analyst-based measure of investment opportunities suggested by Bond et al. (2004).

Introduction

Given our findings in the first two papers, we look next at a similar study which supports the view that measurement error in standard measure of the Tobin's average Q might explain the apparent importance of cash flow measures in the standard Tobin's Q models. We study the Bond et al. (2004) working paper and check its robustness. We find that cash flow sensitivity cannot be dismissed in the presence of the authors' alternative measure used to control for investment opportunities. This paper is organized as follows. Section 3.1 briefly explains the problems associated with the measurement error in Tobin's Q model. Section 3.2 describes the dataset for publicly-traded UK firms, and its construction. Section 3.3 checks the robustness of the results of Bond et al. (2004) and concludes that they are not robust when using a two-step GMM estimator with alternative valid instruments. Section **??** discusses possible implications for the excess cash-flow sensitivity given in the literature and empirical strategies to isolate the sources of this sensitivity.

3.1 Measurement Error in Tobin's Q

The hypothesis that Tobin's average Q can, at all times, reliably reflect the expected net present value of the firm's discounted expected profits is important for the validity of excess sensitivity tests based on the average Q model. If this is not the case, the key explanatory variable is measured with error, and depending on the nature of the error this could have important implications for empirical results.[2] Assuming the stock valuation has a 'bubble' (or error) component, the type of the error will determine which instruments might be valid. Bond and Cummins (2001) discuss four types of measurement error. The first type is the ideal situation in which this error term is serially uncorrelated and independent of the fundamentals of the firm. In particular, it should be independent of the replacement cost of capital (i.e. the

[2]Bond and Cummins (2001) have a detailed discussion in Section 2.2 (p. 7-12) and formal derivations on the discussion that follows.

denominator of Tobin's Q). If this is the case, lagged values of the observed Tobin's Q are admissible instrumental variables for itself. The second type is an error that follows an $MA(k)$ process but continues to be independent of fundamentals. In this case higher order lags of observed Tobin's Q remain admissible instruments. The third type is one where the error term is serially correlated but independent of fundamental variables such as profits, sales or investment. In this case, lagged values of these fundamental variables will be admissible instruments, although current values of these variables are likely to be correlated with the shock to investment adjustment costs and are thus ruled out as valid instruments. However, if the error component is serially correlated and not independent of fundamental variables then there may be no valid instruments that would allow for consistent estimation of the parameters. This form of measurement error is consistent with bubble processes, or other sources of mis-pricing of equities, considered by Blanchard and Watson (1982), Froot and Obstfeld (1991) and Campbell and Kyle (1993). It is this last type of measurement error that Bond et al. (2004) would like to address.

To address this final type of measurement error Bond et al. (2004) look for alternative and direct measures of expected future profitability. "To the extent that financial variables like cash flow have been found to be significant simply because they provide information about expected future profitability that is missing from the standard Tobin's average Q measures, then we would expect these financial variables to become less significant when we condition on these direct measures of expected future profitability" (Bond et al., 2004, p.12). This more direct measure of expected future profitability is similar in spirit to the $\hat{Q}$ measure developed by Cummins et al. (2006) and outlined in Chapter 1. However, departing from Cummins et al. (2006), Bond et al. (2004) adopt a less ambitious approach, not by choice, but due to the limited availability of data on analysts' earnings forecasts for UK firms (as compared to US firms). In particular, analysts' forecasts of firms' earnings beyond one-year

ahead are sparsely available in the UK dataset. Hence, their measure is limited to using the available forecasts of future profits in the short term. The next section elaborates on their approach.

3.2 Description of the Dataset

Bond et al. (2004) construct their dataset using firm-level data from two main sources: the Datastream database and the I/B/E/S database. The Datastream database has mainly annual financial information data that are found in financial statements supplied by the individual firms. Datastream covers UK publicly-traded companies from 1968 onwards. The I/B/E/S database provides analysts' forecasts of earnings and covers a subsample of UK publicly-traded firms from 1987, which is the starting period of the dataset. Similarly to Blundell et al. (1992), the capital stock measure is constructed using the perpetual inventory method. The authors initialize the capital stock ($K_{i,t}$) using the book value of property, plant, and equipment. The subsequent values are calculated using the following recursive formula:

$$p^K_{t+1} K_{i,t+1} = p^K_{t+1}(1-\delta)K_{i,t} + p^K_{t+1} I_{i,t+1} \tag{3.1}$$

where p^K_t is a price deflator for investment goods which uses the quarterly business investment deflator implied by the UK National Accounts to construct a series in constant 1995 prices. The depreciation rate (δ) is taken to be 0.08 as in Bond et al. (1999). Investment spending ($p^K_t I_{i,t}$) equals capital expenditure minus sales of capital goods plus net additions due to acquisitions. Daily market values of the firms are taken from Datastream. The market value is taken near the beginning of year t. This is to ensure that the information set is similar to that available to the analysts who make earnings forecasts. The measure of Tobin's Q adjusts for the firm's use of debt financing. The book value of stock of debt is added to the market

value of equity to obtain the numerator of Tobin's Q. The denominator of Tobin's Q is the replacement cost of capital that the firms inherit from the previous period. Further information on the construction of the capital stock, investment, Tobin's Q and other key variables is provided in the data appendix(Bond et al., 2004, p.35-39).

To come up with an alternative to Tobin's Q which might address the measurement error issue, Bond et al. (2004) use I/B/E/S data and replace the numerator of Q with a net present value of expected profits. Approved securities analysts provide earnings-per-share forecasts for individual firms for the current year and future years. However, forecasts beyond one-year ahead are rare. Bond et al. (2004) sidestep any heterogeneity across individual analysts by using the mean forecast which is commonly referred to as the consensus forecast. These consensus earnings forecasts are used to calculate two indicators of the expected profitability of the firm. The numerators of these ratios could be said to provide measures of (discounted) expected profits. We note that the numerator of $E\Pi_{i,t}$ contains the first two terms in their expressions for $\hat{V}$, the numerator of $\hat{Q}$ constructed by Cummins et al. (2006), ignoring any debt and tax adjustments.[3]

$$E\Pi_{i,t} = \frac{\hat{\Pi}_{i,t} + \beta_{t+1}\hat{\Pi}_{i,t+1}}{p_t^K(1-\delta)K_{i,t-1}} \tag{3.2}$$

$$E\Pi 1_{i,t} = \frac{\hat{\Pi}_{i,t+1}}{p_t^K(1-\delta)K_{i,t-1}} \tag{3.3}$$

$\hat{\Pi}_{i,t}$ denotes expected profits in year t as forecasted by the analysts. It is calculated by multiplying the consensus forecast of earnings-per-share by the number of shares

[3]Full rationality of the forecasts is not necessary and Brown (1996) has found forecast errors to be predictable. For our purposes, forecasts remain useful as long as they provide a better proxy for the fundamentals that drive investment. See Brown (2000) for a bibliography review covering nearly 600 articles on analysts' earning forecasts.

outstanding. The discount factor β_t is constructed as the inverse of $1 + r_t + \sigma$, where r_t is the nominal yield on a 20-year UK government bond and σ is a constant risk premium, which the authors set at 0.08. The full unbalanced panel dataset consists of 5669 observations between 1987 and 2000 for 703 firms. The key variables used for estimation and subsampling are real sales in billions of 1995 pounds (Y), Tobin's Q ($Q_{i,t}$), the investment rate ($\frac{I}{K}_{i,t}$), the two alternative measures of expected profitability ($E\Pi_{i,t}$ and $E\Pi 1_{i,t}$), a cash flow measure ($\frac{CF}{K}_{i,t}$)[4], and a cash stock measure ($\frac{CS}{K}_{i,t}$)[5]. The median observation of $\frac{I}{K}_{i,t}$ indicates that 50% of the firm-year observations had investment rates of 13% or above of the estimated replacement cost of installed tangible capital. The median value of $E\Pi 1_{i,t}$ indicates that 50% of the firm-year observations had forecast net incomes greater than 20% of the estimated value of the replacement cost of installed tangible capital. Cash stock reserves for the median observation were around 14% of the replacement cost of installed tangible capital. The summary statistics of these key variables are presented in Table 3.1.

Table 3.1: Bond et al. (2004) Dataset

	mean	**std.dev**	**first quartile**	**median**	**third quartile**
$Q_{i,t}$	2.60	2.10	1.30	2.00	3.20
$\frac{I}{K}_{i,t}$	0.14	0.13	0.08	0.13	0.20
$E\Pi_{i,t}$	0.44	0.33	0.22	0.35	0.57
$E\Pi 1_{i,t}$	0.25	0.19	0.12	0.20	0.33
$\frac{CF}{K}_{i,t}$	0.25	0.15	0.15	0.22	0.32
$\frac{CS}{K}_{i,t}$	0.26	0.35	0.04	0.14	0.33
$Y_{i,t}$	1.10	3.60	0.07	0.20	0.82

Notes: The total number of observations is 5669 and there are a total of 703 firms. The sample period is from 1987 to 2000.

[4]The numerator (CF) is constructed by adding after tax profits and depreciation.
[5]The numerator (CS) is the firm's stock of cash and cash equivalents at the end of period t.

3.3 Main Estimation Results

In this section, we first replicate the main results from Bond et al. (2004).[6] Similarly to the previous two papers, difference GMM is used in all estimations presented in this paper.[7] Following Bond et al. (2004), we first report one-step GMM estimates. The instruments used in these estimations are lagged values of investment rates and the cash flow variable, as in Cummins et al. (2006) and in most estimations presented in the first two chapters of this thesis. Note, however, that Bond et al. (2004) used the second and third lags of these variables as instruments, and the Hansen tests of overidentifying restrictions do not signal any concern with the validity of these instruments. Note also that Bond et al. (2004) included the lagged cash flow term $(\frac{CF}{K})_{i,t-1}$, not the current cash flow term $(\frac{CF}{K})_{i,t}$, in their excess sensitivity test specifications. This is the timing of the cash flow variable that we found to be informative in our analysis of the dataset for US companies from Cummins et al. (2006), as reported in Chapter 1. We had no trouble precisely replicating the results from Bond et al. (2004) as shown in Table 3.2. The main story can be summarized as follows. Column (i) shows a significant lagged cash-flow term which could be attributed, amongst other things, to financing constraints or measurement error in Tobin's Q. The following columns investigate if the significance of this cash flow term can be explained by the weakness of Tobin's Q as a measure of expected future profitability. This would be in line with findings of Erickson and Whited (2000), Bond and Cummins (2001) and Cummins et al. (2006). If 'bubbles' cause the market valuation to deviate persistently from the net present value of expected profits, this could be an important driver of the failures of Tobin's Q models.[8] Column (ii) shows that the inclusion of the short horizon expected prof-

[6]The dataset and all codes needed to replicate our results are included in the online appendix accessible via the following link: https://bit.ly/34RWiUe.

[7]A short discussion of the methodology is included in Appendix A and a short discussion of the basic Tobin's Q model is included in Appendix B.

[8]Gomes (2001), and Cooper and Ejarque (2001) also note that this can occur if there is a persistent difference between average Q and marginal Q (i.e. when the Hayashi conditions are not satisfied).

itability term $E\Pi_{i,t}$ makes the previously highly significant lagged cash-flow term in column (i) become statistically insignificant. Column (iii) confirms that even after omitting forecasts of current-period earnings, the alternative measure of expected future profitability, namely $E\Pi 1_{i,t}$, is highly significant while the lagged cash-flow term remains statistically insignificant. The remaining two columns confirm that $E\Pi_{i,t}$ is indeed a significant factor in determining investment, even in the absence of the lagged cash-flow term or Tobin's Q. We check the robustness of this relationship by adding current cash flow and using various alternative instrument sets. The main results are largely unaffected by the inclusion of current cash flow and/or by changes to the instrument set when using a one-step GMM estimator, as shown in Table C.1 and C.2 of Appendix C.

We present our main results in Table 3.3 where we use a two-step GMM estimator and additionally include second and third lags of the $E\Pi$ term in the instrument set. The reported standard errors for the two-step GMM estimator are computed using the finite-sample correction proposed by Windmeijer (2005).[9] We now find a positive and statistically significant coefficient on lagged cash flow ($\frac{CF}{K}_{i,t-1}$) even in the presence of the direct measures of expected profitability (i.e. $E\Pi$ or $E\Pi 1$). Moreover, the coefficients on $E\Pi$ or $E\Pi 1$ are less significant, as seen by the respective t-statistics, and these coefficients have at least halved in 3 out of the 4 estimations when compared to the main results of Bond et al. (2004) presented in Table 3.2.

The inclusion of the lagged $E\Pi$ terms in the instrument set plays an important role in identifying a significant coefficient on the lagged cash flow variable when we include one or both of the direct measures of expected profitability in the specifications reported in Table 3.3. The Hansen tests of overidentifying restrictions, reported in Table 3.3, do not signal any concern with the validity of these additional instru-

[9]Software to compute reliable standard errors for two-step GMM estimators was not widely available at the time when the Bond et al. (2004) paper was written.

ments. In addition to the standard Hansen test, we can consider both Difference Hansen and Hausman tests of the validity of these additional instruments. The former consider the effect of including these additional instruments on the minimised value of the GMM criterion function. The latter consider the effect of including these additional instruments on the GMM estimates of the coefficients, either individually or jointly.[10] None of these tests reject the validity of the additional lagged $E\Pi$ instruments. We present a summary of these test results in Table 3.4.[11]

[10] A short discussion of these overidentification tests is included in Appendix A.

[11] In Table 3.4 we have omitted column (*iii*) to focus our attention on the $E\Pi$, which incorporates information included in $E\Pi 1$. However, results of these tests are similar to the ones provided and can be made available upon request.

Table 3.2: **Tobin's Q, lagged cash flow and expected profits**

First-difference *one-step* GMM
Dependent Variable: $\frac{I}{K}_{i,t}$

	(i)	(ii)	(iii)	(iv)	(v)
$Q_{i,t}$	0.027	0.017	0.015	0.017	
	(0.008)	(0.008)	(0.009)	(0.009)	
	[3.190]	[2.068]	[1.811]	[2.008]	
$\frac{CF}{K}_{i,t-1}$	0.152	-0.078	-0.085		-0.071
	(0.058)	(0.094)	(0.095)		(0.095)
	[2.606]	[-0.827]	[-0.898]		[-0.745]
$E\Pi_{i,t}$		0.248		0.194	0.305
		(0.089)		(0.049)	(0.083)
		[2.783]		[3.952]	[3.683]
$E\Pi 1_{i,t}$			0.445		
			(0.157)		
			[2.838]		
$\frac{I}{K}_{i,t-1}$	0.088	0.068	0.071	0.075	0.081
	(0.029)	(0.028)	(0.027)	(0.027)	(0.028)
	[3.009]	[2.449]	[2.581]	[2.792]	[2.896]
Hansen p-value	0.522	0.405	0.419	0.416	0.353
Sargan df	43	42	42	43	43
Sargan statistic	41.82	43.56	43.21	44.32	45.91
$m1$ statistic	-10.7	-10.4	-10.5	-10.4	-10.4
$m2$ p-value	0.956	0.757	0.785	0.816	0.721
$m3$ p-value	0.355	0.362	0.384	0.344	0.359
$m4$ p-value	0.772	0.999	0.980	0.935	0.991

Sample information: The total number of observations in the untransformed dataset is 5669. The sample period is from 1987 to 2000. The number of observations in first-differences for column (i) is 4263 while the number of groups is 703. The average number of observations per group is 6.1. These statistics are identical for all other columns.

IVs: $\frac{CF}{K}$:$t-2$, $t-3$; $\frac{I}{K}$: $t-2$, $t-3$

See Table 2.2 for further notes.

Table 3.3: **Tobin's Q, lagged cash flow and expected profits**

First-difference *two-step* GMM
Dependent Variable: $\frac{I}{K}_{i,t}$

	(i)	(ii)	(iii)	(iv)	(v)
$Q_{i,t}$	0.022	0.016	0.016	0.016	
	(0.007)	(0.007)	(0.007)	(0.007)	
	[3.134]	[2.227]	[2.138]	[2.304]	
$\frac{CF}{K}_{i,t-1}$	0.184	0.120	0.117		0.122
	(0.056)	(0.057)	(0.057)		(0.057)
	[3.272]	[2.120]	[2.040]		[2.155]
$E\Pi_{i,t}$		0.102		0.151	0.166
		(0.054)		(0.047)	(0.050)
		[1.888]		[3.178]	[3.325]
$E\Pi 1_{i,t}$			0.180		
			(0.093)		
			[1.933]		
$\frac{I}{K}_{i,t-1}$	0.103	0.090	0.091	0.082	0.096
	(0.026)	(0.025)	(0.025)	(0.025)	(0.026)
	[3.967]	[3.550]	[3.611]	[3.333]	[3.660]
Hansen p-value	0.502	0.570	0.557	0.431	0.478
Sargan df	66	65	65	66	66
Sargan test statistic	65.27	62.34	62.72	67.35	65.97
m_1 test statistic	-9.83	-9.92	-9.99	-10.00	-9.89
m_2 p-value	0.961	0.904	0.910	0.836	0.812
m_3 p-value	0.348	0.332	0.342	0.367	0.333
m_4 p-value	0.718	0.793	0.800	0.873	0.749

Sample information: The number of observations in first-differences for column (1) is 4263 while the number of groups is 703. The average number of observations per group is 6.06. These statistics are identical for all other columns.

IVs: $\frac{CF}{K}$: $t-2$, $t-3$; $\frac{I}{K}$: $t-2$, $t-3$; EPi: $t-2$, $t-3$

See Table 2.2 for further notes.

Table 3.4: **Overidentification Tests**

Reported p-values

	Estimation Column			
	(i)	(ii)	(iv)	(v)
Difference in Sargan/Hansen p-value	0.449	0.717	0.464	0.685
Difference in Sargan/Hansen (*xtabond2 command*)				
IV: gmm($E\Pi$, lag(2 3))	0.462	0.639	0.455	0.629
Hausman Test Variables				
$Q_{i,t}$	0.734	0.718	0.824	n/a
$\frac{CF}{K}_{i,t-1}$	1$\star$	0.469	n/a	0.309
$E\Pi_{i,t}$	n/a	0.550	0.163	0.367
$Q_{i,t}$ and $\frac{CF}{K}_{i,t-1}$	0.944	0.609	n/a	n/a
$Q_{i,t}$ and $E\Pi_{i,t}$	n/a	0.658	0.239	n/a
$E\Pi_{i,t}$ and $\frac{CF}{K}_{i,t-1}$	n/a	0.721	n/a	0.579
$E\Pi_{i,t}$ and $Q_{i,t}$ and $\frac{CF}{K}_{i,t-1}$	n/a	0.797	n/a	n/a
All explanatory variables	0.990	0.907	0.414	0.779

Table notes: 'All explanatory variables' do not include the coefficients for time dummies. n/a indicates that the variable is not part of the specification, hence cannot be included in the test. The Difference in Sargan/Hansen test reports the p-value corresponding to the null hypothesis that the instrument subset is exogenous with respect to the error term.

$\star$ indicates the Hausman-statistic $H \dot{\sim} \chi^2(df)$ is negative.

3.4 Sales Subsampling

Similarly to Bond et al. (2004), we consider subsamples of smaller and larger firms, where the size classification is based on real sales. The results for our pre-

ferred specification are presented in Table 3.5. In Bond et al. (2004), the lagged cash flow term was significant for the subsample of smaller firms when the $E\Pi$ term was omitted from the specification (more precisely, using the specification presented in column (i) of Table 3.5), but was insignificant when the $E\Pi$ term was included in the specification (more precisely, using the specification presented in column (ii) of Table 3.5). [12] In contrast to their results presented in Table 3b (p.30), we find that once a two-step estimator is used and second and third lags of the $E\Pi$ term are included in the instrument set, the lagged cash flow term remains significant for the subsample of smaller firms, even when we control for expected profitability using the $E\Pi$ measure. In particular, in the presence of $E\Pi$ for small firms, the lagged cash flow coefficient is more than quadrupled compared to the original coefficient (0.13 v.s. 0.030) and has a t-statistic of 2.19 as compared with 0.44 in the original results. For the subsample of larger firms, the estimated coefficient on the lagged cash flow term is not significantly different from zero, but has a large standard error, almost twice as large as that for the sample of smaller firms. As a result, we do not reject the hypothesis that this coefficient is equal in the two subsamples. The third column of Table 3.5, reports test results of the hypothesis that each coefficient estimates is equal in the two subsamples. For all four reported coefficients, we do not reject this hypothesis. Hence we cannot be confident that there are significant differences between the investment behaviour of smaller and larger UK firms included in the sample studied by Bond et al. (2004). Nevertheless it is of some interest that the significant coefficient on the lagged cash flow term reported in Table 3.3 is identified mainly from the behaviour of the smaller UK firms in this sample. This pattern is consistent with the possibility that the investment of smaller UK firms is affected by financing constraints, and notably different from the pattern of results for smaller and larger US firms reported in Chapter 2.[13]

[12] For the subsample of larger firms, the lagged cash flow term was significant in neither of these specifications.

[13] Bond et al. (2004) also looked at subsamples based on dividend payments which we have not analysed for lack of the variables that were used to split the sample on that basis in their provided

Table 3.5: **Subsamples: Large vs. Small Firms**

First-difference *Two-step* GMM
Dependent Variable: $\frac{I}{K}_{i,t}$

	Small Firms	Large Firms	Sample Difference
$Q_{i,t}$	0.016	0.023	0.007
	(0.007)	(0.013)	(0.015)
	[2.439]	[1.684]	[0.446]
$\frac{CF}{K}_{i,t-1}$	0.130	0.041	-0.089
	(0.059)	(0.111)	(0.126)
	[2.193]	[0.367]	[-0.710]
$E\Pi_{i,t}$	0.113	0.161	0.048
	(0.052)	(0.080)	(0.095)
	[2.180]	[2.019]	[0.504]
$\frac{I}{K}_{i,t-1}$	0.113	0.045	-0.068
	(0.039)	(0.033)	(0.051)
	[2.878]	[1.365]	[-1.330]
Hansen p-value	0.685	0.440	
m_1 test statistic	-6.98	-6.30	
m_2 p-value	0.682	0.404	
m_3 p-value	0.785	0.291	
m_4 p-value	0.499	0.782	
Firms	351	352	
Observations	1863	2400	

Sample information: Time period from 1987 to 2000.

IVs: $\frac{CF}{K} : t-2, t-3$; $\frac{I}{K} : t-2, t-3$; $E\Pi : t-2, t-3$

Notes: To achieve the sample split we generate a median of net sales over all firms in the sample for the first year they enter the sample. When a firm's first year net sales figure is higher than the median across all firms that enter the dataset on that year, we classify such a firm as Large, and Small otherwise. Time dummies are included as regressors and instruments. Asymptotic standard errors are reported in parentheses, while t-statistics are reported in square brackets. Standard errors are robust to general time-series and cross-section heteroskedasticity.

dataset.

3.5 Implications of Excess Cash-Flow Sensitivity

In our previous discussions in this thesis, we did not explore the implications of the presence of investment excess cash-flow sensitivity. The failure of average Q to be a sufficient statistic could be, amongst other explanations, attributed to the role played by capital market imperfections (Fazzari et al., 1988), or the importance of fixed adjustment cost (Caballero and Leahy, 1996). In addition, average Q might be a poor proxy for marginal Q (Bond and Cummins, 2001; Erickson and Whited, 2000). However, the literature has recognized at least two well-established hypotheses derived from structural models: excess cash-flow sensitivity can be associated with (1) the presence of financing constraints (Bond and Söderbom, 2013) and (2) the presence of imperfect competition (Cooper and Ejarque, 2003). These results can be used to investigate the implications of the investment excess cash-flow sensitivity.

Fazzari et al. (1988) have argued that the presence of excess cash-flow sensitivity might indicate financing constraints. However, Kaplan and Zingales (1997) and their subsequent discussion in Kaplan and Zingales (2000) emphasize that investment to cash-flow sensitivity need not increase monotonically with a cost premium for outside capital. However, such results are only obtained in a static model and refer to the unconditional correlation between investment and cash flow which contrasts with Fazzari et al. (1988) who condition for average Q. If internal finance constrains investment spending, responses to transitory demand shocks or business cycle variations in profits will differ between constrained and unconstrained firms. Moreover, financial constraints may motivate otherwise inefficient takeovers of cash-strapped firms (Bond and Meghir, 1994). It is not clear what the static model found in Kaplan and Zingales (1997) implies for the coefficient on cash flow once we control for average Q. Bond and Söderbom (2013) provide a model with costly external finance where new equity is the only external source of finance and where the cost

premium increases with the equity issued. If both the net revenue function and the cost premium of external finance satisfy linear homogeneity, the authors show that marginal Q and average Q are equal.[14]

In the model presented by Bond and Söderbom (2013), the relationship between investment, average Q and cash flow is not linear. However, they are able to show via simulated data that investment cash-flow excess sensitivity increases monotonically with the cost premium on external finance in linear models. Bond and Söderbom further show that the first order conditions can be estimated directly, and the behaviour of the cash flow follows from omitting an interaction term between an adjusted measure of average Q and the measure of new equity issued which is present in their structural model. Bond and Söderbom (2013)'s paper is an important contribution and provides a benchmark structural model to justify the monotonicity hypothesis assumed by Fazzari et al. (1988) and it highlights that discussions about the unconditional correlation of investment and cash flow might be of little relevance for the investigation of the impact of financing constraints once we condition on measures of Q.[15]

In their study of imperfectly competitive firms with financial constraints, Cooper and Ejarque (2003) find that it is not capital market imperfections, but market power that relates investment to internal funds or profitability. Previous empirical studies based on the Q-theory argue that the sensitivity of investment rates to internal funds is a sign of capital market imperfections. Cooper and Ejarque (2003) show that differently to the Q-theory, variations in Q have been found to have little explanatory power for investment behaviour, but proxies for internal funds, on the contrary, do have predictive power.

Cooper and Ejarque (2003) extend their earlier work of Cooper and Ejarque

[14]Gomes (2001) and Moyen (2004) relax the assumption of linear homogeneity.

[15](Cooper and Ejarque, 2003, p.711) caution against using the excess cash flow sensitivity as a sign of capital market imperfections in part because "no model with borrowing constraints... supports the inference drawn from the Q-theory based empirical results". Bond and Söderbom (2013) fill this particularly important gap in the literature.

(2001) by adding financial frictions to improve the fit of their original model with market power. Their model's structure nests both views of capital market imperfections and market power. They look at the ability of the model to fit some moments such as serial correlation of investment rates and whether the parameter estimates change in any meaningful way. Starting from the basic Tobin's Q model they are unable to match the response of investment to cash flow, given average Q. However, the addition of market power substantially improves the fit of the model. They further add fixed costs to access capital markets and estimate this fixed cost at zero concluding that Q-based investment regressions essentially reflect market power and not capital market imperfections. One limitation of their model is that they do not include any unobserved structural heterogeneity.

Sample splits based on the concentration of sectors or profit margins might be contrasted with sample splits based on credit ratings or measures of availability of internal finance. The results from these sample splits might be used to see if the market power story presented in Cooper and Ejarque (2003) or the financing frictions story presented in Bond and Söderbom (2013) might be more suitable in our datasets. Another approach to identify financially constrained firms controlling directly for measures of imperfect competition is to use investment models relying on Euler equations.

The Euler equation has been heavily relied upon in the study of consumption in the presence of borrowing constraints (e.g. Zeldes (1989) and Runkle (1991)). Whited (1992) argues that the Euler equations can be complementary in studying the role of financial factors in investment with panel data as the equations will allow the exploitation of firm heterogeneity.[16] Whited (1992) introduces a new set of Euler equations to investigate if failure of previous models could be attributed to financial market imperfections.

The Euler equation models of investments have been used to explore the inter-

[16]See (Abel, 1980) and Shapiro (1986) for some earlier research.

dependence of finance and investment as it avoids some of the pitfalls of standard reduced-form investment estimations. According to Whited (1992), the Euler equations obtained from a structural model of investment can help disentangle the role of financing constraints from other factors in investment decisions. Under the assumption of asymmetric information, and that small firms have limited access to outside funds due to low credibility to pay back loans, Whited (1992) argues that financial variables should be included directly in the Euler equations and that the equation should hold for unconstrained firms, but not for constrained ones. The financial variables should be incorporated in the equation through the effect on the Lagrange multiplier when the constraint is a restrictive debt insurance which influences the discount rate of a firm.[17]

The equation does not hold for constrained firms because there is a discrepancy between the marginal costs of investing today and tomorrow which is due to the effect that financial factors have on the discount rate. The standard models do not take this relation into account, while the Euler equation approach does, due to its optimization process. Whited (1992) includes the effect of binding debt constraint because it allows for the indirect measurement of the individual discount rates which improves the performance of the Euler equation. One further advantage of the method is that measurement error problems can be avoided for the investment demand equation. These are the two main results from Whited (1992). The first set of results enforces claims that the financial position of a firm affects its investment decision by using two indicators: 1) the market value of debt relative to market firm value and 2) the ratio of interest expense to the sum of interest expense and cash flow. The second set of results show that the effect of financial variables is more significant for unhealthy firms after firms have been split into healthy and unhealthy based on the indicators mentioned above.

[17]Some key aspects and assumptions of the model include: 1) no explicit modelling of the issue of new shares to avoid the possibility of financial hierarchy, 2) partial equilibrium model with behaviour of the financial sector being exogenous, 3) only present variables are known to the firm, and 4) rational expectations for managers.

Similarly, Bond and Meghir (1994) use the Euler equations for optimal capital accumulation in the presence of convex adjustment costs. They develop and implement formal tests for the hierarchy of finance model controlling for the presence of imperfect competition.[18] To test for the hierarchy of finance model they use publicly-traded UK manufacturing companies between 1974-1986. Bond and Meghir (1994) start by estimating a basic Euler equation model, under the assumption of no financial regimes, where the independent variables of interest are lagged values of investment, investment squared, cash flow, output to capital, and squared debt to capital. They find that the estimated coefficients support the presence of imperfect competition (i.e. a statistically positive coefficient of output), and their implied tax-bankruptcy cost specification lending evidence to their implied structure (i.e. a negative and significant coefficient of the debt term). However, the coefficient of the cash flow variable is positive, as opposed to a negative one under the assumption of no financial regimes. They confirm this excess sensitivity of investment to financial variables by further controlling for current and lagged terms of dividend payments to capital stock and new share issues to capital. They find that these additional terms are jointly significant and indicate the importance of financial policy for investment when financial regimes are not allowed. When allowing for financial regimes, they conclude that the non-linearity implied by the financial regimes makes controlling for the effects of financial policy in a simple linear fashion inadequate. To test for the hypothesis of no financial regimes they define a dummy variable which is equal to one if and only if dividends are positive and there are no new share issues. This dummy variable is interacted with all right-hand side variables. Although they have the expected signs, the differences in the coefficients are jointly not statistically significant but results suggest that cash flow drives the observed difference.[19] Nev-

[18]Previous studies such as Fazzari et al. (1988), Devereux and Schiantarelli (1990), Hoshi et al. (1991) have relied on estimating subsamples based on financial factors or institutional characteristics.

[19]To significantly reduce the excess sensitivity the authors needed to exclude firms that pay low dividends.

ertheless, controlling for financial regimes in their dataset does not fully explain the excess sensitivity of investment to financial variables.

An appealing alternative that would allow us to identify financially constrained firms is to look for exogenous shocks that affect only a subsample of firms. Lamont (1997) conducted important research where he tried to separate cash flow and investment profitability by looking at large segmented firms using data from the 1986 oil price decrease. The two segments are oil and non-oil. He finds that the non-oil segments of multi-segment firms reduce investments in response to exogenous negative cash flow shocks to the oil segment. This paper also raises interesting questions on internal capital allocation. Nevertheless, approaches followed by Lamont (1997) might come with substantial tradeoffs. In particular, the shocks might be relevant to only a small number of firms. Moreover, there might still be other shocks that affected the control group, and the external validity of the results with respect to other unaffected groups or industries might be difficult to establish. In particular, the sample size in Lamont (1997) was around 40 observations and a major tax legislation was also passed during the same period. If these tax reforms raised the cost of capital for oil firms, this might be driving the result.

3.6 Conclusion

Our main conclusion is that, while the novel measures of expected future profitability considered in Bond et al. (2004) are informative explanatory variables for corporate investment behaviour, their conclusion that lagged cash flow terms become insignificant once we control for expected profitability in this way is not robust to the use of a two-step GMM estimator and the inclusion of additional valid instruments. However, the explanatory power of such expected profitability variables for corporate investment, above and beyond a standard measure of Tobin's Q, makes it worthwhile for their role in explaining investment behaviour to be investigated further. In particular, it would be of interest to explore how the explanatory power of such measures has evolved over time by exploring a dataset that extends beyond the year 2000.

Chapter 4

Reconstructing the Bond et al. (2004) Dataset

by Revi Panidha[1]

Abstract

In this paper we follow closely the methods described in Bond et al. (2004) to recreate a dataset for publicly-traded UK firms covering the period 1987 to 2000 using currently available sources. These two datasets are not an exact replica of each other due to data loss, retrospective changes to the raw data, and missing information on the increase in net fixed assets due to acquisitions. Nevertheless, we provide evidence that the two datasets are broadly comparable based on descriptive statistics, time plots of key variables, and the results of estimating econometric models of investment. The results of this paper allow us to make comparisons over time as we extend the dataset to cover more recent years in the next paper.

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Introduction

It is very important to be able to study the evolution of the roles of expected profitability, standard measures of Tobin's Q and cash flow terms over time in general, and how these relationships have evolved before and after the 2008 financial crisis, in particular. This is especially true given the wide use of Tobin's Q-type models in understanding corporate investment and financing constraints, or in building models to account for risk management in Finance (see, for example, Bolton et al. (2011)). The construction of suitable datasets requires significant efforts and involves a myriad of choices.[2] Sometimes these choices are imposed on the researcher by the availability of data. This short paper aims at studying the differences between the Bond et al. (2004) dataset and our reconstructed dataset for the same period, despite our efforts and desire to exactly recreate the earlier dataset. These issues arise because the source of company accounts data for publicly-traded UK companies used by Bond et al. (2004) is no longer available to researchers working today. The paper is organised as follows. Section 4.1 gives an overview comparison of the two datasets, outlining three main sources of differences. Section 4.2 compares descriptive statistics. Section 4.3 presents time plot comparisons, while Section 4.4 compares the results of econometric models of company investment estimated using the two datasets. Section 4.5 concludes.

4.1 Overview Comparison between our Dataset and that of Bond et al. (2004)

Bond et al. (2004) provide two very useful and detailed appendices which cover the construction of their data items, from which interested readers can gain tech-

[2]See Bartlett and Partnoy (2020) for some criticism of some of the choices made in relation to some important topics in corporate law.

nical insights about the construction of the variables beyond that which is already provided in Chapter 3 of this thesis. In this paper, we focus exclusively on the comparison of our reconstructed dataset with the Bond et al. (2004) dataset. While we have access to the original STATA codes used to create their dataset, it is not possible to use the original codes as we do not have access to the raw data that was used to create the Bond et al. (2004) dataset. Their source of data on items reported in the financial statements of publicly-traded UK firms, Datastream, has since been replaced by Worldscope. This renders old codes for variables incompatible. We have identified three issues that have jointly contributed to our reconstructed dataset differing from the dataset constructed by Bond et al. (2004). These issues are data loss, retrospective changes to the raw data, and the absence of a key item used to construct the measure of investment in Bond et al. (2004). This missing item is net *fixed* assets from acquisitions, which was reported separately by Datastream, but which has been combined into a composite variable, *net* assets from acquisitions, by Worldscope. We discuss each of these issues in turn in this section.

Data loss prevents us from obtaining an identical sample of firm-year observations. We worked closely with the data team at Worldscope, and we were able to match all but 265 of the 5669 firm-year observations included in the Bond et al. (2004) dataset.[3] Once availability of all required items from Worldscope is taken into consideration, we are left with 5294 observations. This data loss also introduced gaps in the available time series of observations for some firms. Hence, once we applied the common restriction in the literature of having at least four consecutive observations for each firm, we were able to match only 4301 firm-year observations out of the 5669 firm-year observations from the Bond et al. (2004) dataset for comparisons of estimated econometric models between the two datasets.[4] In sum, data loss has

[3]From an e-mail conversation with the Worldscope data archive team, they confirmed that, unfortunately, when the transition from Datastream to Worldscope was made, some of the previous raw data had been lost. We did not have any data loss issues with the I/B/E/S dataset.

[4]Due to the effective 375 missing firm-year observations we lose a further 993 observations, or an additional 2.65 observations per (effective) missing observation. This is not an improbable outcome as illustrated by the following calculations. There were, on average, 6.1 observations per

contributed to the absence of around 24% of the original 5669 firm-year observations that can be used to compare estimation results between the two datasets.[5]

Retrospective changes to the raw data prevent us from recreating identical key variables that are used in the econometric models. The sales variable is the only variable for which, in principle, we have the same item from company accounts in both Datastream (accessed in the early 2000s) and Worldscope (accessed in 2017). The differences in the raw data could have been caused by retrospective revisions to reported sales. By studying the differences in the sales figures, we can get a sense of the size of the raw data differences between the two sources.[6] When comparing the raw sales measure in the constructed dataset with the original Bond et al. (2004) dataset, we found that 4324 out of the 5294 matched firm-year observations have identical sales figures (i.e. around 82% of the observations that we were able to match). There are 4872 observations out of 5294 that have sales figures within 5% of each other.[7] However, more than half of the firms in the dataset have observations in the subsample where there is some difference between the two sales figures. Hence, the discrepancies are not only due to a handful of firms. Of the observations that have a difference, only around 15% of the observations in our newly reconstructed dataset have sales figures *higher* than in the original dataset. Hence,

firm in the Bond et al. (2004) dataset. Assuming exactly six observations per firm and that the missing observation occurs in a random year, there would be a $\frac{2}{6}$ probability that no additional observations are lost (i.e. the missing observation is at the beginning or the end of the time series), $\frac{2}{6}$ of an additional observation being lost, and a $\frac{2}{6}$ probability of *five* additional observations being lost. The expected additional observations loss in this case would be 4. This number would drop to 2.14 if we assume every firm has exactly seven observations.

[5]If we apply the same restrictions on the sample selection used in Bond et al. (2004) to the full set of publicly-traded UK firms now covered by Worldscope, we could add almost an additional 1000 firm-year observations during the period 1987-2000. That would give a total of 5274 observations, including some firm-year observations that were not previously included in the Bond et al. (2004) dataset. These further observations can be explained by additional data being retrospectively included into Worldscope (e.g. when a firm is listed on an exchange, its financial data for previous years are made available despite the firm not being listed for those earlier years). However, these additional observations are not used for comparison purposes in this chapter, but will be used in the following chapter.

[6]This comparison in the sales figures between the two sources gives us confidence that the matching of firm-year observations has been successful.

[7]A full distribution of the differences can be found on the online Appendix accessible via the following link: https://bit.ly/3A4gxeL.

for the observations that do not have the same sales figure, we observe that the more recently available sales figures tend to be fairly uniformly *lower*. Furthermore, these differences are concentrated after 1992 in the later half of the sample. This is consistent with evidence that companies tend to overstate their sales initially and adjust them downwards subsequently (Bartov and Mohanram, 2004). However, overall, these differences in the distribution of sales between the two datasets are modest. In particular the mean, median, and the first quartile are the same while the third quartile and the standard deviation are slightly larger in the Bond et al. (2004) dataset.[8] In sum, retrospective changes to the raw data will contribute to the differences between the two datasets. However, we believe this contribution to be relatively minor.

The investment measure in levels (i.e. the numerator of our dependent variable) in the newly recreated dataset could not directly account for the increase in net *fixed* assets due to acquisitions. In Worldscope, the only similar item available is a more aggregated variable called '*net* assets from acquisitions'.[9] A crude adjustment has been made , assuming that net fixed assets from acquisitions represent 60% of net total assets from acquisitions, to approximately match median investment levels across the two datasets for the given time period. More specifically, Bond et al. (2004) constructed their measure of the level of investment in the following two ways, depending on the year of the accounts. $I = ds1026 + ds479$ was used after 1990, while $I = ds431 - ds423 + ds479$ was used before 1990. Here **ds1026** is the Datastream item 'Net Payments for Fixed Assets' (where net implies subtraction of sales of fixed assets), **ds479** is the Datastream item 'Net Fixed Assets of Subsidiaries Acquired or Sold', **ds431** is the Datastream item 'Purchases of Fixed Assets', and finally **ds423**

[8]In the aforementioned online Appendix, we provide summary statistics and a comparison of yearly mean and median values of the sales figures for the 5294 matched firm-year observations. All evidence shows relatively minimal differences that could be driven by expected retrospective changes to the reported sales figures.

[9]The online appendix contains technical details on the construction of each item together with a full mapping from old data items previously available in Datasteam to new items, now available in Worldscope.

is the Datastream item 'Sales of Fixed Assets'. We apply a similar approach but have to make a crude adjustment to net assets from acquisitions to approximate the share accounted for by net fixed assets. Hence, we use $I = wc04601 - wc04651 + wc04355 * 0.6$. Here **wc04601** is the Worldscope item 'Capital Expenditure (Additions to Fixed Assets)', **wc04351** is the Worldscope item 'Disposal Of Fixed Assets', and **wc04355** is the Worldscope item 'Net Assets From Acquisitions'. For the matched firm-year observations with non-zero values for the change in the book value of assets due to the acquisition (or disposal) of subsidiaries, the median value of Net Fixed Assets of Subsidiaries Acquired or Sold (**ds479**) is approximately 60% of the median value of Net Assets from Acquisitions (**wc04355**).

We have now discussed for the key sources of the differences between the two datasets. There may be other sources of differences, but we believe them to be relatively unimportant. However, data loss can lead to differences that are more subtle. For example, if a missing firm-year observation was used to initialise the capital stock measure for a given firm using the perpetual inventory method used by Bond et al. (2004), it would imply that even though that firm-year observation would not be included in the sample, a different initialisation of the capital stock measures would create potential differences in the capital variable across the two datasets for later observations on that firm. This, in turn, can lead to differences in *all* ratio variables for that firm across all observations, as the capital stock measure, constructed using the perpetual inventory method, forms the denominator of all these ratio variables. Hence, such a difference in one variable would propagate to all variables. We compare the summary statistics of these two subsamples in the next section.

4.2 Descriptive Statistics

Table 4.1 is a summary statistics table that we were able to replicate with the full dataset from Bond et al. (2004). Table 4.2 presents the same summary statistics for the subsample of 4301 observations for which we could construct similar variables using Worldscope, while the third summary statistics Table 4.3 uses the same 4301 matched observations in the *newly reconstructed* dataset. The comparison of Table 4.1 with Table 4.2 allows us to comment on the potential bias that the missing observations due to data loss could have on results obtained using the newly reconstructed dataset, as shown by the summary statistics. From this comparison, we conclude that the absence of the unmatched observations does not materially change the distributions of the variables used in the dataset of Bond et al. (2004). In particular, four of the seven means are unchanged, with the means of the remaining two ratios being almost unchanged. The medians are unchanged for all six ratios, with the median level of sales being 5% higher in the subsample. We also note that the standard deviations in the 4301 matched observations are smaller for all variables. This might imply that the unmatched observations were not random, as we would have expected standard deviations to be similar if the missing observations were randomly chosen. This, however, could also have been driven by the correlated *nature* of the missing observations rather than the non-random nature of which observations were missing in the first place. A missing firm-year observation will imply both (*i*) that there is a higher likelihood of other observations on the same firm being missing and (*ii*) that there is a higher likelihood of other observations on the same firm being omitted due to the requirement for four consecutive observations that we impose on our dataset.

By comparing Table 4.2 with Table 4.3 we can analyse the differences between the two datasets that could have arisen due to retrospective changes of the raw data and our non-direct measure of net fixed assets from acquisitions. Our measures of Q, CS/K, $E\Pi$ and $E\Pi 1$ shown in Table 4.3 are slightly higher than their Bond et al.

(2004) counterparts shown in Table 4.2, as illustrated by differences in means and medians which increase by around 5-10%. Our measure of CF/K is *lower* on average and has a higher standard deviation. However, the first quartile, median, and third quartile are similar, implying that differences are in the tails of the distribution. We explore this further in our next section where we compare the evolution of the median values of these key variables over time.

Table 4.1: Full Bond et al. (2004) Dataset

	mean	**std.dev**	**first quartile**	**median**	**third quartile**
Q	2.60	2.10	1.30	2.00	3.20
$\frac{I}{K}$	0.14	0.13	0.08	0.13	0.20
$E\Pi$	0.44	0.33	0.22	0.35	0.57
$E\Pi 1$	0.25	0.19	0.12	0.20	0.33
$\frac{CF}{K}$	0.25	0.15	0.15	0.22	0.32
$\frac{CS}{K}$	0.26	0.35	0.04	0.14	0.33
Y	1.10	3.60	0.07	0.20	0.82

Notes: The total number of observations is 5669 and there are a total of 703 firms. The sample period is from 1987 to 2000. For further details see the description of Table 3.1.[a]

[a]During the comparison we noticed that the reported sales figure in the working paper by Bond et al. (2004) were in nominal terms, not in real terms. For comparisons, the Y variable is in nominal terms for all summary statistics tables presented in this chapter.

Table 4.2: Bond et al. (2004) Dataset - Matched Observations only

	mean	**std.dev**	**first quartile**	**median**	**third quartile**
Q	2.60	2.00	1.30	2.00	3.10
$\frac{I}{K}$	0.14	0.12	0.08	0.13	0.20
$E\Pi$	0.43	0.30	0.22	0.35	0.56
$E\Pi 1$	0.25	0.17	0.12	0.20	0.32
$\frac{CF}{K}$	0.25	0.14	0.15	0.22	0.32
$\frac{CS}{K}$	0.25	0.33	0.04	0.14	0.33
Y	1.00	3.40	0.08	0.21	0.79

Notes: The total number of observations is 4301 and there are a total of 594 firms. The sample period is from 1987 to 2000.

Table 4.3: Our dataset - Matched Observations only

	mean	**std.dev**	**first quartile**	**median**	**third quartile**
Q	2.80	2.20	1.40	2.20	3.40
$\frac{I}{K}$	0.15	0.15	0.08	0.14	0.22
$E\Pi$	0.45	0.33	0.23	0.37	0.58
$E\Pi 1$	0.26	0.19	0.13	0.21	0.33
$\frac{CF}{K}$	0.24	0.20	0.15	0.22	0.33
$\frac{CS}{K}$	0.26	0.36	0.04	0.14	0.33
Y	1.00	3.00	0.08	0.21	0.78

Notes: The total number of observations is 4301 and there are a total of 594 firms. The sample period is from 1987 to 2000

In sum, the unmatched firm-year observations due to data loss do not seem to introduce any serious selection bias as shown by the comparison between Tables 4.1 and 4.2. Moreover, a comparison of Table 4.2 and Table 4.3 shows that the sample distributions of the newly constructed variables are similar to those of the corre-

sponding variables used in the original study. The differences in Table 4.2 and Table 4.3 reflect the joint effects of retrospective changes in the raw data and differences in the measures of net fixed assets from acquisitions. In the next section, we try to isolate the former difference by focusing our attention on the subset with zero net assets from acquisitions to explore further the differences in the two datasets.

4.3 Time Plots Comparisons

In order to limit any differences in the key items arising due to the unavailability of a direct measure of fixed assets from acquisitions, we compare time plots of the key variables for the subsample that consists of around 1800 firm-year observations where net assets from acquisitions is zero. In these observations we expect our investment measure to be similar to that of Bond et al. (2004).[10] The time plots in Figure 4.1 to Figure 4.5 make us confident that the differences in raw data are relatively small.[11]

[10]Unfortunately, the replication cost of capital measure does not have to be identical as it is constructed using all previous investment levels which might have included net assets from acquisitions. Furthermore, similar to the sales figures, the capital expenditure measure might have been retroactively changed for some observations.

[11]Moreover, the time plots using all of the the 4301 matched observations, which we present in the online Appendix, also display comparable time plots.

Figure 4.1: $E\Pi$ medians over time

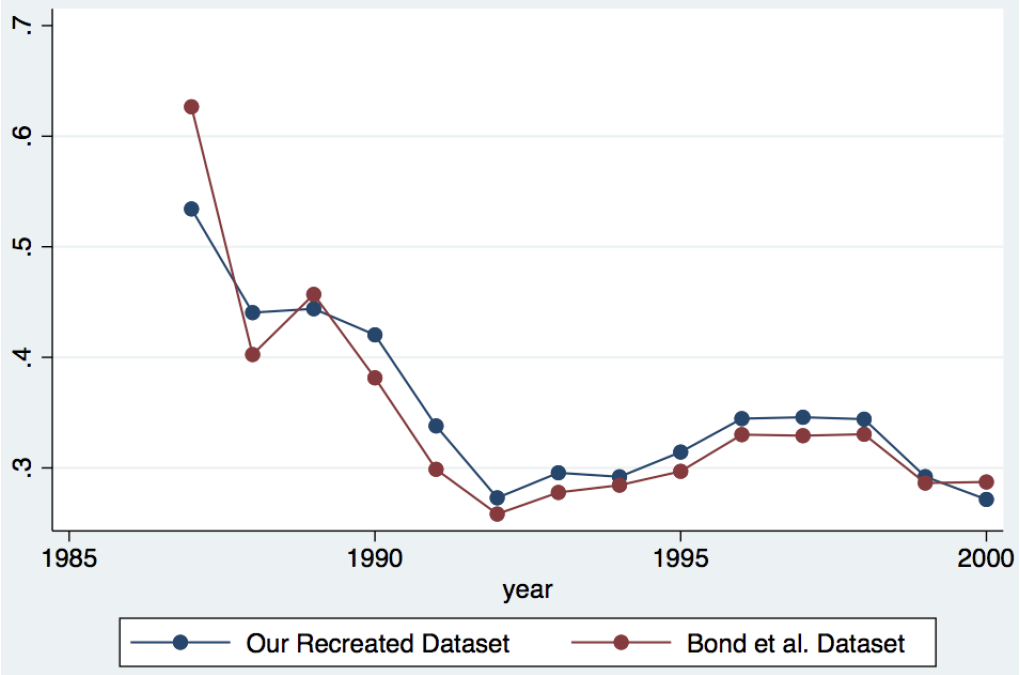


Figure 4.2: $E\Pi 1$ medians over time

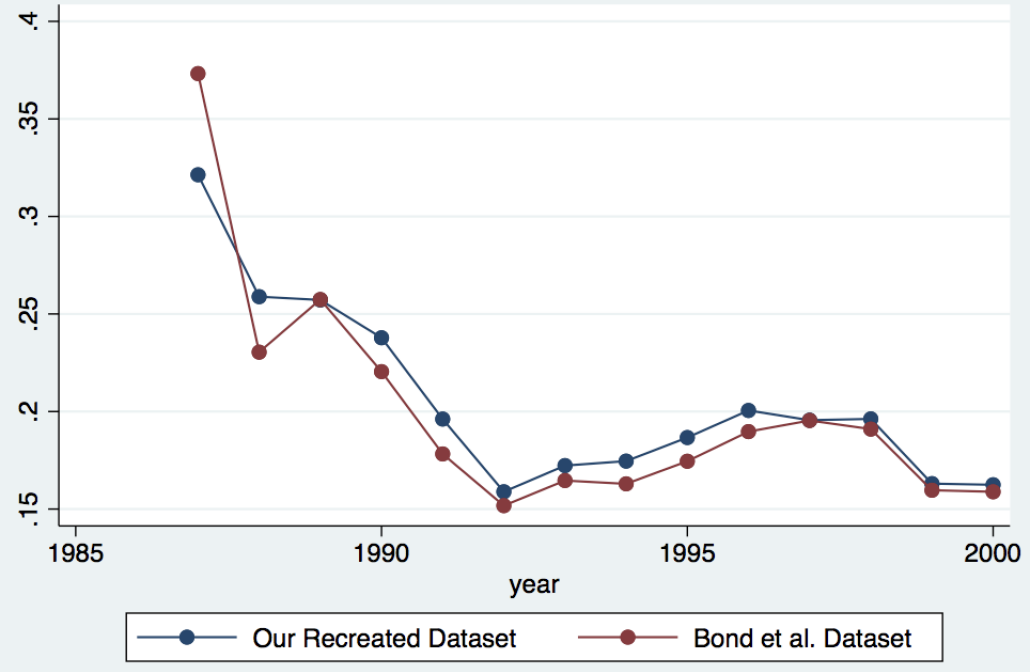


Figure 4.3: Investment *level* medians over time

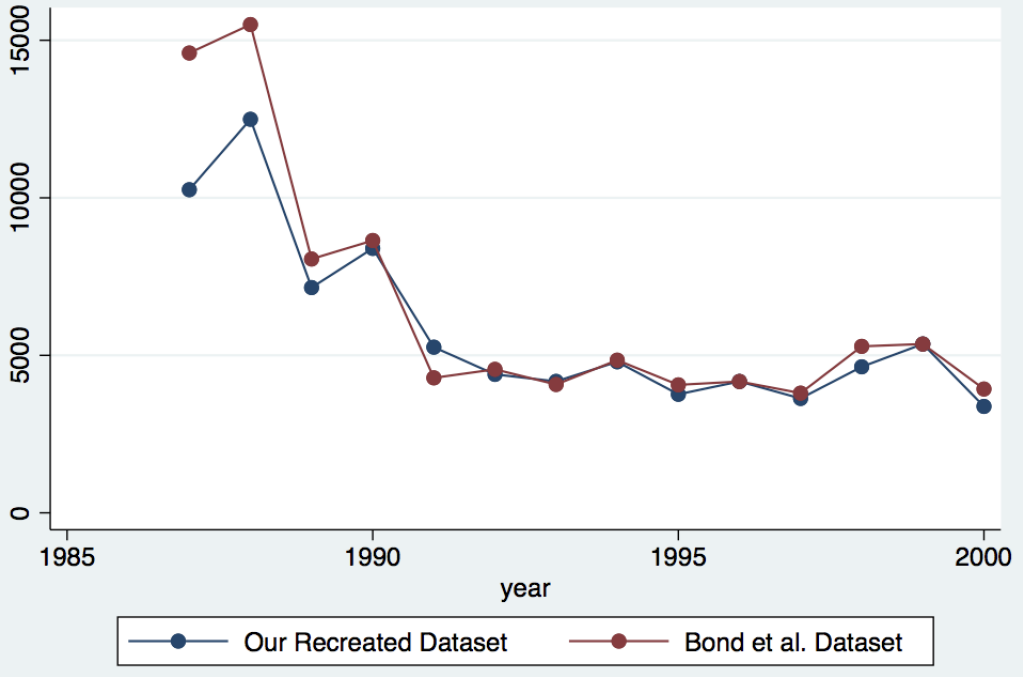


Figure 4.4: Q medians over time

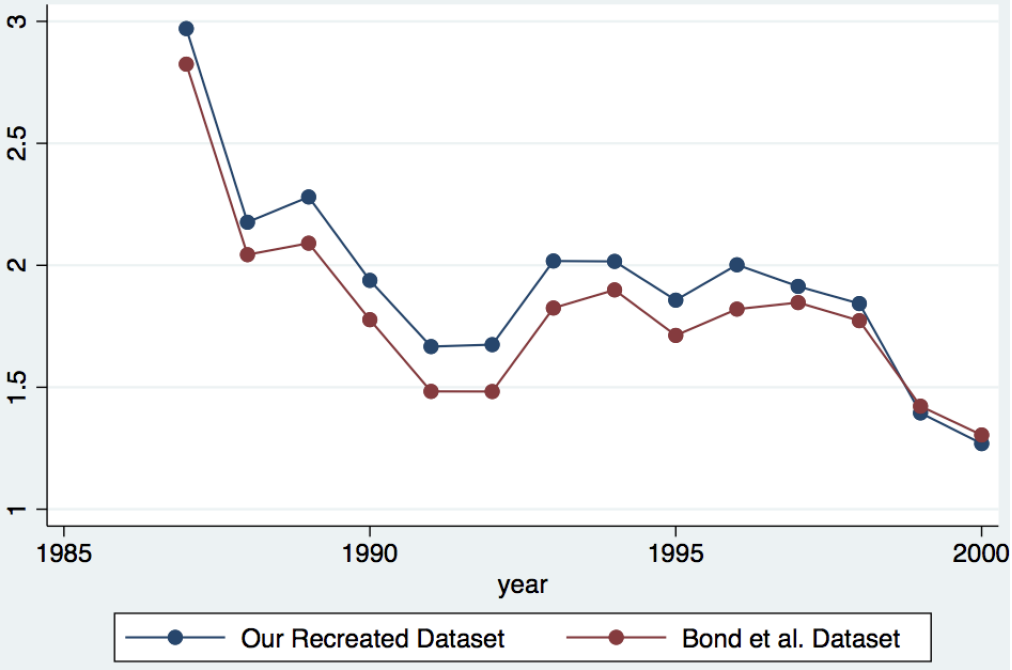
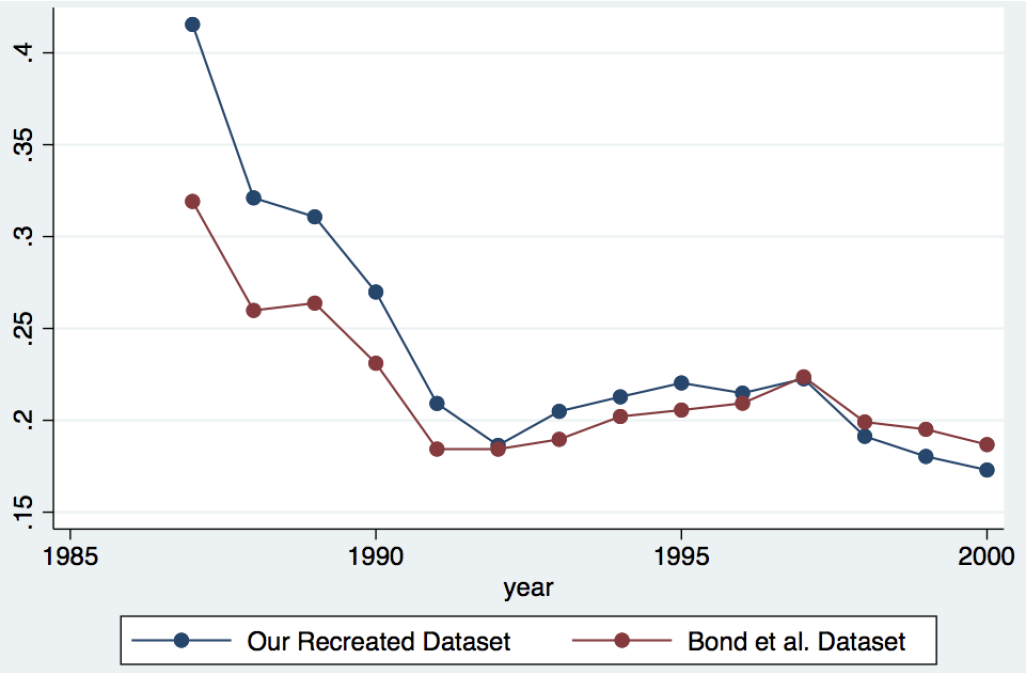


Figure 4.5: $\frac{CF}{K}$ medians over time



The time plots show that the time series for the median values of these variables across the two datasets are broadly comparable. It is useful to note that in 1987 we have only 17 matched observations, compared to at least 93 observations in the subsequent years. Absent this initial year, these time plots, especially for the cash flow variable, would be even closer to each other. The medians of the cash flow variable in the dataset of Bond et al. (2004) are higher for the years prior to 1997 and lower thereafter. Hence, it is possible that, as with sales, the numerator of the cash flow (i.e. CF) was inadvertently not deflated.[12] Similarly to the summary statistics, we see that our measures of Q, $E\Pi$ and $E\Pi 1$ are consistently slightly higher than their counterparts in the Bond et al. (2004) dataset. The above time series plots of medians of some of the key variables indicate that while some differences remain, the construction processes of the two datasets are broadly comparable.[13]

[12]This pattern is even more clear when using the full 5294 matched observations. This is included in the online Appendix.

[13]Further discussion of the comparison between the two datasets is included in the online Appendix.

4.4 Estimation Results Comparison: Bond et al. (2004) vs. the Recreated Dataset

In this final section, we compare the two datasets by looking at various estimation results to observe if differences in the reconstructed dataset, both known and unknown, significantly alter the results obtained when estimating econometric models of company investment rates ($\frac{I}{K}$). Similar to the previous sections, we confirm that results using the two datasets are comparable, despite the unavoidable differences in the construction of the measure of investment. In particular, using the subsample of 4301 matched firm-year observations for which we have at least four consecutive observations on each firm, the results using our newly reconstructed dataset broadly replicate those presented in Bond et al. (2004). We first look at a comparison of OLS results before presenting the GMM results.

4.4.1 OLS Estimations

It is useful to compare some basic OLS results using of the two datasets before moving to GMM specifications replicating the main results presented in Bond et al. (2004). We allow for firm-specific fixed effects in all the specifications reported in Table 4.4, and include year dummies in columns (iii)-(vi). When comparing the estimated coefficients on the two datasets, we find that the signs and the magnitudes of each of the estimated coefficients are similar. The estimated coefficients of the lagged cash flow we do observe are larger for the Bond et al. (2004) for two of the three specifications. The difference in the estimated autoregressive dynamics of investment rates could reflect the differences in how our investment measures were constructed.[14] However, despite these differences in the point estimates, the 95% confidence intervals for any pair of coefficients are similar in most of the comparisons.

[14]The negative coefficient on the lagged investment rate is likely to be due to the Nickell bias (Nickell, 1981).

Hence the main conclusions that we would draw from these OLS results using the two datasets would be similar.[15]

Table 4.4: **OLS Comparisons**

Dependent Variable: $\frac{I}{K}$

	(i) Bond et al.	(ii) Our data	(iii) Bond et al.	(iv) Our data	(v) Bond et al.	(vi) Our data
$Q_{i,t}$	0.018	0.026	0.019	0.028	0.011	0.011
	(0.002)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)
	[7.473]	[7.723]	[7.584]	[7.753]	[4.045]	[2.948]
$\frac{CF}{K}_{i,t-1}$	0.300	0.269	0.265	0.242	0.099	0.159
	(0.038)	(0.036)	(0.039)	(0.038)	(0.048)	(0.042)
	[7.847]	[7.451]	[6.844]	[6.415]	[2.079]	[3.769]
$E\Pi_{i,t}$					0.167	0.225
					(0.037)	(0.039)
					[4.472]	[5.744]
$\frac{I}{K}_{i,t-1}$	-0.043	-0.023	-0.056	-0.035	-0.062	-0.022
	(0.019)	(0.020)	(0.019)	(0.021)	(0.019)	(0.020)
	[-2.263]	[-1.150]	[-2.947]	[-1.667]	[-3.263]	[-1.100]
Year Dummies	No	No	Yes	Yes	Yes	Yes

Sample information: The total number of observations is 4301. The sample period is from 1987 to 2000.

4.4.2 GMM Estimations

In this subsection, we reproduce the main results from Bond et al. (2004) using both the original dataset and our newly constructed dataset, restricting our attention to the 4301 firm-year observations for which we have a match and which satisfy the restriction of having four consecutive observations. The results using this sub-

[15]Formal tests of the null hypothesis that the parameters are common to the two datasets could be considered but the informal comparisons discussed here are sufficient for our purposes.

sample of the original dataset are presented in Table 4.5 while the results using the same subsample of our reconstructed dataset are presented in Table 4.6. Using a Generalised Method of Moments estimator for equations in first-differences allows for correlated firm-specific effects. . The inclusion of the lagged dependent variable is helpful for finding valid moment conditions (see also Blundell et al. (1992)). Here we use the same set of instruments as in the Bond et al. (2004) paper. The results using their full sample of 5669 observations on 703 firms are reproduced in Table 3.2 of Chapter 3. Comparing those results to those presented in Tables 4.5 and 4.6, we see that the main results of the original paper are broadly preserved in both of these datasets.

Column (i) in both Tables 4.5 and 4.6 shows a significant cash-flow term which could be attributed, amongst other things, to financing constraints or to measurement error in Tobin's Q. The two estimated coefficients on the cash flow term in column (i) are similar in magnitude (0.148 and 0.123) with t-statistics greater than 2 in both samples. The original results, replicated in Table 3.2, the estimated coefficient on the cash flow term was 0.152, with a t-statistic of 2.6. Column (ii) in both Tables 4.5 and 4.6 shows that the inclusion of the $E\Pi$ term makes the previously highly significant lagged cash-flow term in column (i) become statistically insignificant.The estimated coefficients on the $E\Pi$ term are 0.179 and 0.178 in Tables 4.5 and 4.6 respectively. These estimates are lower and less significant than the 0.248 reported in Table 3.2 but still significantly different from zero at a 10% significance level. Column (iii) in both tables confirms that, even after omitting forecasts of current-period earnings, the alternative measure of expected profitability, namely $E\Pi 1$, is significant while the lagged cash-flow term remains statistically insignificant. The remaining two columns confirm in both tables that $E\Pi$ is indeed a significant factor in explaining investment, even in the absence of the lagged cash-flow term or Tobin's Q. The main results from Table 3.2 that were emphasised in Bond et al. (2004) are thus reproduced using the subsample of 4301 observations on

594 firms for which we can obtain data from Worldscope (Table 4.5). More importantly, they are also reproduced using measures of the corresponding variables for these firms that we have constructed from the data available in Worldscope (Table 4.6). Compared to the original results in Table 3.2, two notable differences are that the standard measure of Tobin's Q is not a significant explanatory variable in the column (i) specification in Table 4.5, and the estimated coefficients on the lagged dependent variable are lower in Table 4.6, suggesting somewhat less persistence in the measure of investment rates that we have constructed from the data available in Worldscope.

Table 4.5: **Tobin's Q, Lagged Cash Flow and Expected Profits**

First-difference GMM
Dependent Variable: $\frac{I}{K}$
Using original Bond et al. dataset restricted to only matched observations

	(i)	(ii)	(iii)	(iv)	(v)
$Q_{i,t}$	0.012	0.007	0.006	0.007	
	(0.009)	(0.009)	(0.009)	(0.010)	
	[1.333]	[0.776]	[0.648]	[0.718]	
$\frac{CF}{K}_{i,t-1}$	0.148	-0.039	-0.029		-0.029
	(0.071)	(0.114)	(0.115)		(0.117)
	[2.076]	[-0.343]	[-0.252]		[-0.246]
$E\Pi_{i,t}$		0.179		0.154	0.196
		(0.098)		(0.056)	(0.092)
		[1.817]		[2.753]	[2.121]
$E\Pi 1_{i,t}$			0.294		
			(0.171)		
			[1.722]		
$\frac{I}{K}_{i,t-1}$	0.112	0.09	0.093	0.095	0.097
	(0.028)	(0.029)	(0.029)	(0.027)	(0.03)
	[3.934]	[3.061]	[3.229]	[3.542]	[3.294]
Hansen p-value	0.794	0.789	0.787	0.830	0.794
Sargan df	43	42	42	43	43
Sargan test statistic	35.23	34.47	34.52	34.16	35.23
m_1 test statistic	-10.1	-9.93	-10.0	-10.0	-10.0
m_2 p-value	0.902	0.834	0.884	0.870	0.806
m_3 p-value	0.217	0.179	0.196	0.180	0.166
m_4 p-value	0.270	0.315	0.339	0.303	0.293

Sample information: The total number of observations in the untransformed dataset is 4301. The sample period is from 1987 to 2000. The number of observations in first-differences for column (1) is 3113 while the number of firms is 594. The average number of observations per firm is 5.2. These statistics are identical for all other columns.

IVs: $\frac{CF}{K}$: $t-2$, $t-3$; $\frac{I}{K}$: $t-2$, $t-3$

See Table 2.2 for further notes.

Table 4.6: **Tobin's Q, Lagged Cash Flow and Expected Profits**

First-difference GMM
Dependent Variable: $\frac{I}{K}$
Using our newly recreated dataset restricting for matched observations with Bond et al.

	(i)	(ii)	(iii)	(iv)	(v)
$Q_{i,t}$	0.029	0.017	0.015	0.023	
	(0.017)	(0.019)	(0.019)	(0.019)	
	[1.671]	[0.913]	[0.789]	[1.190]	
$\frac{CF}{K}_{i,t-1}$	0.123	0.055	0.052		0.083
	(0.047)	(0.055)	(0.054)		(0.059)
	[2.588]	[1.008]	[0.950]		[1.403]
$E\Pi_{i,t}$		0.178		0.220	0.212
		(0.092)		(0.077)	(0.083)
		[1.927]		[2.851]	[2.574]
$E\Pi 1_{i,t}$			0.332		
			(0.163)		
			[2.033]		
$\frac{I}{K}_{i,t-1}$	0.068	0.066	0.067	0.055	0.081
	(0.029)	(0.027)	(0.027)	(0.025)	(0.026)
	[2.363]	[2.402]	[2.481]	[2.176]	[3.102]
Hansen p-value	0.703	0.729	0.745	0.687	0.700
Sargan df	43	42	42	43	43
Sargan test statistic	37.61	36.05	35.64	38.00	37.68
m_1 test statistic	-9.17	-9.05	-9.13	-9.25	-9.29
m_2 p-value	0.674	0.697	0.730	0.665	0.775
m_3 p-value	0.668	0.742	0.752	0.803	0.701
m_4 p-value	0.415	0.379	0.390	0.364	0.351

Sample information: The total number of observations in the untransformed dataset is 4301. The sample period is from 1987 to 2000. The number of observations in first-differences for column (1) is 3113 while the number of firms is 594. The average number of observations per firm is 5.2. These statistics are identical for all other columns.

IVs: $\frac{CF}{K}$: $t-2$, $t-3$; $\frac{I}{K}$: $t-2$, $t-3$

See Table 2.2 for further notes.

4.5 Conclusion

In this paper we recreated a dataset for publicly-traded UK companies covering the period 1987 to 2000, following closely the methods described in Bond et al. (2004). The construction of these datasets requires significant efforts and involves a myriad of choices. These two datasets are not an exact replica of each other despite our desire and efforts to exactly recreate the dataset. We highlighted a few important sources of these differences including missing raw data, retrospective changes to the raw data, and the unavailability of a direct measure of net fixed assets from acquisitions. Notably, for the empirical analysis of investment behaviour, the data from company accounts available from Worldscope does not include the increase in net fixed assets due to acquisitions, which was a component of the measure of investment used in Bond et al. (2004). Nevertheless, we provide evidence via comparisons of summary statistics, time plots of the medians of key variables, and estimation results for econometric models of investment rates, that these two datasets are similar. It is important to study the evolution of the roles of expected profitability, standard measures of Tobin's Q and cash flow terms over time in general, and how these relationships have evolved before and after the 2008 financial crisis in particular. The results of this paper will allow us to make comparison over time as we extend the dataset for publicly-traded UK companies beyond the year 2000 in the next paper.

Chapter 5

Investment-Cash Flow Excess Sensitivity over Time

by Revi Panidha[1]

In the short run, the market is a voting machine, in the long run, it is a weighing machine

Benjamin Graham

Abstract

In this paper we recreate and extend through to 2016 a similar dataset that was used in Bond et al. (2004). We first reconfirm that while their measure of expected profitability has predictive power for corporate investment, it does not eliminate the explanatory power of cash flow over the same time period (1987-2000). We then explore how the excess sensitivity of investment to cash flow evolved over time for the full dataset. We provide evidence that cash-flow sensitivity has diminished

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for the UK firms in our full sample, echoing similar results found previously for US publicly-traded firms. However, we find heterogeneity in the disappearance of cash flow sensitivity. We explore a novel subsampling based on the volatility of a company's market valuation over our sample. We find significant and interesting differences in results for two subsamples of firms with more volatile and less volatile market valuations. In particular, excess sensitivity of investment to cash flow is significant only for the subsample of firms with less volatile market valuations. This might be the case, but most standard arguments would suggest the opposite. The availability of less information about firms to outside investors would tend to be associated both with more volatile share prices and with a higher cost premium for external finance. This result is robust when looking at estimates using 14-year rolling sample window. For the subsample of firms with more volatile stock market valuations, we find no significant excess sensitivity of investment to cash flow in any sub-period. For the subsample of firms with less volatile stock market valuations, we find significant cash flow sensitivity for periods up to 2007, but no significant cash flow sensitivity for periods after the 2008 financial crisis. The overall decline in cash flow sensitivity for publicly-traded UK firms is thus concentrated among those with more volatile stock market valuations.

Introduction

This paper is organized as follows. Section 5.1 reviews recent and relevant literature on the disappearance of cash-flow sensitivity for US firms. Section 5.2 describes the dataset. Section 5.3 revisits results for the 1987 to 2000 time period using our fully reconstructed dataset and compares our results with those of Bond et al. (2004). Section 5.4 looks at comparisons of results for sub-periods before and after the 2018 financial crisis, and explores differences between the two subsamples, concluding that excess cash flow sensitivity has diminished over time for the full sample of publicly-traded UK firms. Section 5.5 presents a more detailed analysis of change over time by looking at 14-year moving sample windows, again confirming the disappearance of cash flow sensitivity in recent years for UK firms. Section 5.6 provides a brief discussion of the nature of financial markets and why share price volatility may provide a proxy for credit worthiness. Section 5.7 provides further discussion and analysis on the link between share price volatility and firm quality. Section 5.8 presents estimation results and comparisons over time for two subsamples of firms with more volatile and less volatile share prices. Section 5.9 concludes.[2]

5.1 Cash Flow Sensitivity over Time: A Brief Literature Review

Empirical evidence suggests that cash flow sensitivity of corporate investment has decreased over time for US corporations. Chen and Chen (2012) find that, over the period from 1967 to 2009, investment-cash flow sensitivity has markedly declined – if not entirely disappeared for both manufacturing and non-manufacturing sectors of the US economy. Moreover, they find that declining cash flow sensitivity pertains

[2]The online Appendix includes three detailed technical appendixes on the construction of the datasets together with an appendix with further results. These can be accessed at the following link https://bit.ly/3cjlAP8.

to both tangible and intangible investment. As the declining cash flow sensitivity was observed even during periods of widespread credit crunch (i.e. during the period 2006 to 2009), they also conclude that cash flow sensitivity is not a good measure of financial constraints. Agca and Mozumdar (2008) find a substantial decline in tangible investment cash flow sensitivity over rolling ten-year periods from 1970 to 2001. But, in contrast to Chen and Chen (2012), Agca and Mozumdar (2008) find that, despite the declining pattern of cash flow sensitivity, cash flow remains a significant explanatory variable in the majority of their subsamples (i.e. investment-cash flow sensitivity does not disappear). Allayannis and Mozumdar (2004) also find that cash flow sensitivity declines over the period 1977-1996, particularly for the less constrained firms in their sample, suggesting an enduring link between cash flow sensitivity and the extent to which investment is constrained by the availability of finance. Similarly, in contrast to Chen and Chen (2012), Brown and Petersen (2009) find that over the period 1970-2006, while investment cash flow sensitivity has indeed disappeared for physical investment, it remains strong for intangible investment (i.e. R&D), and declines but does not disappear for total investment. However, looking at a subsample of the 100 firms with the largest capital expenditures, Grullon et al. (2018) find that cash flow sensitivities have *increased* over the 30 year period ending in 2015. Furthermore, the study by (Lewellen and Lewellen, 2016, Figure 2, p.1150) also shows declining investment-cash flow sensitivities for US firms over the period 1971-2009. Nevertheless, after adjusting their measure of cash flow to account for extraordinary items, deferred taxes, asset write-downs, gains or losses from the sale of property, plant and equipment (PPE), and depreciation of goods included in the firm's cost of goods sold, Lewellen and Lewellen (2016) find strong evidence that cash flow continues to explain investment beyond Tobin's Q (i.e. we observe excess cash flow sensitivity). Studies looking into the magnitude of cash flow sensitivity should be taken with at least as much caution as studies preoccupied with the measurement of Tobin's Q. For example, (Brown and Petersen, 2009, p. 975) suggest that as R&D is

expensed, conventional cash flow measures are net of R&D expenditures, which may not provide a suitable measure of internally generated funds available to spend on tangible investment. As R&D expenditure has increased over time, the measurement error in standard measures of cash flow may be worsening.[3]

The literature might not be entirely in accord, but most studies suggest that, at least for physical and total investment, cash flow sensitivity has declined over time for US firms. Verona (2020) also finds a declining cash flow sensitivity over time in a more recent paper analysing quarterly *aggregate* US data from 1952 to 2017 using the continuous wavelet tools introduced by Aguiar-Conraria et al. (2018). While the above presented literature concerns US firms, we next provide evidence that cash flow sensitivity has also diminished over time for our full sample of publicly-traded UK firms. Finally, we present results for novel subsamples based on share price volatility where we find clear evidence of heterogeneity in the evolution of cash flow sensitivity over time.

[3] "R&D investment has risen steadily over the past few decades, from £20.4 billion in 1986 to the current total of £38.5 billion (in 2019 prices). This is a real terms increase of 96%." Research and Development Spending Report by the House of Common Library published in September 2021.

5.2 Description of Dataset

We follow closely the methods of Bond et al. (2004) to construct a dataset which covers UK publicly-traded firms from 1987 to 2016. We obtain data for 1108 publicly-traded UK companies.[4] Summary statistics of all key variables for the subsample of 1080 publicly-traded UK firms that fit the same criteria used by Bond et al. (2004) are presented in Table 5.1 below:

Table 5.1: Summary Statistics

	mean	**std.dev**	**first quartile**	**median**	**third quartile**
Q	3.49	3.13	1.40	2.43	4.42
$\frac{I}{K}$	0.15	0.17	0.08	0.14	0.23
$E\Pi$	0.54	0.49	0.22	0.39	0.70
$E\Pi 1$	0.31	0.28	0.12	0.23	0.40
$\frac{CF}{K}$	0.27	0.32	0.14	0.24	0.38
$\frac{CS}{K}$	0.36	0.60	0.06	0.17	0.43
Y	1.58	6.70	0.08	0.24	0.95

Notes: The total number of observations is 9643 and there are a total of 1080 firms. The sample period is from 1987 to 2016. Y represents real sales in billions of 1995 pounds.

In what follows, we compare the summary statistics presented in Table 5.1 with those in Table 4.1 that covered the full sample used by Bond et al. (2004). For this extended dataset we notice the value of Q is higher. For example, the median Q in the extended sample is around 20% higher than in the sample of Bond et al. (2004). This may be due to the ongoing trend that the value of firms is becoming increasingly affected by intangible assets (Orhangazi, 2019). Similarly, we also observe that in our extended sample, firms are on average more profitable per unit of physical capital

[4]See the online Appendix, at the following link https://bit.ly/3cjlAP8, for a detailed account of how the dataset was constructed.

and hold more cash per unit of physical capital (the means are 0.27 vs. 0.25 and 0.36 vs 0.26 respectively). The investment rate is broadly similar, while the measures of expected profitability $E\Pi$ and $E\Pi 1$ are also higher by around 10-15%.[5]

5.3 Cash Flow Sensitivity Revisited for the 1987 to 2000 Time Period

Focusing on the same time period as Bond et al. (2004), we now have 5254 observations that include almost 1000 firm-year observations that were not included in the original dataset of Bond et al. (2004).[6] Similarly to Table 3.3 we use a two-step GMM estimator using the finite sample correction of Windmeijer (2005) to obtain the standard errors. Here we include the fourth lags of each variable in the instrument set. We present these results in Table 5.2.[7] Similarly to Table 3.3, which uses the original dataset, we see a large and statistically significant coefficient on lagged cash flow ($\frac{CF}{K}_{i,t-1}$) in column (i). In contrast to Table 3.3, in the presence of a direct measure of expected profitability (i.e. $E\Pi$ or $E\Pi 1$) the cash flow coefficient is now around 20% lower (from 0.120 to 0.082) but remains significantly different from zero at the 10% level in columns (ii), (iii) and (v). As discussed in Chapter 3, the difference between these results and those of Bond et al. (2004) are mainly due to the inclusion of lagged $E\Pi$ terms in the set of instruments used here. The coefficients on $E\Pi$ and $E\Pi 1$ are also now smaller and no longer significant in columns (ii) and (iii). While the point estimates on Q are similar, the standard errors are larger and the Q term is only marginally significant in the presence of $E\Pi$ or $E\Pi 1$.[8]

[5] See the online Appendix for figures showing the evolution over time of the medians of these variables.

[6] Summary statistics for these subsamples are included in this chapter's online Appendix. As discussed in the previous chapter, some of these firm-year observations might have been added retrospectively to the data available from Worldscope.

[7] The finite sample correction proposed by Windmeijer (2005) to the standard errors for two-step GMM estimators was not widely implemented when Bond et al. (2004) were completing their study.

[8] In addition to the Sargan/Hansen tests of overidentifying restrictions, the 2-step GMM allows us to further consider Sargan/Hansen difference tests and robust Hausman tests of the validity

of the additional instruments used here. The difference in Sargan/Hansen tests and the various Hausman tests we carried out support the hypothesis that the addition of fourth lags in the instrument set is valid. We present a summary of these overidentification tests in this chapter's online Appendix.

Table 5.2: **Tobin's Q, Lagged Cash Flow and Expected Profitability**

First-difference GMM
Dependent Variable: $\frac{I}{K}$

	(i)	(ii)	(iii)	(iv)	(v)
$Q_{i,t}$	0.024	0.016	0.016	0.013	
	(0.006)	(0.009)	(0.009)	(0.008)	
	[4.117]	[1.792]	[1.719]	[1.576]	
$\frac{CF}{K}_{i,t-1}$	0.111	0.082	0.084		0.078
	(0.038)	(0.042)	(0.043)		(0.043)
	[2.907]	[1.936]	[1.944]		[1.801]
$E\Pi_{i,t}$		0.081		0.152	0.160
		(0.061)		(0.046)	(0.039)
		[1.334]		[3.269]	[4.130]
$E\Pi 1_{i,t}$			0.130		
			(0.116)		
			[1.125]		
$\frac{I}{K}_{i,t-1}$	0.087	0.083	0.084	0.074	0.087
	(0.023)	(0.022)	(0.022)	(0.022)	(0.023)
	[3.841]	[3.724]	[3.777]	[3.371]	[3.783]
Hansen p-value	0.783	0.769	0.767	0.766	0.669
Sargan df	96	95	95	96	96
Sargan test statistic	84.92	84.57	84.67	85.66	89.41
m_1 test statistic	-10.6	-10.3	-10.4	-10.3	-10.3
m_2 p-value	0.633	0.596	0.631	0.616	0.584
m_3 p-value	0.569	0.600	0.583	0.667	0.613
m_4 p-value	0.153	0.149	0.147	0.136	0.140

Sample information: The total number of observations in the untransformed dataset is 5254. The sample period is from 1987 to 2000. The number of observations in column (i) for the first-difference two-step GMM is 3816 while the number of firms is 719. The average number of observations per firm is 5.31. These statistics are identical for all other columns.

IVs: $\frac{CF}{K}$: $t-2$, $t-3$, $t-4$; $\frac{I}{K}$: $t-2$, $t-3$, $t-4$; $E\Pi$: $t-2$, $t-3$, $t-4$

See Table 2 for further notes.

In sum, the above estimation results confirm the main finding of Chapter 3 that cash flow remains a significant explanatory variable in the presence of measures of expected profitability proposed by Bond et al. (2004). Next, we look at how the relationship between investment rates and Tobin's Q, cash flow and these expected profitability measures has changed over time and, in particular, how it has changed before and after the financial crisis of 2007-08.

5.4 Cash Flow Sensitivity, Tobin's Q, and Expected Profitability: Before and After the Financial Crisis

In Table 5.3 we present the estimation results for the period 1995 to 2006, a 12-year period prior to the financial crisis of 2007-08. We find evidence of excess cash flow sensitivity as the estimated coefficients on the lagged cash flow term are both large and statistically significantly different from zero at the 1% level despite the presence of Q, $E\Pi$ or $E\Pi 1$ in these econometric models. Moreover, and in contrast to the results presented in Table 5.2, neither the measures of expected profitability nor Q are informative explanatory variables in any of these specifications. During this period, it was the return on installed capital in the previous year, as measured by our lagged cash flow variable, that was the main driver of investment rates. However, these results are reversed for the post-crisis period.

In Table 5.4 we present the estimation results for the 9 year period from 2009 to 2017. In this post-crisis period, the estimated coefficient on the lagged cash flow term is only marginally significant in the column (i) specification and less than a third of its magnitude in the pre-crisis years. Moreover, once any of the expected profitability variables are included in columns (ii) - (v), the estimated coefficient on the lagged cash flow term becomes very small and insignificantly different from zero.

In contrast to the pre-crisis period and also to the results for the period 1987-2000, the measure of expected profitability ($E\Pi$) is statistically significant at the 1% level. Formal tests of the null hypothesis that the coefficients on the cash flow term are equal in the periods 1995-2006 and 2009-17 reject that hypothesis at the 5% level in columns (*ii*), (*iii*), and (*v*).[9] The lagged investment rate is also found to be an uninformative explanatory variable in the results for both 1995-2006 and 2009-2017, although that was not the case using our data for the earlier period 1987-2000 (see Table 5.2).

[9]Formal difference tests are reported in the online Appendix.

Table 5.3: **Tobin's Q, Lagged Cash Flow and Expected Profitability**

First-difference GMM
Dependent Variable: $\frac{I}{K}$

	(i)	(ii)	(iii)	(iv)	(v)
$Q_{i,t}$	0.010	0.010	0.005	0.009	
	(0.009)	(0.013)	(0.013)	(0.012)	
	[1.111]	[0.769]	[0.385]	[0.750]	
$\frac{CF}{K}_{i,t-1}$	0.132	0.128	0.124		0.138
	(0.055)	(0.057)	(0.055)		(0.058)
	[2.400]	[2.247]	[2.255]		[2.379]
$E\Pi_{i,t}$		-0.001		0.102	0.049
		(0.110)		(.118)	(0.083)
		[-0.009]		[0.864]	[0.590]
$E\Pi 1_{i,t}$			0.092		
			(0.186)		
			[0.495]		
$\frac{I}{K}_{i,t-1}$	0.033	0.031	0.030	0.020	0.034
	(0.028)	(0.028)	(0.028)	(0.026)	(0.028)
	[1.179]	[1.107]	[1.071]	[0.769]	[1.214]
Hansen p-value	0.387	0.376	0.336	0.241	0.373
Sargan df	78	77	77	78	78
Sargan test statistic	80.94	80.31	81.69	86.39	81.41
m_1 test statistic	-8.61	-8.14	-8.10	-8.30	-8.15
m_2 p-value	0.017	0.015	0.011	0.008	0.012
m_3 p-value	0.380	0.382	0.341	0.340	0.356
m_4 p-value	0.750	0.748	0.702	0.760	0.681

Sample information: The total number of observations in the untransformed dataset is 3850. The sample period is from 1995 to 2006.

IVs: $\frac{CF}{K}$: $t-2$, $t-3$, $t-4$; $\frac{I}{K}$: $t-2$, $t-3$, $t-4$; $E\Pi$: $t-2$, $t-3$, $t-4$

See Table 2.2 for further notes.

Table 5.4: **Tobin's Q, Lagged Cash Flow and Expected Profitability**

First-difference GMM
Dependent Variable: $\frac{I}{K}$

	(i)	(ii)	(iii)	(iv)	(v)
$Q_{i,t}$	0.029	0.018	0.021	0.017	
	(0.009)	(0.010)	(0.012)	(0.010)	
	[3.175]	[1.763]	[1.807]	[1.676]	
$\frac{CF}{K}_{i,t-1}$	0.038	0.003	0.017		0.002
	(0.023)	(0.032)	(0.027)		(0.037)
	[1.637]	[0.093]	[0.643]		[0.062]
$E\Pi_{i,t}$		0.261		0.266	0.313
		(0.117)		(0.093)	(0.108)
		[2.231]		[2.805]	[2.902]
$E\Pi 1_{i,t}$			0.372		
			(0.212)		
			[1.757]		
$\frac{I}{K}_{i,t-1}$	0.029	-0.024	-0.026	-0.027	-0.021
	(0.050)	(0.045)	(0.046)	(0.043)	(0.049)
	[0.592]	[-0.539]	[-0.563]	[-0.620]	[-0.430]
Hansen p-value	0.865	0.467	0.432	0.522	0.421
Sargan df	51	50	50	51	51
Sargan test statistic	40.06	50.16	51.06	49.79	52.37
m_1 test statistic	-4.49	-4.07	-4.11	-4.13	-4.25
m_2 p-value	0.849	0.821	0.711	0.820	0.835
m_3 p-value	0.012	0.009	0.005	0.008	0.006
m_4 p-value	0.413	0.216	0.241	0.211	0.169

Sample information: The total number of observations in the untransformed dataset is 1973. The sample period is from 2009 to 2016.

IVs: $\frac{CF}{K}$: $t-2$, $t-3$, $t-4$; $\frac{I}{K}$: $t-2$, $t-3$, $t-4$; $E\Pi$: $t-2$, $t-3$, $t-4$

See Table 2.2 for further notes.

5.5 Cash Flow Sensitivity, Tobin's Q, and Expected Profitability: A Further Analysis of Changes over Time

To further understand the evolution of the relationship between investment rates and Tobin's Q, cash flow and expected profitability measures, Figure 5.1 presents results using 14-year rolling sample windows. Each of the four columns presents two-step GMM results for the specifications reported in columns (i), (ii), (iv), and (v) of the previous tables.[10] Each of the 4 rows represents, from top to bottom, the estimated coefficients on the explanatory variables Q, $\frac{CF}{K}$, $E\Pi$, and $\frac{I}{K}$. The order of the rows is the same as the order of these variables in the previous tables. The green line has been constructed by connecting the estimated coefficients on the relevant variable in different sample periods. The magnitude of these estimated coefficients in shown on the left y-axis. The blue shaded area around the green line represents a 95% confidence band around these point estimates. The orange dots plot the p-values for the Sargan/Hansen test of overidentifying restrictions in the different sample periods. These p-values are shown on the right y-axis, and are the same for eac graph in a given column. The final year of each 14 year sample period is shown on the x-axis. The first period is from 1987 to 2000, with results which correspond to those presented in Table 5.2. For example, considering column (i) of Table 5.2, we note that the estimated coefficient on Q is 0.024 while the estimated coefficient on $\frac{CF}{K}$ is 0.111, and these are both significantly different from zero. The estimated coefficients on cash flow are shown by the level of the green line in the graph located in the first column and second row for the year 2000 (i.e. the starting point of the graph). The significance of this estimated coefficient is captured by the fact that the confidence band for that coefficient in that year does not include the

[10] We have not included results for specification (iii), which uses the alternative expected profitability measure $E\Pi 1$, for compactness and presentational reasons.

zero line as shown on the left y-axis. Similarly, the estimated coefficient on Q is shown by the level of the green line in the graph located in the first column and first row for the year 2000, for which the 95% confidence interval also excludes the value of zero. The Hansen p-value reported in column (i) of Table 5.2 is 0.783, which is shown by the orange dot for the year 2000 with reference to the right y-axis for *all* the graphs presented in the first column. The results for the rolling 14 year sample periods 1988-2001, 1989-2002, ... , 2003-2016 are shown in the same graphs, with the end years of these periods shown on the x-axis. In sum, Figure 5.1 summarises the results obtained using 17 different sample periods, which could have been shown in 17 tables of results similar to Table 5.2. This allows the changes over time in the estimated coefficients in these four models specification to be visualised.



Figure 5.1: Full sample 14-year moving rolling window average GMM estimations

Figure 5.1 confirms the main findings from Tables 5.3 and 5.4. Column (i) of Figure 5.1 illustrates a declining trend in excess cash flow sensitivity where the estimated coefficients on cash flow (i.e. the graph in the second row) more than halve between the period 1987-2000 and the period 2003-16 (i.e. from around 0.11 to 0.05). This estimated coefficient becomes insignificant at the 5% level for periods ending in 2011 or later. This downward trend in the estimated coefficient on cash flow is also seen in the specifications which include $E\Pi_{i,t}$, as shown in columns (ii) and (v). Moreover, in the presence of this measure of expected profitability, the cash flow variable is, at best, only marginally significant in the 14-year periods ending prior to 2007.[11] The direct measure of expected profitability $E\Pi_{i,t}$ also seems to be a better predictor of investment rates than the standard measure of Tobin's Q. As illustrated in column (iv) of Figure 5.1, the estimated coefficient on $E\Pi_{i,t}$ is statistically significant in most of these time periods, while the estimated coefficient on Q is insignificantly different from zero at the 5% significance level in *all* time periods in this specification. We also observe declining autoregressive persistence in UK company investment rates over this period, as reflected in the coefficient on the lagged dependent variable.

In sum, we observe a declining sensitivity of investment to cash flow, echoing results found for US publicly-traded firms. We also observe and reconfirm that measures of expected profitability constructed from analysts' earnings forecasts are at least as good predictors of corporate investment as the standard measure of Tobin's Q for our full sample of publicly-traded UK firms.

5.6 Volatility, Publicly Traded Firms and Famous Investors' Wisdom

In the chapter on long-term expectations in his *General Theory of Employment, Interest and Money*, Keynes wrote about how "decisions to invest in private business of the old-fashioned type were ... decisions largely irrevocable, not only for the community as a whole, but also for the individual. With the separation between ownership and management which prevails today and with the development of organised investment markets ... the Stock Exchange revalues many investments every day and the revaluations give a frequent opportunity to the individual (though not to the community as a whole) to revise his commitments." (Keynes, 1936, p.76). In making Tobin's Q an operational model of investment behaviour we are implicitly assuming that the public market valuation of many businesses, however arrived at, are correct given all the facts which can influence real investment returns, and that they will only change in response to changes in information about the prospective attractiveness of investments in the relevant corporations.

However, Keynes discussed many other considerations which affected market valuations that are not related to the prospective appeal of the underlying investments.[12] Firstly, Keynes believed that, given the increase in the investment "community's aggregate capital investment which is owned by persons who do not manage and have no special knowledge of the circumstances, either actual or prospective, of the business in question, the element of real knowledge in the valuation of investments by those who own them or contemplate purchasing them has seriously declined." Secondly, Keynes observed that changes in profits that were both ephemeral and insignificant in character often had excessive influence on the market. Thirdly, the mass psychology of a growing number of ignorant market participants caused large fluctuations in valuations not proportional to changes in the prospective yields

[12]Keynes was an active participant in the stock market with a respectable track record (see Chambers et al. (2015)).

of underlying investments. Fourthly, the vagaries of the market explained above cannot be corrected by any individual who "unperturbed by the prevailing pastime, continues to purchase investments on the best genuine long-term expectations he can frame". This is because, Keynes argued, there are very few such individuals who can only operate on a small scale and use little, if any, borrowed money. Human nature, he argued, desires quick results and the game of speculation (i.e. anticipation of impending changes in news or general public confidence) is played by the majority of professional investors. Such investors, who invest based on fundamentals, will generally not be involved in the short selling of stocks, due to the potential infinite losses with such a strategy in the short run, and hence have no say in correcting "bubbles"; similarly their relatively small scale would not shore up undervalued securities.

On August 30, 1930, only a few years before the publication of the *General Theory*, Warren Buffett was born in Omaha, Nebraska. He was soon to become arguably the most influential investor of all time.[13] During the years in which he ran an investment partnership, his annual investment returns ranged from 10.4% to 58%, while returns on the Dow ranged from -15.6% to 38.5%.[14] The annual compounded rate for the Buffett partnership was 31.6% while that for the Dow was 9.1%. One hundred dollars invested in the Dow would have become 286 dollars, while 100 dollars invested in the Buffett partnership would have become 1504 dollars (for the limited partners who compounded their money at 25.3% after fees payable to Warren Buffett who was a managing partner). He achieved these spectacular results with *less* risk than the Dow as shown by the fact that he never had a down year. The partnership started with 100,100[15] dollars and had close to 100 million dollars by 1968. The partnership morphed into Berkshire Hathaway (BRK) when the partnership gained

[13]We have followed the business career of Warren Buffett closely and read carefully all his letters to investment partners from 1957-1970 and reviewed the transcripts of all his annual meetings with shareholders of Berkshire Hathaway from 1994 to 2022. The following discussions have been very much inspired by the lessons learned during this part of the research.

[14]The shareholders letters are widely accessible. One source is the following link: https://www.ivey.uwo.ca/media/2975913/buffett-partnership-letters.pdf.

[15]The one hundred being the investment from Warren Buffett himself while the remaining 100 000 from his limited partners.

control of it in 1965 and is now still controlled by Warren Buffett and his proxies. During this second phase of his career, Buffett through BRK purchased many businesses outright, making his writings and interviews an exceptionally valuable source for someone aiming to understand corporate investment. Bringing the record up to date, from 1965 to 2019, Berkshire Hathaway increased its per-share market value at an annualized rate of 20.3% in comparison to 10.0% for the S&P with dividends included.[16] One hundred dollars invested in BRK in 1965 would have been worth over 2.7 million dollars in 2019, while the same amount invested in the S&P would have been worth less than 20 000 dollars. At the time of writing, BRK commands a market valuation of over 500 billion dollars. We are confident that Keynes would have identified Warren Buffett as the long-term investor nonpareil whose primary preoccupation was to purchase businesses by focusing on the best genuine long-term expectations he could frame and compare them with the ongoing price.

Following the career of Warren Buffett, we confirm some of the conclusions of Keynes and challenge others. Firstly, it is true that there are not many long-term oriented investors. Why is it that so few have followed his investment style? Warren Buffett often responds that "people do not want to get rich slowly". Mr. Buffett has often said that you can be right about an overvalued company and still lose a lot of money shorting it, echoing Keynes on the inability of such investors to correct crowd mentality. Moreover, it is also true that Warren Buffett used little to no borrowed money in his investment operations. While Buffett agrees that the market is generally efficient, he often documents speculative behaviour in his writings and annual meetings. For example, he openly talked about the internet bubble in the late 1990s well before the bubble burst (see Schroeder (2009) for a full script of a presentation given at the Sun Valley conference of July 1999). During the annual meetings prior to the 2007-08 financial crisis, he also pointed out that in his opinion and in the opinion of Charlie Munger, vice-president of Berkshire Hathaway, the

[16] Annual letter to shareholders 2019, available online at company website https://www.berkshirehathaway.com.

housing market was experiencing a bubble. However, they found there was relatively little they could do to correct this or profit from it.

Warren Buffett was the most well-known disciple of Benjamin Graham. It was the writings of Buffett and Graham that inspired the novel volatility-based subsampling presented in this paper. Benjamin Graham was both an investment practitioner and an academic who taught investment at Columbia. He co-authored the seminal book on *Security Analysis* (Graham et al., 1934) and popularized some of his ideas in the more accessible book *The Intelligent Investor*.[17] In his writings, he clearly distinguished between speculation and (enterprising) investments. *The Intelligent Investor*, which was first published in 1949 and frequently updated until 1973, talked at length about the speculative nature of the market (e.g. see Chapter 8, *The Investor and Market Fluctuations*). In this book, he gives very colourful illustrations of particular market fluctuations that are due, in his opinion and judging from fundamentals, to the vagaries of the market. Graham often said that "markets are a voting machine in the short run, but a weighing machine in the long run". This is one aspect which is of particular interest to us in Graham's writing and has inspired part of this research. Graham writes "...we find that, for the most part, companies with the best investment characteristics - i.e., the best credit rating - are the ones which are likely to attract the largest speculative interest in their common stocks, since everyone assumes they are guaranteed a brilliant future." (Graham and Zweig, 2003, p.564)[18]

He elaborates further in his writing:

> The whole structure of stock-market quotations contains a built-in contradiction. The better a company's record and prospects, the less relationship the price of its shares will have to their book value. But the

[17] See Lowe (1999) for an excellent collection of Graham's writings and a script of his investment course at Colombia. In part three of the book, one can also find an extract from the Hearings in 1955 before the Committee on Banking and Currency, United States Senate, where Benjamin Graham was asked to participate.

[18] From the address of Benjamin Graham before the annual Convention of the National Federation of Financial Analysts Societies, May 1958.

> greater the premium above book value, the less certain the basis of determining its intrinsic value—i.e., the more this "value" will depend on the changing moods and measurements of the stock market. Thus we reach the final paradox, that the more successful the company, the greater are likely to be the fluctuations in the price of its shares. This really means that, in a very real sense, the better the quality of a common stock, the more speculative it is likely to be - at least as compared with the unspectacular middle-grade issues. Graham (1973)

It is this that forms the basis of the following hypothesis:

- We would expect firms with more volatile stock market valuations to be "more speculative" and higher grade firms. Hence, these firms should face relatively *fewer* financial constraints than their less volatile counterparts. To the extent that excess cash flow sensitivity in a Tobin'sQmodel reflects financing constraints faced by firms, we would expect these more volatile firms to display lower cash flow sensitivity.

In the following sections we analyse whether differences between volatile firms in the volatility of their daily returns, are associated with differences in the sensitivity of investment to cash flow. We further investigate whether cash flow sensitivity has evolved differently over time for subsamples of more volatile and less volatile firm.

5.7 Share Price Volatility, Firm Quality and Estimation Challenges

Moving beyond our previous discussion inspired by the work of Benjamin Graham, the relationship between share price volatility and quality of the firm possesses greater complexities.[19] Higher share price volatility could be related to information asymmetry (Myers and Majluf, 1984), and might be signalling inefficient firms (Stein, 1989) or even weak corporate structure (Jensen, 1986; Shleifer and Vishny, 1997).

Bartram et al. (2012) note that the finance literature distinguishes between good volatility (contributing positively to shareholders) and bad volatility (contributing negatively). For example, good institutions make it advantageous for firms to take risks that lead to greater economic growth (e.g. Obstfeld (1992) and Acemoglu and Zilibotti (1997)). In contrast, political risks or industry-specific risks might lead to bad volatility. Using a model for systematic risk from Bekaert et al. (2012), Bartram et al. (2012) find that U.S. firms have substantial higher volatility compared to their foreign counterparts of the same industry size, age, and market-to-book ratio.[20] This higher volatility is mostly accounted for by greater idiosyncratic risk.

There is increasing evidence that idiosyncratic risk is relevant for expected returns. For example, behavioural finance emphasizes the role of noise traders in pushing stocks away from fundamentals, while agency problems in corporate finance might force insiders to co-invest with outside investors leading managers to "take less risks as more is borne by insiders who can't diversify it away" (Bartram et al., 2012, p.1330). Higher quality firms are likely to have better investor protection. John et al. (2008) show that insiders' claim on future private benefits is equivalent to debt claim on the firm and leads them to take fewer risks. Higher quality firms are likely to

[19] I am particularly grateful to Prof. Michael Devereux and Prof. Fabio Schiantarelli for pushing for this section.

[20] More specifically, the authors show that across 20 000 or so firms over the 1990-2006 period, U.S. firms had annualized average weekly volatility of 25.7% higher than their foreign counterparts.

have more disclosure that can lead to higher volatility (see Jin and Myers (2006)).[21] Assuming that information asymmetries are greater for growth opportunities than for assets in place, this might suggest that firms with more growth opportunities will exhibit greater share price volatility in part due to more idiosyncratic volatility. The important study by Bartram et al. (2012) concludes that US firms have a higher (positive) volatility because volatility increases with investor protection, new patents, and firm-level R&D. In short, the authors provide evidence that the higher volatility is picking up better growth opportunities and better position to take advantages of such opportunities.[22] Extrapolating their results to subsamples of higher volatility firms could be proxying for higher quality firms. However, in light of the literature as a whole, one needs to be cautious before making a definite statement of the relationship between share price volatility and the quality of the firm.

A second important issue relates to the problems of measurement error and of weak instruments. High share price volatility might exacerbate the measurement error in average Q for the subsample of higher volatility firms. Moreover, instruments based on lagged values might have a low correlation with the endogenous variables if firms have a high share price volatility. Stock and Wright (2000) discuss the challenges of using GMM in the presence of weak instruments. Blundell and Bond (1998) propose System GMM which might improve efficiency in the presence of weak instruments. One might consider investigation of the weakness of instruments by looking at first stage regressions for different subsamples, an area worthy of future research. With the above two caveats, we next present the summary statistics of the two subsamples.

[21] LeRoy and Porter (1981) present a model that leads to the opposite prediction under efficient markets and constant discount rates.

[22] Kogan et al. (2017) use the idea that information on stock price volatility and reaction around the time a patent is granted can be used to measure the price value of the patent. Their study also implicitly supports the view that higher price volatility might be expected for firms that are involved in R&D.

5.8 Volatility Subsampling

In this section, we split our sample based on daily return volatility as captured by the daily change in the share price of each firm for the duration of the sample.[23] We do so by splitting the sample in halves or thirds. Here we present the comparison between the bottom third least volatile firms versus the top third most volatile firms. The next subsection discusses differences that are observed by looking at the summary statistics, while the subsequent three subsections compare the estimation results between these two subsamples in three time periods: before 2001, before the financial crisis and after the financial crisis. The final subsection looks at changes over time using a 14-year rooling sample windows similar to the analysis presented in Figure 5.1.[24]

5.8.1 Summary Statistics by Volatility Levels

Table 5.5 and Table 5.6 show summary statistics for the top third most volatile firms and for the bottom third least volatile firms respectively. The sales figure (Y) in billions of 1995 pounds shows that the high volatility firms are significantly smaller with median sales approximately one third of median sales for the low volatility firms. However, the more volatile firms also invest at a higher median rate (0.15 vs. 0.13), hold more cash per unit of tangible assets (0.21 vs. 0.16), earn *less* per unit of tangible assets (0.23 vs. 0.25), while being valued *more* per unit of tangible assets as captured by the higher median value of Tobin's Q (2.51 vs. 2.39). This higher median value of Tobin's Q is also consistent with median values of the two forward-looking higher expected profitability measures, $E\Pi$ and $E\Pi 1$. To provide an analogy, one can think of the more volatile firms as "growth" firms versus the less

[23] A detailed discussion on the subsampling procedure is provided in the online Appendix. In this appendix we also discuss how our volatility measure compare to measures of 'uncertainty' based on share price volatility, used in the investment literature by Leahy and Whited (1995) and by Bloom et al. (2007).

[24] The results for the bottom half and the top half are presented in the online Appendix and show similar patterns. We also split our sample by volatility in the first year that the firm entered the sample and this yielded similar results.

volatile firms as "value" firms. The growth firms tend to be smaller and hold more cash to finance future growth opportunities, but are currently less profitable than the "value" firms. The former may be heavily investing/spending to build their brand or to gain market share or build a new product (e.g. via marketing expenditure or research and development). The summary statistics seem to fit well Benjamin Graham's prediction that the more volatile shares represent higher quality firms in terms of growth opportunities and future business prospects.

Table 5.5: Top third volatile firms

	mean	**std.dev**	**first quartile**	**median**	**third quartile**
Q	3.65	3.31	1.32	2.51	4.85
$\frac{I}{K}$	0.16	0.19	0.07	0.15	0.26
$E\Pi$	0.57	0.51	0.21	0.42	0.75
$E\Pi 1$	0.33	0.30	0.12	0.25	0.44
$\frac{CF}{K}$	0.21	0.42	0.11	0.23	0.37
$\frac{CS}{K}$	0.43	0.77	0.07	0.21	0.51
Y	0.68	1.80	0.05	0.14	0.44

Notes: The total number of observations is 2577 and there are a total of 360 firms. The sample period is from 1987 to 2016.

Table 5.6: Bottom third volatile firms

	mean	**std.dev**	**first quartile**	**median**	**third quartile**
Q	3.48	3.12	1.45	2.39	4.34
$\frac{I}{K}$	0.14	0.15	0.08	0.13	0.21
$E\Pi$	0.52	0.46	0.22	0.39	0.68
$E\Pi 1$	0.29	0.26	0.13	0.22	0.38
$\frac{CF}{K}$	0.29	0.23	0.15	0.25	0.39
$\frac{CS}{K}$	0.32	0.47	0.05	0.16	0.39
Y	2.52	9.91	0.11	0.38	1.49

Notes: The total number of observations is 3374 and there are a total of 360 firms. The sample period is from 1987 to 2016.

5.8.2 The Time Period from 1987 to 2000

In Table 5.7 and Table 5.8 we present the estimation results for the top third most volatile firms and the bottom third least volatile firms respectively, for the period from 1987 to 2000 (i.e. the same period covered by Bond et al. (2004)).

The results for the more volatile firms (i.e. the "growth" firms) in column (i) of Table 5.7 show that the coefficient on cash flow is insignificantly different from zero and Tobin's Q is the only statistically significant explanatory variable. However, in the remaining columns, the forward-looking expected profitability measures ($E\Pi$ or $E\Pi 1$) are the only statistically significant explanatory variables. In sum, for this subsample cash flow is not a significant predictor of investment rates and the analyst-based measure of expected profitability is a better predictor than Tobin's Q for the corporate investment rate.

However, we find markedly different results in Table 5.8 for the less volatile firms (i.e. those we have labelled as "value" firms). For such firms, we find significant excess cash flow sensitivity in the presence of Q and/or $E\Pi$. Both Q and the expected

profitability measures are also informative explanatory variables (columns (i) and (v)), although the standard measure of Q is found to be the more informative explanatory variable for this subsample when both are included together with lagged cash flow (columns (ii) and (iii)). Lagged investment rates are also significant explanatory variables for current investment rates for these less volatile firms. In the next subsection we compare results for these two subsamples in the period from 1995 to 2006, in the run-up to the financial crisis.

Table 5.7: **Tobin's Q, Lagged Cash Flow and Expected Profitability**

First-difference GMM
Dependent Variable: $\frac{I}{K}$

	(i)	(ii)	(iii)	(iv)	(v)
$Q_{i,t}$	0.021	0.003	0.005	0.002	
	(0.008)	(0.011)	(0.011)	(0.010)	
	[2.659]	[0.238]	[0.490]	[0.206]	
$\frac{CF}{K}_{i,t-1}$	0.103	0.040	0.056		0.039
	(0.076)	(0.085)	(0.082)		(0.085)
	[1.368]	[0.466]	[0.690]		[0.459]
$E\Pi_{i,t}$		0.172		0.192	0.182
		(0.074)		(0.053)	(0.049)
		[2.313]		[3.622]	[3.697]
$E\Pi 1_{i,t}$			0.257		
			(0.131)		
			[1.965]		
$\frac{I}{K}_{i,t-1}$	0.029	0.024	0.024	0.027	0.024
	(0.044)	(0.045)	(0.044)	(0.044)	(0.045)
	[0.651]	[0.530]	[0.551]	[0.614]	[0.528]
Hansen p-value	0.582	0.664	0.648	0.675	0.684
Sargan df	95	94	94	95	95
Sargan test statistic	91.52	87.66	88.25	88.25	87.89
m_1 test statistic	-4.98	-4.68	-4.74	-4.66	-4.68
m_2 p-value	0.316	0.234	0.269	0.265	0.224
m_3 p-value	0.767	0.605	0.584	0.592	0.585
m_4 p-value	0.052	0.038	0.044	0.029	0.038

Sample information: The total number of observations in the untransformed dataset is 1240. The sample period is from 1987 to 2000. The number of observations in first-differences for column (1) is 864 while the number of firms is 188. The average number of observations per firm is 4.60. These statistics are identical for all other columns. The sample is for the top-third most volatile firms.

IVs: $\frac{CF}{K}$: $t-2$, $t-3$, $t-4$; $\frac{I}{K}$: $t-2$, $t-3$, $t-4$; $E\Pi$: $t-2$, $t-3$, $t-4$

See Table 2.2 for further notes.

Table 5.8: **Tobin's Q, Lagged Cash Flow and Expected Profitability**

First-difference GMM
Dependent Variable: $\frac{I}{K}$

	(i)	(ii)	(iii)	(iv)	(v)
$Q_{i,t}$	0.028	0.024	0.023	0.023	
	(0.008)	(0.011)	(0.012)	(0.013)	
	[3.450]	[2.099]	[1.928]	[1.755]	
$\frac{CF}{K}_{i,t-1}$	0.259	0.233	0.224		0.243
	(0.079)	(0.088)	(0.088)		(0.088)
	[3.263]	[2.637]	[2.553]		[2.748]
$E\Pi_{i,t}$		0.055		0.188	0.182
		(0.083)		(0.082)	(0.062)
		[0.657]		[2.304]	[2.948]
$E\Pi 1_{i,t}$			0.124		
			(0.147)		
			[0.840]		
$\frac{I}{K}_{i,t-1}$	0.073	0.070	0.070	0 .049	0.082
	(0.031)	(0.031)	(0.032)	(0.031)	(0.035)
	[2.378]	[2.237]	[2.211]	[1.569]	[2.367]
Hansen p-value	0.32	0.288	0.275	0.250	0.244
Sargan df	96	95	95	96	96
Sargan test statistic	101.9	102.2	102.7	104.9	105.2
m_1 test statistic	-6.29	-6.21	-6.18	-6.08	-6.01
m_2 p-value	0.311	9.283	0.263	0.218	0.201
m_3 p-value	0.482	0.464	0.458	0.395	0.517
m_4 p-value	0.200	0.184	0.180	0.116	0.168

Sample information: The total number of observations in the untransformed dataset is 1994. The sample period is from 1987 to 2000. The number of observations in first-differences for column (1) is 1474 while the number of firms is 260. The average number of observations per firm is 5.67. These statistics are identical for all other columns. The sample is for the bottom-third least volatile firms.

IVs: $\frac{CF}{K}$: $t-2$, $t-3$, $t-4$; $\frac{I}{K}$: $t-2$, $t-3$, $t-4$; $E\Pi$: $t-2$, $t-3$, $t-4$

See Table 2.2 for further notes.

5.8.3 Before the Financial Crisis: 1995 to 2006

The results for the period before the financial crisis for the two volatility subsamples are presented in Table 5.9 and Table 5.10 for high volatility and low volatility firms respectively. For the more volatile firms (Table 5.9), the results are broadly similar to those reported in Table 5.7. In particular, we again find no significant sensitivity of investment to cash flow for this subsample. One difference is that, in the period 1995-2006, the standard measure of Q is found to be a more informative explanatory than the analyst-based measures of expected profitability for this subsample of firms. For the less volatile firms (Table 5.10), we again find strong evidence of excess sensitivity to cash flow. For this subsample, in the period 1995-2006, we find much larger and highly significant positive coefficients on the expected profitability measures, and insignificant or even negative coefficients on the standard measure of Q.[25] Which of these measures of 'fundamentals' provides the more informative explanatory variable for company investment rates appears to be quite sensitive to the subsample of firms and the time period considered. The lagged dependent variable is also insignificant for the less volatile firms in the period 1995-2006. The next subsection presents results for these two types of firms in the period after the financial crisis.

[25]Negative estimated coefficients on Q have been reported earlier in the literature. For example, Gallegati and Ramsey (2013) find negative coefficients on Q during the 1980s, for their sample, which they view as evidence of structural instability in the estimated investment-Q relationship. In our case the negative coefficients on Q may be driven by strong correlation between the included Q and $E\Pi$ explanatory variables in columns (ii)-(iv).

Table 5.9: **Tobin's Q, Lagged Cash Flow and Expected Profitability**

First-difference GMM
Dependent Variable: $\frac{I}{K}$

	(i)	(ii)	(iii)	(iv)	(v)
$Q_{i,t}$	0.023	0.018	0.022	0.018	
	(0.005)	(0.009)	(0.008)	(0.010)	
	[4.742]	[2.067]	[2.838]	[1.833]	
$\frac{CF}{K}_{i,t-1}$	-0.016	-0.029	-0.015		-0.031
	(0.029)	(0.031)	(0.030)		(0.054)
	[-0.550]	[-0.945]	[-0.484]		[-0.565]
$E\Pi_{i,t}$		0.070		0.050	0.197
		(0.098)		(0.101)	(0.070)
		[0.718]		[0.500]	[2.797]
$E\Pi 1_{i,t}$			0.055		
			(0.121)		
			[0.449]		
$\frac{I}{K}_{i,t-1}$	0.035	0.034	0.030	0 .038	0.044
	(0.041)	(0.041)	(0.041)	(0.041)	(0.042)
	[0.843]	[0.833]	[0.743]	[0.918]	[1.054]
Hansen p-value	0.663	0.568	0.555	0.559	0.437
Sargan df	78	77	77	78	78
Sargan test statistic	72.21	74.25	74.63	75.51	79.32
m_1 test statistic	-4.79	-4.70	-4.75	-4.72	-4.61
m_2 p-value	0.617	0.591	0.617	0.615	0.566
m_3 p-value	0.897	0.976	0.943	0.898	0.870
m_4 p-value	0.863	0.848	0.876	0.954	0.930

Sample information: The total number of observations in the untransformed dataset is 974. The sample period is from 1995 to 2006. The sample is for the top-third most volatile firms.

IVs: $\frac{CF}{K}$: $t-2$, $t-3$, $t-4$; $\frac{I}{K}$: $t-2$, $t-3$, $t-4$; $E\Pi$: $t-2$, $t-3$, $t-4$

See Table 2.2 for further notes.

Table 5.10: **Tobin's Q, Lagged Cash Flow and Expected Profitability**

First-difference GMM
Dependent Variable: $\frac{I}{K}$

	(i)	(ii)	(iii)	(iv)	(v)
$Q_{i,t}$	0.021	-0.041	-0.040	-0.029	
	(0.014)	(0.020)	(0.023)	(0.020)	
	[1.495]	[-2.040]	[-1.760]	[-1.480]	
$\frac{CF}{K}_{i,t-1}$	0.448	0.375	0.363		0.358
	(0.148)	(0.124)	(0.128)		(0.139)
	[3.017]	[3.023]	[2.835]		[2.577]
$E\Pi_{i,t}$		0.738		0.806	0.424
		(0.138)		(0.157)	(0.090)
		[5.332]		[5.128]	[4.692]
$E\Pi 1_{i,t}$			1.317		
			(0.290)		
			[4.537]		
$\frac{I}{K}_{i,t-1}$	-0.011	0.019	0.019	-0.020	0.008
	(0.043)	(0.052)	(0.055)	(0.053)	(0.044)
	[-0.259]	[0.370]	[0.345]	[-0.385]	[0.184]
Hansen p-value	0.257	0.504	0.434	0.226	0.414
Sargan df	78	77	77	78	78
Sargan test statistic	85.74	76.21	78.39	87.06	80.06
m_1 test statistic	-4.61	-3.80	-3.74	-4.01	-4.02
m_2 p-value	0.028	0.013	0.023	0.020	0.013
m_3 p-value	0.380	0.408	0.405	0.602	0.400
m_4 p-value	0.396	0.693	0.646	0.905	0.618

Sample information: The total number of observations in the untransformed dataset is 1289. The sample period is from 1995 to 2006. The sample is for the bottom-third least volatile firms.

IVs: $\frac{CF}{K}$: $t-2$, $t-3$, $t-4$; $\frac{I}{K}$: $t-2$, $t-3$, $t-4$; $E\Pi$: $t-2$, $t-3$, $t-4$

See Table 2.2 for further notes.

5.8.4 After the Financial Crisis: 2008 to 2016

Turning to the post-crisis period, the results are shown in Table 5.11 and Table 5.12, for the most volatile and least volatile firms respectively. In the most recent period, lagged cash flow is an insignificant explanatory variable for both types of firms in all specifications. This finding echoes results for US publicly-traded firms suggesting the disappearance of cash flow sensitivity (i.e. Chen and Chen (2012)). For the more volatile firms (Table 5.11), Tobin's Q is the more informative explanatory variable. For the less volatile firms (Table 5.12), the analyst-based measures of expected profitability are the more informative explanatory variables. This pattern is similar to that which we found for the period 1995-2006, but opposite to that which we found for the earlier period 1987-2000.

Table 5.11: **Tobin's Q, Lagged Cash Flow and Expected Profitability**

First-difference GMM
Dependent Variable: $\frac{I}{K}$

	(i)	(ii)	(iii)	(iv)	(v)
$Q_{i,t}$	0.017	0.013	0.013	0.012	
	(0.012)	(0.006)	(0.009)	(0.006)	
	[1.448]	[2.230]	[1.511]	[2.232]	
$\frac{CF}{K}_{i,t-1}$	0.012	0.001	0.003		-0.008
	(0.022)	(0.023)	(0.024)		(0.023)
	[0.538]	[0.049]	[0.137]		[-0.348]
$E\Pi_{i,t}$		0.091		0.099	0.117
		(0.088)		(0.074)	(0.088)
		[1.036]		[1.332]	[1.330]
$E\Pi 1_{i,t}$			0.160		
			(0.167)		
			[0.959]		
$\frac{I}{K}_{i,t-1}$	0.079	0.043	0.044	0 .045	0.040
	(0.068)	(0.058)	(0.056)	(0.058)	(0.062)
	[1.156]	[0.731]	[0.779]	[0.773]	[0.639]
Hansen p-value	0.689	0.608	0.639	0.636	0.423
Sargan df	51	50	50	51	51
Sargan test statistic	45.55	46.66	45.89	46.92	52.31
m_1 test statistic	-2.69	-2.61	-2.63	-2.63	-2.75
m_2 p-value	0.422	0.264	0.263	0.275	0.344
m_3 p-value	0.470	0.445	0.418	0.431	0.514
m_4 p-value	0.642	0.497	0.554	0.495	0.307

Sample information: The total number of observations in the untransformed dataset is 577. The sample period is from 2009 to 2016. The sample is for the top-third most volatile firms.

IVs: $\frac{CF}{K}$: $t-2$, $t-3$, $t-4$; $\frac{I}{K}$: $t-2$, $t-3$, $t-4$; $E\Pi$: $t-2$, $t-3$, $t-4$

See Table 2.2 for further notes.

Table 5.12: **Tobin's Q, Lagged Cash Flow and Expected Profitability**

First-difference GMM
Dependent Variable: $\frac{I}{K}$

	(i)	(ii)	(iii)	(iv)	(v)
$Q_{i,t}$	0.036	-0.004	-0.004	-0.007	
	(0.012)	(0.013)	(0.011)	(0.012)	
	[2.946]	[-0.305]	[-0.378]	[-0.552]	
$\frac{CF}{K}_{i,t-1}$	0.107	0.059	0.065		0.061
	(0.076)	(0.079)	(0.081)		(0.081)
	[1.415]	[0.747]	[0.798]		[0.751]
$E\Pi_{i,t}$		0.548		0.562	0.526
		(0.128)		(0.137)	(0.102)
		[4.284]		[4.112]	[5.139]
$E\Pi 1_{i,t}$			0.866		
			(.220)		
			[3.929]		
$\frac{I}{K}_{i,t-1}$	0.030	-0.033	-0.031	-0.076	-0.027
	(0.122)	(0.117)	(0.126)	(0.132)	(.105)
	[0.243]	[-0.284]	[-0.247]	[-0.577]	[-0.261]
Hansen p-value	0.609	0.552	0.433	0.525	0.563
Sargan df	51	50	50	51	51
Sargan test statistic	47.60	48.05	51.02	49.70	48.75
m_1 test statistic	-1.86	-1.21	-1.37	-1.15	-1.25
m_2 p-value	0.848	0.578	0.960	0.469	0.506
m_3 p-value	0.063	0.340	0.196	0.228	0.341
m_4 p-value	0.309	0.664	0.529	0.663	0.650

Sample information: The total number of observations in the untransformed dataset is 681. The sample period is from 2009 to 2016. The sample is for the bottom-third least volatile firms.

IVs: $\frac{CF}{K}$: $t-2$, $t-3$, $t-4$; $\frac{I}{K}$: $t-2$, $t-3$, $t-4$; $E\Pi$: $t-2$, $t-3$, $t-4$

See Table 2.2 for further notes.

5.8.5 A Further Analysis of Changes over Time

In Figures 5.2 and 5.3 we present the results using 14-year rolling window sample periods for the more volatile firms and the less volatile firms respectively. The sample periods considered are again 1987-2000, 1988-2001, ... , 2003-2016. These figures are constructed in the same way as Figure 5.1.

For the more volatile firms (Figure 5.2), we find no evidence that investment is sensitive to cash flow in any specification or in any sample period. Tobin's Q is an informative explanatory variable, with a stable coefficient close to 0.02, in the column (i) specification, but not when $E\Pi$ is included in the model. Conversely, the expected profitability measure $E\Pi$ is an informative explanatory variable, with a coefficient between 0.1 and 0.25, in the column (v) specification. When Tobin's Q is also included in the model, we find a significant coefficient on $E\Pi$ for the earlier sample periods, but not for the periods which end after 2005. In these later sample periods, the investment rates of the more volatile firms do vary with the 'fundamentals' captured by these explanatory variables, as we see from the column (i) and column (v) specifications, but it is unclear whether the standard measure of Tobin's Q or the measure of expected profitability based on short-horizon analysts' earnings forecasts provides the more informative measure of these 'fundamentals'.

For the less volatile firms (Figure 5.3), we find evidence of more interesting changes over time in their investment behaviour. In the initial sample period 1987-2000, we find a significant coefficient on the lagged cash flow variable, even when the expected profitability measure $E\Pi$ is included in the model (as shown in Table 5.8 and discussed in section 5.8.2). In the later sample periods, we find a marked decline in the sensitivity of investment to cash flow. In the specifications which include $E\Pi$ (columns (ii) and (v)), the coefficient on lagged cash flow is insignificant in the sample periods which end after 2013 (for which most of the observations are after the 2008 financial crisis). This is consistent with the results presented in Table 5.12 and discussed in section 5.8.2. The decline in the sensitivity of investment to cash

flow for our full sample of publicly-traded UK firms, shown in Figure **??**, reflects this change in investment behaviour for firms with less volatile share prices.

Over the same period that investment-cash flow sensitivity was decreasing for these less volatile firms, their investment rates became more responsive to our analysts-based measure of expected profitability. For the column (v) specification, the coefficient on $E\Pi$ doubled from 0.2 in the period 1987-2000 to 0.4 in the period 2003-16. When Tobin's Q is also included in the column (ii) specification, the coefficient on $E\Pi$ was insignificant in the period 1987-2000, but significantly different from zero in all sample periods from 1991-2004 onwards. Conversely, the coefficient on Q in the column (ii) specification was significant only in the initial sample period 1987-2000. For the later sample periods, in which most observations are after the 2008 financial crisis, the forward-looking measure of expected profitability is the only informative explanatory variable for this subsample of firms with lower share price volatility.

In sum, the investment behaviour of high volatility and low volatility UK firms became more similar over this period, with no significant sensitivity to lagged cash flow for either subsample of firms in the most recent sample periods. Our measures of 'fundamentals' help to explain investment rates in the most recent sample periods for both types of firms, with the analysts-based measure of expected profitability being a more informative explanatory variable than a standard measure of Tobin's Q for the subsample of less volatile firms, though not for the subsample of more volatile firms.

A potential concern with the results presented here is that differences between firms in share price volatility may be proxying for other differences, for example in firm size or in leverage. We investigated these concerns directly by considering subsamples based on firm size, measured by real sales, and subsamples based on measures of leverage. We did not find similar differences in investment behaviour over this period between subsamples based on these alternative characteristics. Some

of these robustness checks are presented in the online Appendix.



Figure 5.2: Top 33%: 14-year moving rolling window average GMM estimations



Figure 5.3: Bottom 33%: 14-year moving rolling window average GMM estimations

5.9 Conclusion

In this paper, we recreate and extend to cover later years a dataset similar to that used by Bond et al. (2004). We confirm our finding from Chapter 3 that, while the direct measure of expected profitability proposed by Bond et al. (2004) is an informative explanatory variable for corporate investment rates, its inclusion in econometric models does not eliminate the sensitivity of investment to lagged cash flow for publicly-traded UK firms in their sample period (1987-2000).

We then explore changes over time in the relationship between corporate investment rates and Tobin's Q, cash flow and these measures of expected profitability, initially using data for our full sample of firms. We present evidence that the sensitivity of investment to cash flow has diminished for our full sample of UK firms, echoing similar results found for US publicly-traded firms.

We then investigate differences in the relationship between investment rates and these explanatory variables between subsamples of publicly-traded UK firms with relatively high and relatively low share price volatility, and how this relationship has changed over time for these two subsamples. More specifically, we construct subsamples based on a time-invariant firm-specific measure of daily share price volatility over the period for which we have data on each firm. We find substantial and interesting differences in investment behaviour between these two subsamples. In particular, we find excess investment-cash flow sensitivity in the period 1987-2000 only for the subsample with relatively low share price volatility. This might be, at least in part, because higher share price volatility for better credit worthiness of a firm, as suggested by Graham (1973). We also find that investment-cash flow sensitivity declined over time for our subsample of less volatile firms, and is statistically insignificant in later sample periods for which most observations are after the 2008 financial crisis. In this respect, the investment behaviour of low volatility firms has become more similar to that of high volatility firms.

There is as yet no satisfactory answer as to what has caused the decline in investment-cash flow sensitivity and we do not aim to provide one. It might be due to factors that have alleviated capital market imperfections (Agca and Mozumdar (2008)) or to public subsidies, which, according to Colombo et al. (2013), reduce the cash flow sensitivity of firms, not only during the period they are subsidised, but also after the subsidies have ceased. Financing constraints due to a cost premium for external finance are binding only when desired investment spending exceeds the level that can be financed internally, and so may be less binding in a period of weak investment demand and high corporate profitability following the 2008 financial crisis. Unpacking the factors that explain the decline in the sensitivity of investment to cash flow during this period will be a challenge for the literature in the years to come.

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Appendix A

Econometric Methodology

In this paper, we estimate dynamic models using unbalanced panel data. The data has a "small T, large N" structure, in that we observe a large number of firms over a relatively short period of time. The independent variables in the model are not strictly exogenous, and autocorrelation and heteroskedasticity are likely to be present within firms. We use Arellano-Bond style GMM estimators, also known as Difference GMM. In this section we briefly outline the generalized method of moments and its appeal given our data.[1]

As we have more moments than parameters, we need an approach that weighs the relative importance of these moment conditions. Hansen (1982) extended the method of moments approach to deal with this scenario. One of the most appealing features of GMM is that it provides a more unified way of viewing different estimators. Special cases of GMM coincide with various estimation techniques which have seemingly very different approaches. Particular GMM estimators coincide with OLS, 2SLS, FGLS, GLS etc. Moreover, GMM provides a way to extend our methods to nonlinear models.

[1]Notable sources for this section are Bond (2002), and unpublished lecture notes for graduate level econometrics courses at the University of Oxford by Bond (2014) and at the London School of Economics by Schankerman (2014).

A.1 The Arellano-Bond Difference GMM estimator

We present the Arellano-Bond estimator as an application of GMM. Arellano and Bond (1991) and Holtz-Eakin, Newey, and Rosen (1988) present a way to exploit more moment conditions than the typical IV estimation in a panel setting, and they do so without losing observations for earlier time periods. This estimation procedure allows the set of instruments to vary with the time period considered.

The model considered is:

$$y_{it} = \gamma y_{it-1} + x_{it}\beta_x + w_{it}\beta_w + c_i + u_{it} \qquad t = 2, ..., T \tag{A.1}$$

where $|\gamma| < 1$, x_{it} is a $1 \times k_1$ vector of strictly exogenous variables and (y_{it-1}, w_{it}) is a $1 \times (k_2+1)$ vector of sequentially exogenous, or predetermined variables, conditional on c_i.

An important assumption to be tested is that u_{it} is serially uncorrelated. After first-differencing we obtain the following equation:

$$y_{it} - y_{it-1} = \gamma(y_{it-1} - y_{it-2}) + \Delta x_{it}\beta_x + \Delta w_{it}\beta_w + \Delta u_{it} \qquad t = 3, \ldots, T \tag{A.2}$$

The IV-style set of instruments in a GMM setting restricts the instruments to ensure they are the same for each observation. For unit i at time t, it is given by:

$$z_{it} = (y_{it-2}, w_{it-1}, x_{it} - x_{it-1})$$

which is uncorrelated with the error term $u_{it} - u_{i,t-1}$, i.e., $E(z'_{it}\Delta u_{it}) = 0$

This choice of instruments generates $(1+k_1+k_2) \times (T-2)$ moment conditions and the $(T-2) \times (1+k_1+k_2)(T-2)$ matrix of instruments for individual i generating

these moment conditions is given by:

$$Z_i = \begin{pmatrix} y_{i1} & 0 & & & w_{i2} & 0 & & & x_{i3} - x_{i2} \\ 0 & y_{i2} & & & 0 & w_{i3} & & & x_{i4} - x_{i3} \\ \vdots & & \ddots & & \vdots & & \ddots & & \\ 0 & 0 & & y_{iT-2} & 0 & 0 & & w_{iT-1} & x_{iT} - x_{iT-1} \end{pmatrix}$$

We can write $E(Z_i' \Delta u_i) = 0$, where Δu_i is a $(T-2) \times 1$ vector.

Arellano and Bond's insight is that if Z_i is a valid instrument matrix, so is the matrix Z_i^*:

$$Z_i^* = \begin{pmatrix} y_{i1} & 0 & 0 & & & & & w_{i1} & w_{i2} & & & & x_{i3} - x_{i2} \\ 0 & y_{i1} & y_{i2} & & & & & 0 & 0 & \ddots & & & x_{i4} - x_{i3} \\ \vdots & & & \ddots & & & & \vdots & & & & & x_{i3} - x_{i2} \\ 0 & 0 & 0 & y_{i1} & y_{i2} & \cdots & y_{iT-2} & 0 & 0 & w_{i1} & w_{i2} & \cdots & w_{iT-1} & x_{iT} - x_{iT-1} \end{pmatrix}$$

All these moment restrictions can be written as:

$$E(Z_i^{*'} \Delta u_i) = E(Z_i^{*'}(\Delta y_i - \Delta x_i \beta_x - \Delta w_i \beta_w - \gamma \Delta y_{i(1)})) = 0$$

For these conditions to be valid we are heavily relying on the assumption that u is serially uncorrelated. Arellano and Bond develop the m_1 and m_2 tests to check for correlation between Δu_{it} and Δu_{it-1}, and between Δu_{it} and Δu_{it-2}, respectively. Under the null hypothesis that u_{it} is serially uncorrelated, we should reject the null hypothesis of no correlation between Δu_{it} and Δu_{it-1}, and fail to reject the null hypothesis of no correlation between Δu_{it} and Δu_{it-2}. Moreover, we should expect to find negative correlation between Δu_{it} and Δu_{it-1}, and hence reporting the value of the t-statistic of the m_1 test is informative, despite not always being reported in the literature. If the test statistic on m_1 is either insignificant or significantly positive, we should reconsider our moment conditions accordingly. This is why, in our results, we report the t-statistic of the m_1 test as opposed to just its p-value. These test statistics have an asymptotic standard normal distribution under the null

hypothesis. Further details can be found in Arellano and Bond (1991). These tests have been extended to consider third order and fourth order autocorrelation in Δu_{it} (m_3 and m_4) and we report these tests also in our tables of results.

Further assuming (conditional) homoskedasticity:

$$E(\Delta u_{it}\Delta u_{it}^{'}) = \sigma_u^2 \begin{pmatrix} 2 & -1 & 0 & \cdots & 0 \\ -1 & 2 & -1 & & \vdots \\ 0 & -1 & 2 & \ddots & 0 \\ \vdots & & \ddots & \ddots & -1 \\ 0 & \cdots & 0 & -1 & 2 \end{pmatrix} = \sigma_u^2 H$$

In this setting, the optimal (non-unique) weighting matrix for GMM is proportional to the inverse of:

$$V = Var(Z^{*'}\Delta u \Delta u^{'} Z^{*}) = \sigma_u^2 E(Z^{*'} H Z^{*})$$

This weighting matrix can be consistently estimated by:

$$\hat{V}_n^{-1} = [\frac{1}{n}\sum_{i=1}^{n} Z^{*'} H Z^{*}]^{-1}$$

The one-step GMM estimator is:

$$\hat{\beta}_{GMM} = [\sum_{i=1}^{n} X_i^{*'} Z_i^{*} \hat{V}_n^{-1} \sum_{i=1}^{n} Z_i^{*'} X_i^{*}]^{-1} \sum_{i=1}^{n} X_i^{*'} Z_i^{*} \hat{V}_n^{-1} \sum_{i=1}^{n} Z_i^{*'} Y_i^{*}$$

where $X_i^{*} = (\Delta y_{i(1)}, \Delta x_i, \Delta w_i)$ and $Y_i^{*} = \Delta y_i$

The two-step GMM estimator, which allows for arbitrary heteroskedasticity, uses the same formula except that the weighting matrix is replaced by:

$$\hat{V}_n^{-1} = [\frac{1}{n}\sum_{i=1}^{n} Z^{*'} \Delta\hat{u}_i \Delta\hat{u}_i^{'} Z_i^{*}]^{-1}$$

where $\Delta\hat{u}_i$ are residuals calculated using the one-step estimator.

A.2 Further Theoretical Notes on Methodology and Tests Used

One-step vs. Two-step Difference GMM

Dynamic panel estimators, designed for situations of "small T, large N", accommodate potential endogeneity of independent variables, individual fixed effects, and non-spherical disturbances within (but not across) individuals. This paper employs a difference GMM estimator and makes use of the xtabond2 command in Stata to implement this estimator. Our model is overidentified, i.e. the number of instruments exceeds the number of endogenous variables in the first-differenced equations. The GMM estimator is consistent, but similarly to 2SLS, it is generally biased in finite samples.

In one-step estimation, basing the choice of the moment weighting matrix on an incorrect assumptions about the variance of the errors does not render the parameter estimates inconsistent. However, classical standard errors would not be robust to either heteroskedasticity or serial correlation in Δu_{it}. This can easily be addressed by using the *robust* option after the xtabond2 command. For one-step estimation, *robust* specifies that a cluster-roobust estimator of the covariance matrix of the parameter estimates is calculated. The resulting standard errors and test statistics are consistent in the presence of any pattern of heteroskedasticity and autocorrelation within panels.

In two-step estimation, conventional standard errors are also consistent, but have been shown to be unreliable in small samples when the number of instruments used is large. The standard errors can then be seriously downward biased, so much so that two-step GMM becomes unreliable for inference. Windmeijer (2005) devised a small-sample correction for the two-step standard errors. In two-step estimation, the standard covariance matrix is already robust in theory - but typically yields standard errors that are downward biased. The xtabond2 option *twostep robust* implements

Windmeijer's finite-sample correction for the two-step covariance matrix (Roodman, 2009).

Windmeijer (2005) also found that, in difference GMM estimation on simulated panels, two-step GMM performs somewhat better than one-step GMM in estimating coefficients, with lower bias. Overall, two-step estimation with corrected standard errors was found to be modestly superior to cluster-robust one-step estimation.

Sargan/Hansen Test of Overidentifying Restrictions

Given that the model is overidentified we can implement tests to detect invalidity of the instruments used. The Hansen test coincides with the Sargan test if the assumptions of homoskedasticity and no serial correlation hold. However, once nonsphericity is suspected in the errors, the Sargan statistic becomes inconsistent. A theoretically superior overidentification test for the one-step estimator is the Hansen statistic from the two-step estimator based on the same moment conditions. The xtabond2 command quietly performs the two-step GMM whenever the user requests the Sargan test for *robust* one-step GMM estimation, and reports a consistent Hansen test. The tests of overidentifying restrictions reported in this paper are robust Hansen tests, whether we are reporting one-step or two-step GMM estimates. The power of this test becomes weaker as the number of overidentifying restrictions increases, keeping the sample size fixed.

We also employ the Sargan/Hansen Difference test (also known as the C test) to investigate the validity of specific subsets of the instruments. By performing estimation with and without the subset of suspect instruments, under the null hypothesis of joint validity of the full instrument set, the difference between the two corresponding Sargan/Hansen test statistics is asymptotically χ^2, with degrees of freedom equal to the number of suspect instruments. The power of this test becomes weaker as the number of moment conditions tested increases, keeping the sample size fixed.

Internal vs. External IV

A key aspect of the Arellano and Bond strategy for dynamic panel data models is the use of lagged 'internal' instruments, i.e. lagged values of the instrumented explanatory variables. These estimators do allow the inclusion of external instruments as well. The choice of instruments is not a question of whether internal instruments are theoretically superior, but a practical issue of what is available at the disposal of the researcher. According to Roodman (2009) "because the estimators are designed for general use, they do not assume that good instruments are available outside the immediate dataset. In effect, it is assumed that the only available instruments are internal - based on lags of the instrumented variables. We are building an estimator for general application, in which we choose not to assume that the researcher has excellent instruments waiting in the wings. So we must draw instruments from within the dataset". Kiviet (2009) also says that "internal instruments suffice, since higher-order lags of (possibly transformed) regressors constitute an abundance of instruments".

Appendix B

Q Theory of Investment: Marginal vs. Average Q

"...there is no sense in building up a new enterprise at a cost greater than that at which a similar existing enterprise can be purchased." Keynes (1936) (p. 151)

Grunfeld (1960) looked at determinants of corporate financing and Tobin (1969) built on this work. Through an arbitrage argument, Tobin showed that (under certain conditions) a firm should invest if the ratio of the market valuation of a firm's capital stock to its replacement value (Tobin's q) is greater than one. Intuitively, the stock price tells firms how much the market values their installed capital; thus it is a signal of how much the market is willing to pay for an additional unit of capital. A convenient way to show this result is in a static 2-period model with no market frictions and perfect information.

Assume a representative firm with a constant return to scale production function ($Y(K, N)$) with labour (N) and capital (K) as inputs. Define I_1 to be investment in period one, w_1 to be the real wage in period one and d to be the depreciation rate on capital between periods one and two. The firm is endowed with K_1 units of capital in period one. Investment (I_1) in period one determines the stock of capital in period two, which is then sold for its end-of-period (depreciated) value. Normalising the

fixed and exogenous output price at unity, current profits (π_1) are:

$$\pi_1 = Y_1 - w_1 N_1 - I_1 \tag{B.1}$$

Future profits (π_2) are:

$$\pi_2 = Y_2 - w_2 N_2 + (1-d)K_2 \tag{B.2}$$

The future capital stock (K_2) is:

$$K_2 = (1-d)K_1 + I \tag{B.3}$$

The present value of profits (V) for the firm:

$$V = \pi_1 + \frac{\pi_2}{(1+r)} \tag{B.4}$$

The representative chooses I_1 and N_1 to maximize V. Substituting for I_1 using (B.3), the firm's problem is to choose (N_1, N_2, K_2) to maximize:

$$Y_1 - w_1 N_1 - [K_2 - (1-d)K_1] + \frac{Y_2 - w_2 N_2 + (1-d)K_2}{(1+r)} \tag{B.5}$$

Through the first order condition, we find that the optimal K_2 equates the marginal product of capital and the user cost of capital $(r+d)$:

$$\frac{\frac{\partial Y_2}{\partial K_2} + 1 - d}{(1+r)} = 1 \rightarrow MPK_2 - d = r \tag{B.6}$$

Next, we show that this condition is equivalent to Tobin's investment rule based on the value of q. The market value of installed capital is:

$$\frac{Y_2 - w_2 N_2 + (1-d)K_2}{1+r} \tag{B.7}$$

Exploiting the assumptions of perfect competition and constant returns to scale (B.7) can be written as:

$$\frac{(MPK_2)K_2 + (1-d)K_2}{1+r} \tag{B.8}$$

The real replacement cost of installed capital is K_2. Hence Tobin's q is:

$$q = \frac{\frac{(MPK_2)K_2+(1-d)K_2}{1+r}}{K_2} = \frac{(MPK_2) + (1-d)}{1+r} \tag{B.9}$$

If, and only if, $q > 1$ then $MPK_2 - d > r$ and the firm should invest more.

At the optimal K_2, we also have $q = 1$. While the above model is instructive and simple, it does not take into account any adjustment costs to capital. We can enrich the model by assuming an infinite horizon, uncertainty and adjustment costs of a specific type. This enrichment is common in modern q theory. The first-order conditions require the marginal adjustment and purchase cost of an additional unit of capital to be equal to the shadow value of capital, which is known as marginal q. Marginal q gives us the firm's expectation of the marginal contribution of investment to net present value of future profits. The assumption of quadratic investment costs allows us to rearrange the first-order condition as a linear regression in which the investment rate is the dependent variable and marginal q is the only regressor. However, we can rarely observe marginal q and hence an observable counterpart is needed. Hayashi (1982) shows, formally, conditions under which marginal q is equal to Tobin's average q. We then have a linear relation between the rate of investment (I/K) and the average q ratio, which is the ratio of the firm's valuation of installed capital to the replacement cost of installed capital. Moreover, if financial markets are efficient, then the firm's valuation of installed capital is equal to the market's valuation. Hence, Hayashi's contribution allows us to find an empirical counterpart to the unobservable marginal q and test this theory. In the next subsection we provide more details.

B.1 Basic Investment Model

We use the investment model that is standard in this branch of the literature. The Neoclassical q theory gives a (linear) relation between the rate of investment $\left(\frac{I}{K}\right)$ and the average q ratio. Assuming the absence of debt and taxes for simplicity, the average q ratio has the form:

$$q_t = \frac{E_t[\sum_{s=0}^{\infty}[\beta_s \pi_{t+s}]]}{(1-\delta)K_{t-1}} = \frac{V_t}{(1-\delta)K_{t-1}}$$

where β_s is the discount factor which applies to cash flows s periods ahead, π_{t+s} is the net cash distribution from the firm to its owners (dividend paid minus value of new shares issued) in period $t+s$, and $E_t[.]$ denotes the expected value given information at time t. V_t is the objective which the firm is assumed to maximize.

The standard approach assumes that the stock market correctly values expected future net cash flows, and nothing else, in which case we can measure V_t using the stock market value V_t^E and obtain equity q, i.e q_t^E. This will be problematic if there is also a bubble component to the stock market value (so $V_t^E = V_t + \nu_t$) since the bubble component ν_t will necessarily be highly persistent, and is likely to be correlated with the fundamental value V_t (Shiller, 1989, 2000).

Cummins et al. (2006) instead propose the use of a novel valuation model to estimate V_t using analysts' forecasts of current and future net profits of the firm

$$\hat{V}_t = \sum_{s=0}^{T} \bar{\beta}_s \hat{\pi}_{t+s}^{NP} + TVA$$

where $\hat{\pi}_{t+s}^{NP}$ is the analysts' forecast of net profits in period $t+s$, $\bar{\beta}_s$ is an imposed discount factor, T is the time horizon over which forecasts are available, and TVA is a terminal value adjustment. There are several obvious reasons why $\hat{V}_t \neq V_t$, including: net profits are not equal to the net cash distribution to shareholders;

$\bar{\beta}_s \neq \beta_s$; $T < \infty$ and the terminal value adjustment is arbitrary; the timing of available forecasts does not coincide with start of financial year, etc. The hope is that the resulting measurement error $(\hat{V}_t - V_t)$ may be easier to deal with than bubble-type measurement error, i.e. $\beta_t = (V_t^E - V_t)$.

Cummins et al. (2006) assume the following quadratic adjustment cost function:

$$G(I_{i,t}, K_{i,t}) = \frac{b}{2}\left(\frac{I_{i,t}}{K_{i,t}} - a - \varepsilon_{i,t}\right)^2 K_{i,t}$$

where a and b are constant parameters, $K_{i,t}$ is firm i's stock of capital, $I_{i,t}$ is its gross investment and $\varepsilon_{i,t}$ is a technology shock. We assume that capital depreciates at the constant rate δ.

Then under the aforementioned assumptions from Hayashi (1982), the following investment equation can be derived:

$$\left(\frac{I}{K}\right)_{i,t} = a + \frac{1}{b}\left[\frac{V_{i,t}}{p_t^k(1-\delta)K_{i,t-1}} - 1\right]\frac{p_t^k}{p_t} + \varepsilon_{i,t} = a + \frac{1}{b}Q_{i,t} + \varepsilon_{i,t}, \tag{B.10}$$

where p_t is the price of output, ${p_t}^k$ is the price of capital goods and the explanatory variable, Q is the product of $(q-1)$ and the real price of capital goods, where q is Tobin's average q.[1]

Equation (B.10) can be used to test the excess sensitivity of investment to cash flow. We use the first lag of ratio of cash flow to the capital stock, $(CF/K)_{i,t-1}$. Thus, we have:

$$\left(\frac{I}{K}\right)_{i,t} = a + \frac{1}{b}Q_{i,t} + \gamma\left(\frac{CF}{K}\right)_{i,t-1} + \varepsilon_{i,t} \tag{B.11}$$

With no cost premium for external finance, and under all the other assumptions of the baseline average q model, we should have the restriction $\gamma = 0$. Equation (B.11)

[1] A detailed derivation can be found in Appendix A of Cummins et al. (2006)

is the benchmark model for our analysis.

Appendix C

Further robustness checks for the Bond et al. (2004) sample

C.1 One-step GMM with Alternative Instruments

In these estimations, we notice that the coefficient on cash flow is now large and statistically significant at a 10% significance level. Focusing on column (ii) we notice that the cash flow coefficient is now 0.114 versus the -0.078 in the original estimation. Moreover, while the coefficient of EPi is statistically significantly different from zero, its size has more than halved. In short, judging by this estimation table alone, one cannot convincingly conclude that the inclusion of a direct measure of profitability (i.e. EPi or $EPi1$) mutes the excess cash flow sensitivity found in column (i). When comparing the original results with the above results we also notice that the *sum* of cash flow coefficient and EPi coefficient remains largely unaffected in magnitude. For column (ii) we have 0.17 versus 0.21 for the original and our estimation respectively. For column (iii) we have 0.36 versus 0.278 and for column (v) we have 0.234 versus 0.263. This might show the inability of our estimation with the new set of instruments to disentangle the effects of cash flow and the expected profitability measures (i.e. EPi and $EPi1$).

Table C.1: **Tobin's Q, lagged cash flow and expected profits**

First-difference *one-step* GMM
Dependent Variable: $\frac{I}{K}_{i,t}$

	(i)	(ii)	(iii)	(iv)	(v)
$Q_{i,t}$	0.024	0.015	0.014	0.015	
	(0.007)	(0.007)	(0.006)	(0.007)	
	[3.565]	[2.265]	[2.231]	[2.255]	
$\frac{CF}{K}_{i,t-1}$	0.180	0.106	0.101		0.104
	(0.059)	(0.068)	(0.068)		(0.069)
	[3.072]	[1.549]	[1.480]		[1.515]
$E\Pi_{i,t}$		0.107		0.156	0.159
		(0.049)		(0.038)	(0.046)
		[2.163]		[4.076]	[3.482]
$E\Pi 1_{i,t}$			0.191		
			(0.085)		
			[2.253]		
$\frac{I}{K}_{i,t-1}$	0.088	0.083	0.084	0.076	0.094
	(0.029)	(0.029)	(0.028)	(0.027)	(0.029)
	[3.001]	[2.911]	[2.958]	[2.785]	[3.303]
Hansen p-value	0.512	0.557	0.546	0.403	0.505
Sargan df	66	65	65	66	66
Sargan statistic	64.98	62.73	63.02	68.16	65.19
m_1 statistic	-10.6	-10.7	-10.8	-10.6	-10.9
m_2 p-value	0.914	0.825	0.832	0.754	0.808
m_3 p-value	0.344	0.337	0.346	0.367	0.349
m_4 p-value	0.750	0.827	0.835	0.910	0.790

Sample information: The total number of observations in the untransformed dataset is 5669. The sample period is from 1987 to 2000. The number of observations in first-differences for column (1) is 4263 while the number of groups is 703. The average number of observations per group is 6.06. These statistics are identical for all other columns.

IVs: $\frac{CF}{K}$: $t-2$, $t-3$; $\frac{I}{K}$: $t-2$, $t-3$; $E\Pi$: $t-2$, $t-3$

See Table 2.2 for further notes.

Table C.2: **Tobin's Q, lagged cash flow and expected profits**

First-difference *one-step* GMM
Dependent Variable: $\frac{I}{K}_{i,t}$

	(i)	(ii)	(iii)	(iv)	(v)
$Q_{i,t}$	0.024	0.016	0.016	0.016	
	(0.006)	(0.006)	(0.006)	(0.006)	
	[3.999]	[2.677]	[2.714]	[2.583]	
$\frac{CF}{K}_{i,t-1}$	0.183	0.114	0.115		0.108
	(0.057)	(0.067)	(0.068)		(0.067)
	[3.232]	[1.690]	[1.697]		[1.606]
$E\Pi_{i,t}$		0.096		0.149	0.155
		(0.049)		(0.037)	(0.045)
		[1.952]		[3.994]	[3.473]
$E\Pi 1_{i,t}$			0.163		
			(0.084)		
			[1.947]		
$\frac{I}{K}_{i,t-1}$	0.093	0.088	0.088	0.080	0.100
	(0.029)	(0.028)	(0.028)	(0.027)	(0.028)
	[3.239]	[3.124]	[3.178]	[3.002]	[3.546]
Hansen p-value	0.615	0.611	0.605	0.516	0.514
Sargan df	96	95	95	96	96
Sargan test statistic	91.34	90.50	90.73	94.76	94.83
m_1 statistic	-10.7	-10.8	-10.8	-10.7	-10.9
m_2 p-value	0.976	0.893	0.905	0.816	0.876
m_3 p-value	0.342	0.336	0.343	0.368	0.348
m_4 p-value	0.747	0.817	0.820	0.905	0.780

Sample information: The total number of observations in the untransformed dataset is 5669. The sample period is from 1987 to 2000. The number of observations in first-differences for column (1) is 4263 while the number of groups is 703. The average number of observations per group is 6.06. These statistics are identical for all other columns.

IVs: $\frac{CF}{K}$: $t-2$, $t-3$, $t-4$; $\frac{I}{K}$: $t-2$, $t-3$, $t-4$; $E\Pi$: $t-2$, $t-3$, $t-4$

See Table 2.2 for further notes.

C.2 Two-step Further Results

A two-step GMM estimation does not change the main story of **?** when their original instrument set is used. However, as shown in Table C.3 we do notice that the lagged cash flow estimated coefficients are usually larger, and the estimated coefficients for the predictive profitability measures (i.e. $E\Pi$ and $E\Pi 1$) are generally smaller, and less significant, as indicated by the smaller t-statistics across column (ii) to (v) when compared to Table 3.2 in the main text.

Table C.3: **Tobin's Q, lagged cash flow and expected profits**

First-difference *two-step* GMM
Dependent Variable: $\frac{I}{K}_{i,t}$

	(i)	(ii)	(iii)	(iv)	(v)
$Q_{i,t}$	0.023	0.018	0.017	0.017	
	(0.008)	(0.009)	(0.009)	(0.008)	
	[2.789]	[2.057]	[1.870]	[2.083]	
$\frac{CF}{K}_{i,t-1}$	0.190	0.035	0.033		-0.011
	(0.056)	(0.130)	(0.127)		(0.142)
	[3.380]	[0.271]	[0.263]		[0-.077]
$E\Pi_{i,t}$		0.164		0.190	0.263
		(0.116)		(0.055)	(0.118)
		[1.408]		[3.446]	[2.220]
$E\Pi 1_{i,t}$			0.293		
			(0.202)		
			[1.449]		
$\frac{I}{K}_{i,t-1}$	0.109	0.084	0.084	0.085	0.085
	(0.026)	(0.028)	(0.028)	(0.025)	(0.030)
	[4.197]	[2.934]	[3.023]	[3.356]	[2.826]
Hansen p-value	0.511	0.402	0.419	0.412	0.323
Sargan df	43	42	42	43	43
Sargan statistic	42.07	43.62	43.21	44.40	46.68
m_1 statistic	-9.84	-9.36	-9.53	-9.71	-9.20
m_2 p-value	0.868	0.898	0.893	0.923	0.738
m_3 p-value	0.336	0.341	0.354	0.341	0.344
m_4 p-value	0.722	0.884	0.897	0.905	0.905

Sample information: The total number of observations in the untransformed dataset is 5669. The sample period is from 1987 to 2000. The number of observations in first-differences for column (1) is 4263 while the number of groups is 703. The average number of observations per group is 6.06. These statistics are identical for all other columns.

IVs: $\frac{CF}{K}$: $t-2$, $t-3$; $\frac{I}{K}$: $t-2$, $t-3$

See Table 2.2 for further notes.

Table C.4: **Tobin's Q, lagged cash flow and expected profits**

First-difference *two-step* GMM
Dependent Variable: $\frac{I}{K}_{i,t}$

	(i)	(ii)	(iii)	(iv)	(v)
$Q_{i,t}$	0.023	0.019	0.019	0.018	
	(0.007)	(0.007)	(0.007)	(0.007)	
	[3.295]	[2.637]	[2.610]	[2.530]	
$\frac{CF}{K}_{i,t-1}$	0.191	0.128	0.131		0.133
	(0.057)	(0.064)	(0.064)		(0.071)
	[3.364]	[1.997]	[2.035]		[1.876]
$E\Pi_{i,t}$		0.079		0.134	0.142
		(0.048)		(0.041)	(0.049)
		[1.658]		[3.290]	[2.879]
$E\Pi 1_{i,t}$			0.13		
			(0.080)		
			[1.630]		
$\frac{I}{K}_{i,t-1}$	0.104	0.096	0.097	0.087	0.109
	(0.025)	(0.025)	(0.025)	(0.024)	(0.026)
	[4.203]	[3.852]	[3.933]	[3.663]	[4.131]
Hansen p-value	0.615	0.611	0.605	0.516	0.514
Sargan df	96	95	95	96	96
Sargan test statistic	91.34	90.50	90.73	94.76	94.83
m_1 statistic	-9.650	-9.670	-9.720	-9.840	-9.680
m_2 p-value	0.920	0.988	0.998	0.910	0.954
m_3 p-value	0.332	0.326	0.332	0.363	0.331
m_4 p-value	0.709	0.763	0.763	0.847	0.697

Sample information: The total number of observations in the untransformed dataset is 5669. The sample period is from 1987 to 2000. The number of observations in first-differences for column (1) is 4263 while the number of groups is 703. The average number of observations per group is 6.06. These statistics are identical for all other columns.

IVs: $\frac{CF}{K}$: $t-2$, $t-3$, $t-4$; $\frac{I}{K}$: $t-2$, $t-3$, $t-4$; $E\Pi$: $t-2$, $t-3$, $t-4$

See Table 2.2 for further notes.

Bibliography

Bond, S., Klemm, A., Newton-Smith, R., Syed, M., and Vlieghe, G. (2004). The Roles of Expected Profitability, Tobin's Q and Cash Flow in Econometric Models of Company Investment. *The Institute of Fiscal Studies*.