Slowing Investment Rates in Developing Economies: Evidence from a Bayesian hierarchical model

Ilan Strauss and Jangho Yang*

Abstract

Using a large unbalanced panel of 11,812 publicly listed firms covering 11 major developing economies between 1997-2017, we detail a slowdown in investment rates post-2008 – from 2013 for Chinese incorporated firms and 2008 for firms incorporated elsewhere. We test competing explanations for slowing investment rates using a Bayesian 'mixed effects' model consisting of time-varying and country-varying coefficients. Firms' estimated underlying mean impetus to invest (their 'animal spirits') falls more sharply than raw investment rates from 2008 to record lows by 2017. One-third of the variation in falling 'animal spirits' over time is statistically explained by the corporate sector's changing median leverage, which declines by 40% since 2008. Firms' investment rates have increasingly been sustained by external financing constraints loosening (as cash flow coefficients decline), and through firms becoming more responsive to investment opportunities – reflected by time-varying Q regression coefficients increasing. At the country-level, we find that loosening external financing constraints is associated with greater responsiveness by firms to investment opportunities.

JEL Codes: C55, D22, D25, E22.
Keywords: Developing Economy Firms; Investment Rates; Finance Constrained; Tobin's Q; Bayesian Econometrics; Leverage.

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1 Introduction

This paper investigates the nature and causes of the investment slowdown for publicly listed firms from 11 key developing economies.[1] After decades of strong growth for many diversified developing economies, growth and investment rates are now slowing. This not only risks reversing considerable progress in poverty reduction and employment generation, but has further knock-on effects for advanced economies given the increasing share of developing economies in global investment and GDP (A. Kose et al. 2017). There is much disagreement, however, about the precise timing and the severity of the decline in developing economy investment rates (Magud and Sosa 2015; A. Kose et al. 2017; Borensztein and Ye 2018; Islamaj et al. 2019). There is instead more agreement on possible causes of the slowdown in emerging and developing economies. These focus on both global as well as domestic (firm-level) factors (Carrière-Swallow and Céspedes 2013; Magud and Sosa 2015; Li et al. 2015b; Ozkan et al. 2020), given that most developing economies rely on global demand, prices, and monetary conditions for growth and financing.[2] Among firm-level (domestic) predictors, most common are cash flow, Tobin's Q, and leverage (Fazzari et al. 1988; Ozkan et al. 2020) owing to the use of a cash flow-Q theory of investment, which we also adopt.[3]

We focus on three types of causes for declining investment rates among publicly listed firms. The first consists of anything which changes firms' responsiveness to investment opportunities (i.e. Q values) over time. Following the Q theory of investment demand (Hayashi 1982), marginal Q – which we approximate using the book-to-market value of the firm's assets – summarises the firm's investment opportunities. The estimated time-varying Q coefficient in our investment demand equation serves as our proxy to assess the impact of growing market concentration in particular on the investment decision (Crouzet and J. Eberly 2019); but may also reflect financial market imperfections (Q. Chen et al. 2007; R. Chen et al. 2017) – such that with fewer financial market imperfections or less market power (Andrei et al. 2019), firms would be more responsive to Q.

[1] See Appendix C for further details on our sample. Investment rate = capx/capital stock, where capital stock= intangible assets + inventories + gross property, plant, and equipment.

[2] Among external channels: Li et al. (2015b) focus on financial shocks. They find that higher U.S. interest rates and financial volatility negatively impacts investment among emerging and developing economy and that this impact is also conditional on the firm's balance sheet strength as well as the country's financial buffers. Magud and Sosa (2017) investigates the impact of 'country-specific' commodity prices and capital inflows and finds commodity prices to be an important determinant. Capital inflows are also often included and found generally to relax firms' external financing constraints (Magud and Sosa 2015). Negative terms-of-trade shocks and declining foreign direct investment inflows are also explored in several papers (Serena and Sousa 2017; A. Kose et al. 2017; Islamaj et al. 2019).

[3] Although we focus on firm-level predictors of investment demand in what follows, in practice they will reflect, and be partially reliant on, changing global economic conditions.

Quantitative Easing launched by advanced economy central banks post-2008 Global Financial Crisis (GFC) may have played a key role in reducing both financial constraints for developing economy firms and increasing their responsiveness to Q. A number of factors might have reasonably led to growing market concentration within developing economies (Diez et al. 2018; Bonfiglioli et al. 2019; Chortareas et al. 2020), and even a 'financialization' of their investment decision,[4] both of which may have made firms *less* responsive to investment opportunities (Gutiérrez and Philippon 2017a,b, 2018; Döttling et al. 2017).[5] On the other hand, growing access to global capital markets for developing economies may have seen firms become *more* responsive to investment opportunities (M. A. Kose, Nagle, et al. 2020), as financing constraints have declined.

The second type of cause we estimate are external financing constraints: are financing constraints for publicly listed developing economy firms severe or becoming worse (Love and Zicchino 2006; Magud and Sosa 2015; Li et al. 2015b; Ozkan et al. 2020)?[6] Following Fazzari et al. (1988), if external and internal finance are not perfect substitutes, owing to external finance being more costly, then firms' demand for investment may not rely solely on marginal Q, but also on the availability of internal investment funds. If the firm's investment is sensitive to changes in its internal funds – proxied by present cash flow – then it is said to be 'financially constrained'. To allow for this possibility finance constrained investment models have coefficients that vary according to whether the firm is likely, *a priori*, to face a financing constraint or not.[7] Given that Q is invariably subject to measurement error (Erickson and Whited 2012), and that this can bias upwards cash flow coefficients, testing the finance constrained hypothesis requires correcting for measurement error, as we do.

The third type of cause we investigate includes anything which impacts the underlying impetus of firms to invest at their baseline, other things being held equal. This represents exogenous shifts in firms' marginal product of capital, or 'animal spirits', and may reflect spillover effects from weakening aggregate demand growth in advanced economies or China post-2008 GFC. These in turn

[4] As firms focus on maximizing short-term shareholder returns (Lazonick et al. 2014; Bortz and Kaltenbrunner 2018).

[5] These theories have no obvious relationship to the 2008 global financial crisis (GFC) though (Fernald et al. 2017), even though this is when the major turning point is for developing economy firms' investment rates.

[6] Our sample, consisting of relatively larger firms, may plausibly be less financially constrained than small and medium sized enterprises (SMEs) in developing economies and certain non-listed firms too (Alter and Elekdag 2016).

[7] We use 'cash flow' for short, including when talking about a cash flow-Q model, but really it is cash flow divided by capital stock and so is a 'rate' variable. For critique of this interpretation with respect to dynamic models see: Strebulaev, Whited, et al. (2012).

may ultimately be driven by ageing populations, slowing technological change, or increasing levels of inequality (Summers 2015). If this impetus to invest is declining, this can be seen as establishing the thesis that investment has been low relative to Q (Gutiérrez and Philippon 2017b).[8]

In addition, we can use 'group-level' versions of the above predictors to try and explain 'macro-contextual' variation (Kreft and De Leeuw 1998; Gelman and Hill 2006), defined as variation in firms' estimated behaviour *between* countries or years (rather than *within* them). Adding predictors at the group level in a multi-level model corresponds to the classical method of contrasts in the analysis of variance (Gelman and Hill 2006, p. 497). To achieve this we use median leverage across years to try and explain the estimated underlying 'animal spirits'. We also use financing constraints (proxied by relative median interest expenses) to explain variation in the responsiveness of firms in different countries to investment opportunities (Q).

A focus on the above factors is relevant for developing economy firms – especially the larger publicly listed firms of our sample[9] – as the economies in which they predominately operate have transitioned to middle-income status and above.[10] These firms increasingly face structural "middle-income traps" (Qureshi et al. 2014), arising from declining fertility rates (Jones 2020; Harding 2020), growing income inequality, and slowing capital accumulation creating a vicious cycle of low innovation and income growth (Fund 2014; A. Kose et al. 2017; M. A. Kose and Ohnsorge 2019). Exogenous factors still help shape their (globally consolidated) investment rates, as domestic demand remains limited outside of China and India; but exogenously given commodity price movements are likely less relevant drivers of investment for most firms in our sample (cf. with Magud and Sosa 2017) – apart from firms in Brazil and to some extent South Africa (UNCTAD 2019).[11]

Our findings are consistent with developing economy firms being at serious risk of their post-2008 investment rates languishing at persistently low levels for the foreseeable future, unless demand-side measures are taken to offset corporate deleveraging. We find that:

1. Pooled raw investment rates of developing economy firms are largely cyclical between 1997-2013. From 2014 they fall below previous lows, especially for firms in the top half of the

[8] Also known as 'low relative to fundamentals'.

[9] Who now comprise a major portion of employment and turnover in key developing economies (Tsebe et al. 2018)

[10] In our sample we have: Brazil (upper-middle), China (upper-middle), Malaysia (upper-middle), South Africa (upper-middle), Thailand (upper-middle), Indonesia (lower-middle / on the cusp of upper-middle), Pakistan (lower-middle), India (lower-middle), Poland (high), South Korea (high), and Taiwan (high), based on the World Bank's definition of GNI per capita between \$3,996-\$12,375, calculated using World Bank Atlas method for 2019.

[11] See Appendix C.4 for the industry composition of our sample.

investment distribution. This apparent cyclicality is due to two opposing and offsetting effects in our sample: the increase in Chinese investment rates between 2010-2012 and declining investment rates in other developing economies from 2008.

2. Based on our 'cash flow-Q' investment demand estimation, we find a much clearer and steeper decline in the underlying mean impetus of firms as a whole to invest (their 'animal spirits') after 2008. This falls to the lowest levels since at least 1997 (when our sample begins). The fall is moderated until 2011 - probably by temporarily higher rates of Chinese investment. This sharper fall in animal spirits when compared to raw investment rates probably reflects weakening external financing constraints post quantitative easing pushing investment rates above what it otherwise would have been based on these estimated investor sentiments.

3. One-third of the variation over time in the underlying mean impetus of firms to invest is explained by the corporate sector's changing leverage behaviour, which increased at the median during the early 2000s and then fell considerably since 2008, leading to a fall in firms' estimated investment rates. This deleveraging is a combination of strong equity issuance and a sharp fall in long-term debt outside of china, along with a shift towards shorter-term debt. This in turn may reflects firms' finding deleveraging a more optimal use of funds (Ozkan et al. 2020) than investment post-2008 global slowdown.

4. There is considerable variability across countries in the degree of external financing constraints facing firms and in firms' responsiveness to investment opportunities. Our model's variance-covariance structure estimates an inverse correlation, such that firms who are in countries which are less financially constrained are also more responsive to investment opportunities. This is supported by evidence we provide which shows a strong cross-country relationship between the median size of firms' interest expenses relative to $EBIT$ in a country and our model's estimated responsiveness of firms' in that country to investment opportunities.

5. External financing constraints are moderate for firms in most developing economies, though structurally higher compared with advanced economy firms (Strauss and Yang 2020). Firms' responsiveness to investment opportunities is relatively high, including compared with previous estimates in the literature (Erickson and Whited 2006; Andrei et al. 2019), and relative to developed economy firms (Strauss and Yang 2020).

6. After the 2008 global financial crisis (GFC), and in the face of declining 'animal spirits', investment rates by developing economy firms have increasingly been sustained through firms becoming gradually *more* responsive to investment opportunities and through external finance constraints loosening, mostly like as access to cheap financing and surplus internal funds has grown. This also indicates that 'financialization' and growing market concentration have not depressed how responsive firms are to investment opportunities.

We make several novel contributions to the literature: First, we provide cross-country and time-varying evidence on the existence and nature of the secular slowdown in investment rates. Our evidence is considerably more robust than previous studies due to our Bayesian econometric method's ability to exploit information in our large sample. Our sample consists of 91,069 observations on 11,812 unique firms, across 11 major developing economies for 21 years between 1997-2017. When we apply our Bayesian mixed fixed and random effects model (also known as a 'hierarchical model', Greene 2003, chapter. 16) to this dataset, we can *jointly* estimate 832 parameters concurrently to ensure that unobserved country, year, and country-specific year effects are explicitly modelled through varying slopes and intercepts for all key parameters (Hsiao 2014),[12] thereby modelling the correlations directly (Wooldridge 2010).

Second, following on from the above, our mixed-effects econometric model allows us to extend the key insight of finance constrained models: that 'fixing' coefficients to be equal across firms facing fundamentally different external constraints can lead to seriously misleading and even nonsensical inferences if 'average' coefficients differ greatly between cross-sectional units and clusters (Barcikowski 1981; Pesaran and Smith 1995; Pepper 2002; Hsiao 2014). Assuming a single constant slope parameter across time, however, is the bedrock of most cash flow-Q empirical papers (with Hsiao and Tahmiscioglu 1997 being a notable exception). This is partly because the dominant measurement error correction estimator used, including in Gutiérrez and Philippon (2017b), requires this assumption (Erickson and Whited 2000; Erickson, Jiang, et al. 2014).[13]

[12] This excludes group predictors added later. 231×3 random country:year effects, 11×3 random country effects, 21×3 random year effects, 3×3 variance parameters per group, 3×3 correlation parameters per group, $2\times$ t-distribution parameters, $22\times$ population-level predictors, and $1\times$ AR error process coefficient.

[13] This is the default approach, despite the fact that tests of constant slopes over time – when they are rarely conducted – are in fact rejected in such studies (Erickson, Jiang, et al. 2014, p.219). Assuming that parameters of interest are constant over time rules out many of the most interesting questions which this study tries to explore. Moreover, it makes it difficult to assess the accuracy of the finding that there has been 'under-investment relative to Q', which pervades previous advanced economy studies (Gutiérrez and Philippon 2017b; Crouzet and J. Eberly 2019); since this finding is based on the implicit assumption that time-varying intercepts ('fixed effects') can properly measure this even when time-varying slopes are omitted.

Third, our time-varying and country-varying coefficient estimates are much more stable – and need a smaller sample size – than previous studies (Magud and Sosa 2015; A. Kose et al. 2017). Coefficient estimates from multiple interaction effects become highly unstable due to its sensitivity to sample size (Magud and Sosa 2015; Li et al. 2015b; Gelman 2019). This is why Magud and Sosa (2015), who similarly estimate 'cash flow-Q' investment regression coefficients which vary by region and firm type,[14] have random effect coefficient which change in and out of statistical significance. We overcome this issue through estimating coefficients jointly. As a type of James-Stein estimator, this minimizes the collective mean-square error through the 'partial pooling' of information across coefficients.[15] In addition, we can apply measurement error correction – a common problem in cash flow-Q regressions – on top of this Bayesian model to ensure that our core results are not driven by attenuation bias (Appendix D). This is absent from most previous investment studies on developing economies.

Finally, unlike the current literature, our model allows us to explore variation not only between firms *within* different countries and years (micro-level variation), but also variation of firms *between* countries and years. In a classical regression, the group-level coefficients (as data to now be explained) and the group-level predictors, would be collinear and instead must be run as two separate regressions, as in Hsiao and Tahmiscioglu (1997). This problem is avoided in a Bayesian model because of the partial pooling of the random group-level coefficients toward the group-level linear model.

Section 2, the next section, describes our 'cash flow-Q' investment model and then provides a brief overview of our data and empirical movements in raw investment rates. Section 3 explains our regression equation and estimation procedure using a Bayesian mixed effects hierarchical model with 'partial pooling' (detailed further in Strauss and Yang 2020). Section 4 reports the model's key findings and Section 5 extends the model by adding a group-level predictor to explain differences between the time-varying random effect intercepts. Section 6 concludes. Online Appendices detail our Bayesian model further, including priors and model fit (Appendix B); dataset and variables (Appendix C); descriptive statistics on key variables (Appendix C.5); and measurement error model (Appendix D).

[14] They cover a different time period and two dozen more countries than us. They also find that financing constraints vary significantly across regions and firms.

[15] A phrase introduced by John W. Tukey (Brillinger et al. 2002).

2 Investment Model and Data

2.1 Cash Flow-Q Investment Model

Following the formulation in J. Lewellen and K. Lewellen (2016), the value of the firm V_t is maximized with respect to the control variable investment I_t, given the capital stock K_t in period t and subject to the net present value of its profits $\Pi(K_t, s_t)$, less adjustment costs related to investment $C(I_t, K_t, \lambda_t)$, and less investment expenditure I_t. Profits are a function of a state variable s_t, reflecting past investment decisions and the firm's capital stock K_t. Quadratic investment adjustment costs are related to an exogenous stochastic parameter λ_t. The recursive Hamilton-Jacobi-Bellman equation is:

$$V_t = \Pi(K_t, s_t) - I_t - C(I_t, K_t, \lambda_t) + \beta E_t[V_{t+1}]. \tag{1}$$

Assuming quadratic adjustment costs $C(\cdot)$ and also quadratic (and positive) external financing costs $b \geq 0$ (ibid.),[16] this leads to the following regression specification which we estimate:

$$\frac{I_t}{K_t} = -\frac{1}{a+b} + \frac{1}{a+b} q_t + \frac{b}{a+b}\left(\frac{\Pi_t}{K_t}\right) + \frac{a}{a+b}\lambda_t. \tag{2}$$

Equation 2 estimates firms' investment demand schedule, with a slope of q in investment-Q space. Following Andrei et al. (2019), a smaller (i.e. flatter) q slope can be due to increased market power arising from decreasing returns to scale. This implies a growing wedge between average and marginal Q (Abel and J. C. Eberly 1993; Eggertsson et al. 2018).[17] We do not derive and integrate the microfoundations of that model here, though its model is sufficiently generalizable to warrant its interpretation of the q coefficient being applicable here. The resulting time-varying slope coefficient in an investment-Q regression is then interpreted the changing 'responsiveness' of firms to investment opportunities under the assumption of potential market power. It can, however, also be interpreted as the changing efficiency of investment under information asymmetries in markets (Q. Chen et al. 2007; R. Chen et al. 2017)

Cash flow, Π_t/K_t, enters directly into the regression equation and reflects a 'Pecking Order' of preferred sources of financing for the firm, with external finance being more costly than internal

[16] This is not fully equal to the amount of capital raised because it ignores adjustment costs.

[17] Other interpretations of market power within a Q investment framework – which amount to the same thing – are as a strictly concave profit function (Cooper and Ejarque 2001) which implies decreasing returns to scale in the profit function (Cooper and Ejarque 2003; Andrei et al. 2019), or as a mark-up parameter (Gutiérrez and Philippon 2017b; Döttling et al. 2017)

finance (Myers 1984; Myers and Majluf 1984). As a result, following Fazzari et al. (1988), a positive and large cash flow coefficient is normally interpreted as a sign of positive external financing constraints (as investment is sensitive to cash flow). Though in practice this coefficient will be of little significance if the cost of external finance $b \to 0$; if the firm has no need (or desire) to access external finance, such that $I_t/K_t < \Pi_t/K_t$. In our case we find this diminished external financing constraint also reflects a re-prioritization of funds towards repaying down debt to deleverage. A more detailed version of the model can be found in Appendix A.

2.2 Data Construction

This section provides a brief overview of the key features of our data (Appendix C for further details). Our sample covers non-financial publicly listed firms from developing economies. It is constructed first by merging S&P's Compustat Global and Compustat North America databases and then, after cleaning and trimming, and creating all variables, selecting our sub-sample.[18] Our final sample consists of 91,069 observations on 11,812 unique firms across 11 countries and 21 years between 1997-2017. This includes most major developing economies, except Russia, Mexico, Saudi Arabia, and Turkey due to their small sample sizes.[19] Country categorisation is first based on average GDP per capita (nominal) US$ between 1997-2017 of $15,000 or less. The country then requires a minimum of 1,400 observations to be included to help ensure sufficient credible intervals for our results. The firm's country is based on country of incorporation, rather than country of listing. We choose not to combine developed and developing economy firms since they show different investment dynamics. This then allows us to better isolate their unique time effects.

Our focus on publicly listed firms follows from the fact that they are becoming of greater relevance to developing economies. Our sample uses non-financial publicly listed firms. Larger firms – often publicly listed – now comprise 40-60% of employment and turnover in key developing economies, far in excess of their proportion of total enterprises (Tsebe et al. 2018).[20] While in the universe of public firms, developing economies are of growing importance, with China overtaking

[18]This data comes consolidated at the firm-level.

[19]Vietnam was excluded due to erratic behaviour in its capital stock. The countries in our sample account for the vast majority of investment spending for all developing and emerging markets on a population or GDP weighted basis (with Saudia Arabia, Mexico, Turkey, and Russia notable omissions).

[20]Based on the OECD's Structural and Demographic Business Statistics (SDBS) database which includes data on production and employment by firm size for South Africa, Brazil, Israel, Poland, Portugal, Turkey, and Brazil among other developing economies.

the U.S. in number of listed firms (OECD 2018; Wigglesworth 2019).[21]

Our sample is fairly well dispersed across different countries of incorporation: China accounts for 24,486 observations (though beginning largely from 2001), followed by Taiwan (15,411), India (14,294), Korea (12,579), and Malaysia (8,832).[22] The countries chosen are not commodity-dependant exporters, according to UNCTAD's classification (UNCTAD 2019), except Brazil and to some extent South Africa.[23] We use an unbalanced panel since a balanced design, with no gaps in observations for a firm between any two years, would exclude most of the largest developing economy firms in existence today and create considerable survivor bias. The panel structure of our data helps ensure that our results are not by chance or due to measurement error of intangibles (Farhi and Gourio 2018).[24] Variable definitions differ somewhat by country due to differing implementations of IFRS accounting guidelines.[25] Though the standardization of Compustat Global is considered in line with the regulations and standards of IFRS and is a major benefit of the data, with any country deviations for a variable noted in the database (Dai 2012).[26] Values are converted into nominal US$ using the Compustat Global currency file and instructions. Our variables are reported gross, before amortization and depreciation, but after tax, unless stated otherwise.

Capital stock is the denominator used for the cash flow rate, investment rate, and capital-output ratio. We define the capital stock as Compustat's PPEGT + INTAN + INVT, which is equal to the sum of gross property, plant, and equipment; intangible assets; and inventories. Cash flow is defined as Compustat's OANCF from the cash flow statement, measured gross after taxes and interest payments, and after making adjustments for changes in working capital and other non-operating income. We use the firm's market-to-book ratio (MTB), calculated as the market value of the firm's *total assets* (equity plus debt) over the book value of these assets, as our proxy for Tobin's Q. This creates the least amount of outliers and the greatest degree of similarity in the

[21] Between 2008-2018, Asian non-financial companies raised through initial public offerings (IPOs) almost half of all capital raised by non-financial firms worldwide (Splender 2018).

[22] As one of the 'Asian Tigers' Taiwan has quite different economic dynamics to China, as so it makes sense to treat firms incorporated there differently.

[23] See Appendix C for further details. During the period 2008–2012 when energy prices peaked, Indonesia became temporarily energy export dependent even though it is considered to be a non-commodity exporting country with a sizeable energy sector (UNCTAD 2019).

[24] Accounting guidelines for capitalizing intangible expenditure is much stricter under U.S. GAAP than IFRS.

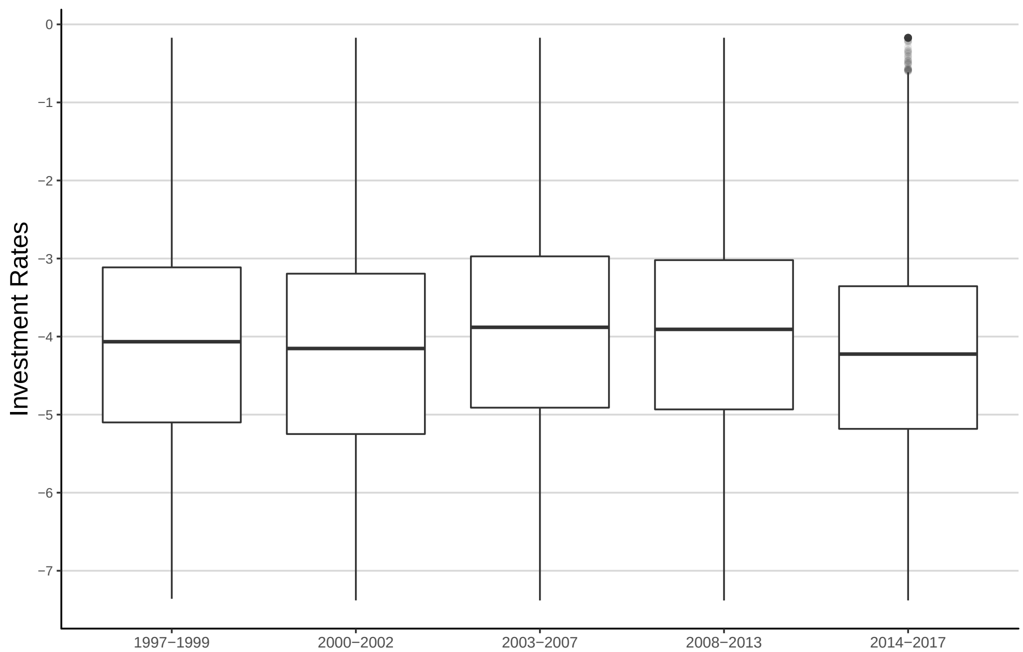
[25] China's national standards are substantially converged with IFRS Standards, India less so. For further discussion and a list see Deloitte, 'Use of IFRS by jurisdiction', accessed 18 September 2020: https://www.iasplus.com/en/resources/ifrs-topics/use-of-ifrs.

[26] Variable ACCTSTD indicates the Accounting Standard followed. 'DI' means Domestic standards generally in accordance with or fully compliant with International Financial Reporting Standards (IFRS).

shape of Q distributions across developing economies. Importantly, using total assets, as opposed to just the firm's *capital stock*, helps keep Q strictly positive. If not then Q becomes negative during the 2008 GFC and for specific countries. The procedure for calculating Q values in Compustat is discussed further in Appendix C.

2.3 Initial Data Description

Figure 1. Pooled Developing Economy Firm-Level Investment Rates, by Time Period, 1997-2017



Note: *Showing box plots of log2() firm-level investment rates with 'outliers' (observations outside of 1.5 x IQR) as dots, and period median as bold horizontal lines within each box. Sample consists of firms incorporated in Brazil, India, Pakistan, Poland, South Africa, Taiwan, Korea, Thailand, Malaysia, Indonesia, and China.*

Figure 1 shows the boxplot[27] for log investment rates over five consecutive time periods on our pooled sample (see also Figure 11 Appendix). A cyclical pattern with a mildly upward trend is evident across the first four time periods' boxplots. The fifth and final time period, between 2014-2017 (inclusive), shows a sharp fall in investment rates especially for the top 50% of our sample: the 75th percentile (the top hinge) and the median both fall far below that of previous time periods. The cyclical movement in firms' investment rates has been accompanied by median investment opportunities — Q values — and cash flow rates (profitability) being stable or increasing (see

[27]For each box plot the lower and upper hinges correspond to the first and third quartiles (the 25th and 75th percentiles). The upper whisker extends from the hinge to the largest value no further than 1.5 x IQR from the hinge (where IQR is the inter-quartile range, or distance between the first and third quartiles). The lower whisker extends from the hinge to the smallest value at most 1.5 * IQR of the hinge. Data beyond the end of the whiskers are "outliers" and are plotted individually.

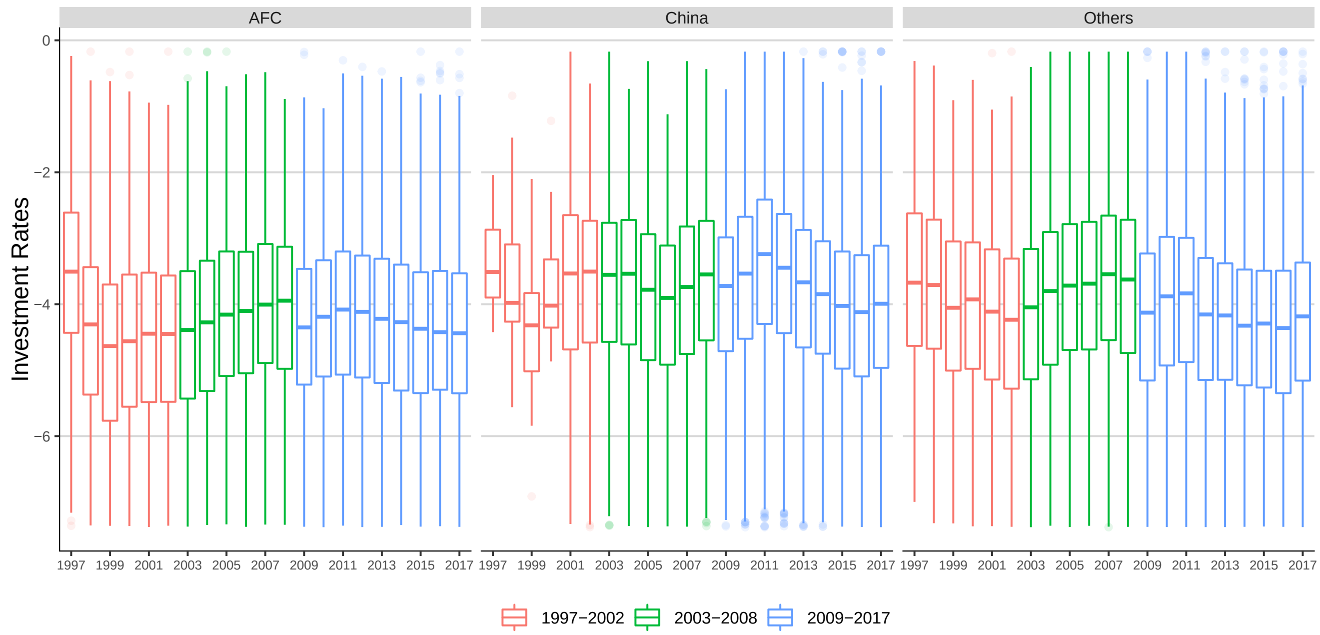
Appendix C.5).

For Magud and Sosa (2015), using national accounts data, private investment rates remains near pre-crisis trends after peaking in 2011. While for A. Kose et al. (2017), investment rates decline sharply since 2010 to well below both pre-crisis and long-term averages. We see that raw investment rates decline to at or below pre-2002 levels.

The apparent cyclicality in the above plot is due to two opposing and offsetting affects in our sample though: the increase in Chinese investment between 2010-2012 and a fall in other developing economy investment rates from 2008. As a result, compared to advanced economies (Strauss and Yang 2020), the fall in raw investment rates for developing economy firms as a whole post-2008 has been less severe and initially far more muted (owing partly to Chinese firms' investment rates helping offset the decline). China's 2011 investment peak is evident in Figure 2 which shows box plots for each country group for each year. In comparison, firms from the other countries in our sample show an investment peak around 2007. The upswing of the investment boom starts at different times for each group of countries, as can be seen from Figure 2. For firms incorporated in the 1997 Asian Financial Crisis (AFC) countries of Thailand, Korea, Malaysia, and Indonesia, investment rates bottom in 1999 before recovering from 2000 fairly continuously. While for firms in the 'Other' developing economies category, consisting of the heterogeneous group of Brazil, India, Pakistan, Poland, South Africa, and Taiwan, investment rates bottom in 2002 before picking up for the next cycle in 2003. These differing dynamics across firms in different countries makes neat periodizations and group categorizations difficult.

Plots of raw investment rates have obvious limitations though. By definition they overfit the sample, allowing more sampled countries to dominate since no regularization takes place. It also does not account for changes in firms' ability to access external financial markets or the availability of good investment opportunities. We do this next when we estimate firms' investment demand function using a regularization estimator (a full Bayesian multilevel model).

Figure 2. Developing Economy Firm-Level Investment Rates, by Country Group, 1997-2017



Note: *Showing box plots of log2() firm-level investment rates with 'outliers' as dots and the year median as the bolded horizontal line. Log2(6.2% investment rate) is = -4, which China's firms' investment rates remain around while others are below this. China sample is too small prior to 2001 to make any precise inference for those years. 'Others' consists of Brazil, India, Pakistan, Poland, South Africa, and Taiwan; 'AFC' (Asian Financial Crisis) countries consists of Korea, Thailand, Malaysia and Indonesia.*

3 Econometric Model

This section details the Bayesian hierarchical model which we use to estimate our 'cash flow-Q' investment regressions. A full treatment of this model can be found in Strauss and Yang (2020) and are repeated in Appendix B.

Our hierarchical model is a mixed effects model, which combines fixed and random coefficients (Greene 2003; Sims 2010; Hsiao 2014; Meager 2019). This allows for the degree of variation between *countries* and *years* to be estimated directly from the data; rather than imposed *a priori* as a constraint, either by assuming no relevant differences between clusters of countries and years (complete pooling), or by assuming no relatedness between countries or years (no pooling, complete independence).[28] Instead, the parameters within each group are estimated together as draws from a common prior distribution (with common global parameters estimated from the data), allowing the inferences for one country (or year) to potentially 'learn' (or 'borrow strength') from another (McElreath 2018). In this way the estimator regularizes estimates of the individual effects towards

[28]For a discussion on the relationship between the Bayesian hierarchical estimator to the fixed effects and random effects estimators see Greene (2003, Chapter 16.7).

the grand mean estimated from the data. There is more learned pooling when clusters are similar to one another (as reflected by a small group-level standard deviation), and more smoothing for individual clusters (countries or years) with fewer observations. This helps ensure that countries or years with small samples do not overfit their data (liked in a fixed effect model), or that over-sampled countries or years do not unfairly dominating the inference (liked in a pooled regression). This is particularly useful for developing economy studies where sample sizes can be small for any cluster. This joint estimation approach produces a lower *total* mean squared error for the sum of the parameters within a group than a maximum likelihood estimator which estimates each parameter separately (W. James and Stein 1961; Kreft and De Leeuw 1998; Lehmann and Casella 1998).[29]

Following the investment demand function specification in eq. 2, the firm's investment rate is determined by Q and the *cash flow* rate. Our hierarchical regression model allows the intercept of the firms' investment demand function, the slope of Q, and the slope of *cash flow* to vary by year and country, and also to be estimated as a 'fixed' pooled coefficient. Our baseline regression estimation, where $y_{c,t[i]}$ is the investment rate of firm i in country c and time t, is:

$$y_{c,t[i]} = (\alpha + \alpha_{c,t}) + \left(\beta^{q} + \beta^{q}_{c,t}\right)\mathrm{Q}_{c,t[i]} + \left(\beta^{cf} + \beta^{cf}_{c,t}\right)\mathrm{CF}_{c,t[i]} \ + \text{Controls} + \epsilon. \tag{3}$$

$\mathrm{Q}_{c,t[i]}$ and $\mathrm{CF}_{c,t[i]}$ are the Q and *cash flow* variables for firm i in country c and time t used to estimate the 'fixed effects' population coefficients α, β^{q}, and β^{cf}. These 'fixed' coefficients represent the global 'average' intercept coefficient and global slope coefficients for Q and *cash flow* for our total pooled sample. Their 'random' effect counterparts are the coefficients $\alpha_{c,t}$, $\beta^{q}_{c,t}$, and $\beta^{cf}_{c,t}$ and have subscripts showing that they vary by country and year. They represent the intercept coefficient, and the slope coefficients of Q and *cash flow* for each of the 11 countries, c, and 21 years, t. We also have a country:year group j (with $11 \times 21 = 231$ clusters), which serves largely as a control group and so is not included as an additional subscript in the above equation. The random effects coefficients estimate how each variable's impact, for a given country or year, deviates from the coefficient's population average, such that $\beta^{q}_{c,t}$ shows how the impact of Q on firms' investment rates in country c, or year t, deviates from the average impact of Q taken across all countries and years. Controls consist of $\gamma'^{cor}\mathrm{CoR} + \gamma'^{k}\mathrm{K} + \gamma'^{sic}\mathrm{SIC}$, where CoR, K, and SIC are the categorical control variables that represent the capital-output ratio, capital stock size, and 1-digit NAICS industry code. ϵ is an

[29] A bias-variance trade off arises in this estimation as with most regularization estimators (G. James et al. 2013).

error term discussed further in Strauss and Yang (2020) and Appendix B. We include an AR(1) error process to account for the panel nature of our data.[30]

Our random effects already effectively explore differences in financing constraints across firms in different years and countries. As a result we do not divide firms *a priori* into further groups, such as firm size, based on the degree of external financing constraints they might possibly face. Instead we use firm size and industry code as fixed effects control variables (Whited 1992; Hsiao and Tahmiscioglu 1997; Kaplan and Zingales 1997). Moreover, we do not find meaningful patterns in coefficients when estimating our random effects by firm size, revenue, or industry code.

From a Bayesian estimation perspective our model is simply an extension of Bayes rule. We use a student-t likelihood and multivariate normal prior on our random effects, which are drawn from a common distribution, and estimated jointly. This leads to the following joint posterior parameter distribution, with N number of observations, K number of predictors and, L number of groups:

$$\begin{aligned} p(\theta|y) &\propto p(y|\theta)\, p(\theta|\phi)\, \mathrm{p}(\phi) \\ &\propto \underbrace{\prod_{l=1}^{L} \text{student-t}(y_{.l}|\beta_l, \nu, \sigma_y)}_{\text{Likelihood}} \; \underbrace{\prod_{l=1}^{L} \text{MVN}(\beta_l|\boldsymbol{M}_{\boldsymbol{\beta}}, \boldsymbol{\Sigma}^{\boldsymbol{\beta}})}_{\text{Prior}} \; \underbrace{p(\boldsymbol{M}_{\boldsymbol{\beta}}, \boldsymbol{\Sigma}^{\boldsymbol{\beta}})}_{\text{Hyper prior}} \end{aligned} \tag{4}$$

where y and θ denote the data and parameters of the likelihood function, respectively, and ϕ is the parameters of the prior distribution on group-varying components of θ. $p(\boldsymbol{M}_{\boldsymbol{\beta}}, \boldsymbol{\Sigma}^{\boldsymbol{\beta}})$ is the prior distribution on the parameters of the prior distribution, also called the *hyper prior* distribution. A detailed discussion on the choice of priors can be found in Appendix B.4.

4 Results

Applying our Bayesian hierarchical ('mixed effects') model to estimate the 'cash flow-Q' equations allows us to test the following three hypotheses on the causes and nature of the investment slowdown among development economy firms:

[30]An AR(2) process did not improve the model fit by a relevant amount.

4.1 Hypotheses

i **The investment slowdown since 2008 has been sharp and largely persistent** (sharply declining *intercept* coefficients since 2008 – $\alpha_{c,t} \downarrow$): The intercept of the investment demand curve, reflecting firms' animal spirits or exogenous shifts in the marginal product of capital, is declining since the 2008 GFC despite countervailing policy measures in force.

ii **Moderate external financing constraints, loosening over time** (potentially relevant but diminishing *cash flow rate* coefficients – $\beta_c^{cf} \rightarrow$ *smaller*): Firms are moderately financially constrained, due either to external financing being costly and/or relative demand for external financing being high (Gutiérrez and Philippon 2017b; Döttling et al. 2017). But this is declining over time as global monetary conditions ease and profitability remains strong.

iii **Cyclical responsiveness to investment opportunities, increasing more recently** (Q coefficients – $\beta_t^q \rightsquigarrow$): Firms are not becoming less responsive to investment opportunities over time due to market concentration or 'financialization' (Lazonick et al. 2014; Gutiérrez and Philippon 2018), and in fact are gradually becoming more responsive to investment opportunities as firms struggle to maintain high levels of investment amidst structurally weaker global demand yet easy financing conditions.

4.2 Findings

Table 1 presents the primary summary output from our hierarchical regression model. Further details on the estimation method can be found in Strauss and Yang (2020). Predictors are mean-centred. Not reported in the table is the calculated Bayesian R^2, which indicates the model 'fit' is moderate and lies between $[0.352, 0.36]$ for the 90% credible interval.[31] Our core findings are robust to measurement error (Appendix D).

Table 1 reports the fixed effects coefficients and the variation in the random effect coefficients for each group (year, country, and year:country control). The variation in the random coefficients within each group c, t, j is captured in the standard deviation of that group's random effect, such that σ_{α_t} shows the variation in the random effect intercept across years.

[31] The fit is almost identical when looked at before and after the 2008 GFC. A large portion of the fit comes from autoregressive error term. The fit of this model appears to be better for advanced economies (Strauss and Yang 2020). Though the models are not identical given different sample sizes and one different dummy variable in Strauss and Yang (ibid.).

Table 1. Summary of Hierarchical Model Regression Results

	Variable	Estimate	Est.Error	l-95% CI	u-95% CI	$\hat{\mathbf{R}}$
Fixed Effects	α	-3.00	0.08	-3.16	-2.85	1.00
	β^q	0.25	0.03	0.20	0.31	1.00
	β^{cf}	0.19	0.04	0.10	0.28	1.00
Country Random Effects	σ_{α_c}	0.15	0.04	0.09	0.25	1.00
	$\sigma_{\beta^q_c}$	0.09	0.02	0.05	0.15	1.00
	$\sigma_{\beta^{cf}_c}$	0.11	0.04	0.06	0.20	1.00
Year Random Effects	σ_{α_t}	0.17	0.03	0.12	0.25	1.00
	$\sigma_{\beta^q_t}$	0.02	0.01	0.00	0.04	1.00
	$\sigma_{\beta^{cf}_t}$	0.07	0.03	0.02	0.12	1.00
Country:Year Random Effects	σ_{α_j}	0.14	0.01	0.12	0.16	1.00
	$\sigma_{\beta^q_j}$	0.04	0.01	0.02	0.05	1.00
	$\sigma_{\beta^{cf}_j}$	0.13	0.02	0.09	0.18	1.00
Student-t Parameters	σ	0.68	0.00	0.68	0.69	1.00
	ν	8.24	0.24	7.78	8.73	1.00

Note: *Results are for Regression Model 3. For each coefficient, the mean (estimate), standard deviation (Est.Err), 5% and 95% percentiles (l-95% CI and U-95% CI) of the posterior distribution is reported. The latter two percentile ranges represent the 90% credible/uncertainty interval.* $\hat{\mathbf{R}}$ *is the convergence metric and close to one when the MCMC chains are well-mixed and converged.*

The degree of the variation in our random effects does not support using a pooled regression or a fixed effect estimator. A higher standard deviation coefficient, indicating larger estimated variation between countries (or years) in a coefficient's estimates, makes a pooled model which estimates a single coefficient inappropriate. As the standard deviation of the coefficient within each group increases, a fixed effects model becomes more appropriate, reflecting higher estimated variability in coefficients between countries and years. In general, coefficients show somewhat greater variation between countries (than between years), with higher estimated standard deviations, making a pooled model inappropriate for coefficients in this group in particular. A fixed effect model would only be appropriate in this case, however, if the standard deviation was approaching a very large number (Gelman and Hill 2006). If it was our model would in practice effectively estimate something comparable to separate regressions for each year or country. Instead, we see sufficient similarities between coefficient estimates within each group that a fixed effect model cannot be justified. Finally, Table 1 shows that there is little variation in Q coefficients over time, i.e. between years, since

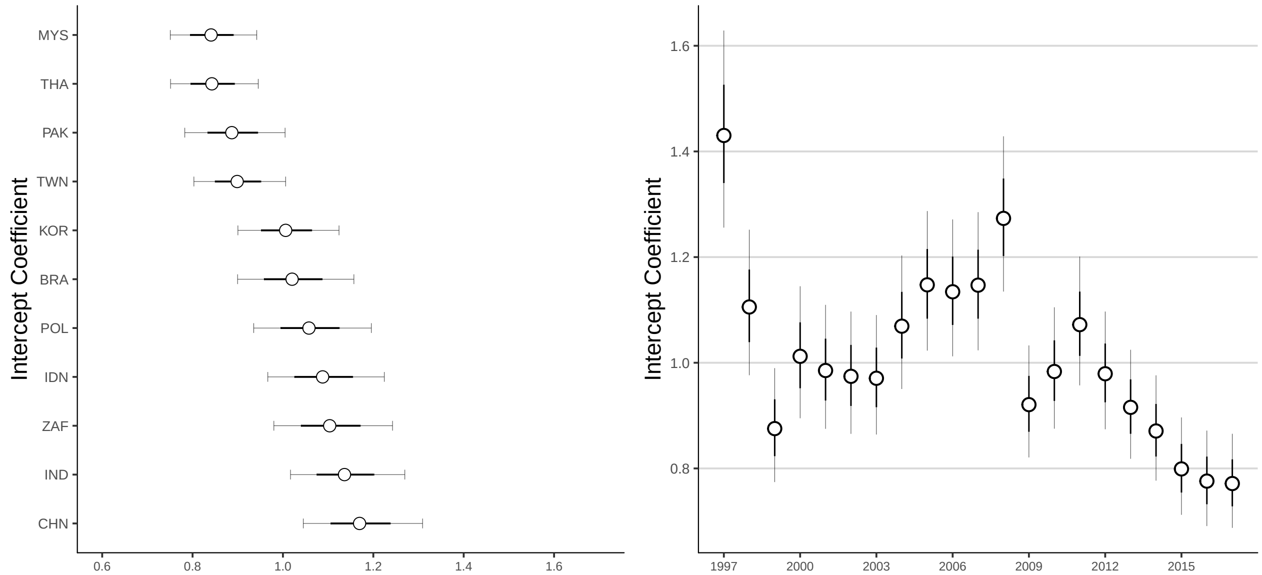
$\sigma_{\beta_t^q} = 0.02$. But note that this is a *finding* of our model based on the data, rather than a modelling assumption imposed by the researcher *a priori* regardless of how it fits the data.

Several key findings stand out. Firstly, as shown in Figure 3, the slowdown in developing economy firms' estimated investment rates shows a strong cylicality but also a sharp weakening after the 2008 GFC, falling continuously after a modest recovery lasting until 2011. This is reflected in the estimated movement of our mean-centred random effects intercept coefficients over time, which captures the underlying impetus of firms to invest, all else being held equal.[32] Figure 3 shows that the attempted recovery in baseline investment rates among developing economy firms collapses after 2011 (probably as Chinese incorporated firms' investment rates slow and sink to their lowest levels in our sample). In general our estimates have more uncertainty at the time-level than at the country-level and this is shown in wider Bayesian credible intervals. These credible intervals become tighter for later years as our sample size increases. China and India have the highest intercept coefficients indicating a greater underlying impetus to investment. We show later in section 5 that one third of the variation over time in the time-varying random effects intercepts in Figure 3 can be explained by the corporate sector's changing leverage behaviour, which increased during the early 2000s and then fell considerably since 2008. Given falling financial constraints (below), this likely reflects firm's shifting consideration what they consider to the 'best use' of their funds.

How are we to explain the apparent contrast and incongruity between the estimated intercept investment rates (Figure 3) – which show an incredibly steep and largely persistent decline in baseline investment rates of the investment demand function since 2008 (notwithstanding a modest recovery until 2011) – and the 'raw' investment rates which we plotted in Section 2.3, and which showed a notable but far more modest decline in investment rates post-2008? A major difference between the two is that Figure 3 shows the estimated intercept coefficients which holds constant changing firm-level responsiveness to investment opportunities and changing external financing constraints. This fact is important because, as we

[32] We do not include the fixed effect value of the intercept in this plot as its value is arbitrary and not of interest to us in the case of an intercept coefficient.

Figure 3. Intercept Coefficients by Country and Year, 1997-2017

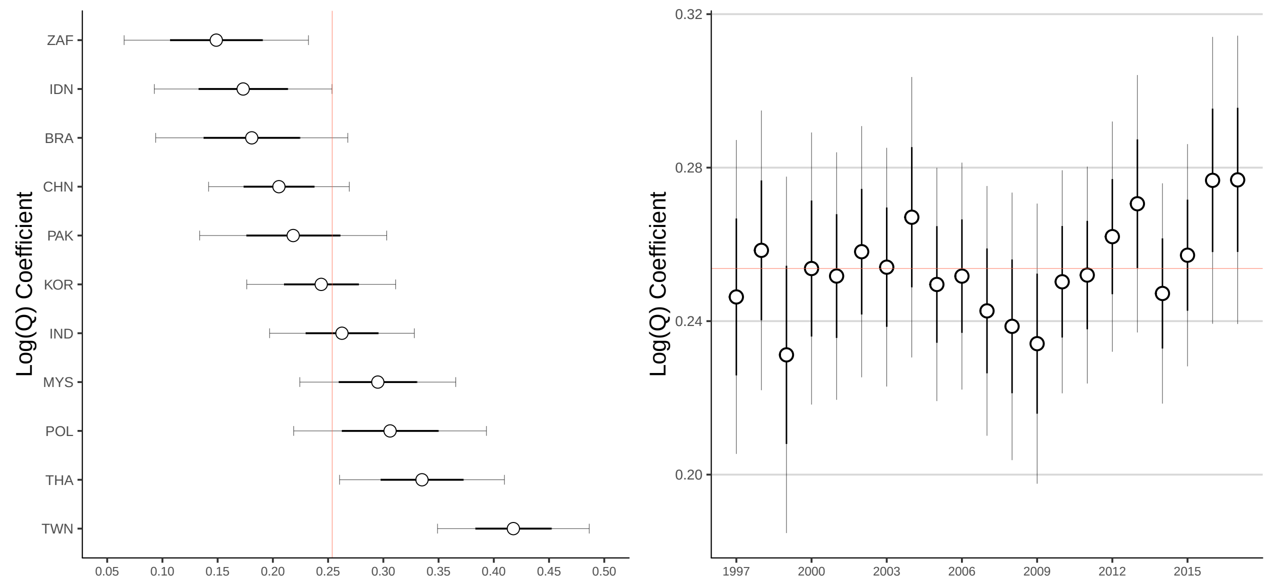


Note: *This shows the exponentiated random intercept coefficient, i.e the predicted mean/median investment rate. An exponentiated intercept coefficient of above (below) 1 shows an increasing (decreasing) mean-centred investment rate from the global average. The intercept falls greatly after the 1997 AFC (right hand side graph), rising during the commodity-boom years between 2003-2008, and then falling subsequently. The recovery in the underlying impetus to invest post-2008 was, however, short-lived and the intercept falls to levels below those seen at the bottom of the AFC. The fixed effects intercept is not included. Bayesian 90% credible intervals display a high degree of certainty for later years and most countries.*

show below, developing economy firms' responsiveness to investment opportunities, and the degree of external financing constraints which they face, have both been changing over time. Another difference between our estimated intercept coefficients and the raw investment rates is that our econometric estimator produces a 'partially pooled' estimate for each coefficient which allows for one year's data to inform another year's; whereas the raw investment rates do not. This 'partial pooling' in the estimator helps ensure that the estimated intercept investment rate for years with less data are not assumed to be higher or lower due only to a smaller sample size.

Secondly, developing economy firms remain responsive to investment opportunities (Figure 4): more so than developed economy firms (where Q coefficients are lower - see Strauss and Yang 2020), and increasingly so over time as the coefficient move above the previously established cyclical pattern after roughly 2012.

Figure 4. Q Coefficients by Country and Year, 1997-2017



Note: *Q coefficient shows strong cyclical movements with no clear tendency to increase or decrease over time, except in the past few years. This upswing indicates that firms are not less responsive to investment opportunities, despite lower investment rates, but in fact the opposite. The Q coefficient is interpreted as an elasticity. The 68% credible interval is shown in dark black, and the 90% credible interval in grey.*

This is depicted in Figure 4 which plots the total Q coefficient for each country and year. This coefficient is equal to the sum of the Q fixed effects β^q, and the country- or year-specific Q random effects coefficients (β^q_c, or β^q_t). We see no signs of growing monopoly power of firms, or growing 'financialization' of firm behaviour making firms less response to investment opportunities over time, since the time-varying Q coefficient is not flattening over time (Lazonick et al. 2014; Gutiérrez and Philippon 2017a, 2018). Though this cannot be interpreted as definitive evidence of market power having no impact on investment spending, since this can instead work through moving firms along their investment demand curve, or through a creating a growing wedge between average and marginal Q (Abel and J. C. Eberly 1993).

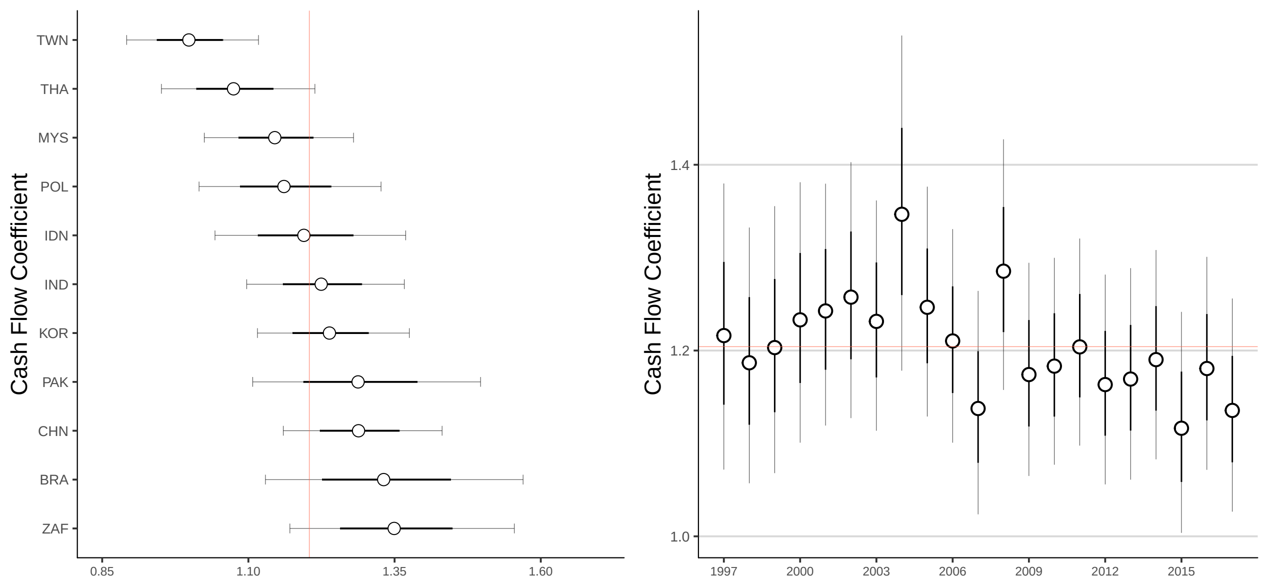
The red vertical line in Figure 4 shows the Q fixed effects coefficient being ≈ 0.25 (Table 1), with the random effects deviating around it. Because both the Q coefficient and the dependant variable are in log form we can interpret this result as an elasticity, such that a 100% increase in the fixed effects value of Q increases firms' investment rate by 25%, from an investment rate of say 5% to 6.25% (a 1.25 percentage point increase). This is considerably higher than the responsiveness of advanced economy firms to investment opportunities (Strauss and Yang 2020). It is also higher than the Q coefficient estimates from previous studies, though our regression specification is not directly comparable (Erickson and Whited 2000, 2012; Peters and Taylor 2017; Andrei et al. 2019). As shown in Figure 4, Taiwan, Thailand, Poland, and Malaysia are the most responsive to investment opportunities, with Taiwan having a coefficient as high as ≈ 0.41. This compares to South Africa at the bottom end with a coefficient as low as ≈ 0.146 and highlights the importance of allowing for heterogeneity across clusters in estimating effects. Note that the credible intervals are large for the year dimension in Figure 4 and improves only moderately over time even though our sample size is much bigger for later years (Appendix C.5).

Finally, we find that developing economy firms do face external financing constraints, but they are not as high as one might expect based on previous studies (Love 2003; Love and Zicchino 2006; Magud and Sosa 2015; Li et al. 2015b). Such external financing constraints have also been declining since the 2008 GFC. This is evident in Figure 5 which plots the total (exponentiated) cash flow coefficient (equal to the sum of the fixed effect and random effects cash flow coefficients). Apart from global monetary easing – which has greatly reduced borrowing costs for developing economy firms and governments (United Nations 2015) – cash flow rates (profitability) have tended to be stable or increasing post-2008 GFC for developing economy firms (Appendix C.5).[33]

The vertical red line in Figure 5 represents the fixed effect cash flow coefficient, with a value of 0.19 (0.04) (Table 1). In comparison, as noted in Strauss and Yang (2020), advanced economy's fixed effect cash flow, at 0.06, is less than one-third of this, indicating their much lower external financing constraints. The credible intervals depicted in Figure 5 are fairly large, nevertheless Brazil and South African firms appear to face the largest degree of external financing constraints with (exponentiated) cash flow coefficients around 1.35. Since this regression relationship is log-level, this means that an exponentiated coefficient above 1 implies a percentage increase in the geometric mean of y for a one unit (i.e. 100%)

[33] Even though this has gone hand-in-hand with raw Q values also increasing for most countries, it appears that firms have had an increasing sufficiency of cash flow to cover them and more – and have still found the need to be more responsive to investment opportunities over time.

Figure 5. Cash Flow Rate Coefficients by Country and Year, 1997-2017



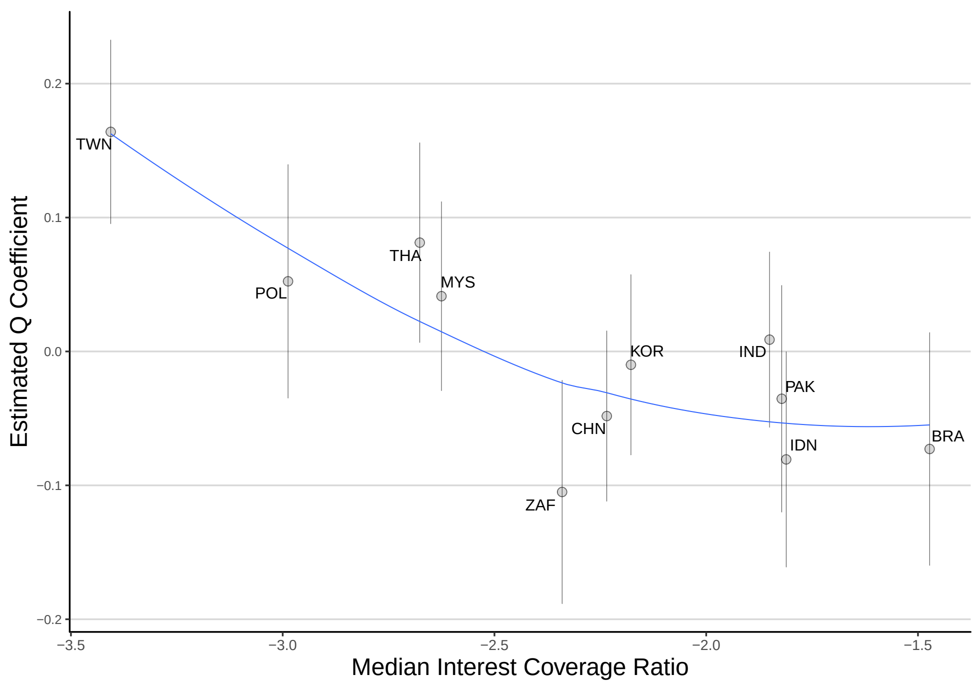
Note: *The 68% confidence interval is shown in grey and the 90% credible interval is shown in dark black. Exponentiated fixed effects coefficients are the red lines at 1.2. Total effect shown for country or year here is equal to the sum of fixed effects and random effects. External financing constraints have been decreasing for firms since 2003 and 2008 in particular, making it easier for firms to respond to investment opportunities.*

increase in cash flow rates, while a coefficient of below one implies a percentage decrease. This means that, with an exponentiated fixed effect cash flow coefficient of 1.35, when cash flow rates increase by 100%, the geometric mean of the investment rate, which is 5.8% in our sample, increases by 35% from 5.8% to 7.8% (a 2 percentage points increase). Taiwan, in contrast, has an economically unimportant cash flow coefficient of ≈ 1; implying no response in investment rates to changes in firms' cash flow rates. Note that firms in countries with small *cash flow* coefficients (Figure 5) tend to also have higher Q values. This reflects the negative correlation which our estimated variance-covariance matrix finds. Although we do not report it in the summary findings table above, our model also estimates the correlation between different coefficients within each group, i.e. cor(intercept, logQ), cor(intercept, cash flow), and cor(logQ, cash flow) among the year, country, and year:country random effects.

We place a weak prior on the variance-covariance matrix of the random effects within each group and find no statistically meaningful correlations except for a negative correlation at the *country level* between cash flow and Q, such that cor(logQ, cash flow) $= -0.43(0.23)$, or

$[-0.80, 0.07]$ for the 90% credible interval. While this estimated correlation does pass through zero, the vast majority of its mass does not, indicating that for firms in a given country, a high Q coefficient is associated with a low *cash flow* coefficient. We interpret this as showing that external financing constraints differ by country, such that in countries with weak cash flow coefficients (lower financing constraints) firms are much more responsive to investment opportunities, while in countries with large cash flow coefficients, the opposite is true and Q coefficients are lower as firms are less able to respond to investment opportunities. This is supported by evidence in our data which shows a strong cross-country relationship between firms' median interest expenses relative to $EBIT$ and the differing estimated responsiveness to investment opportunities between countries (Figure 6 below).[34]

Figure 6. Cross-Country Relationship between estimated Q Coefficients and Median Firm-Level Inverse Interest Coverage Ratio (IICR)



Note: *Showing an inverse relationship between the estimated regression coefficient and IICR, such that countries which are more responsive to* Q *(top left hand corner), have firms with lower relative interest expenses. South Africa ('ZAF') is to some extent an outlier for this and other drivers of cross-country differences in* Q*. Inverse Interest coverage ratio is defined here as Compustat variables* XINT *over* EBIT*. Showing LOESS fitted blue line using a span parameter* $= 1$.

[34]The fit for median leverage is not as tight but, similarly, shows two clear groups of countries emerging, such that countries with firms which have lower median leverage are more responsive to Q.

4.3 Robustness and Endogeneity

We undertake a barrage of tests and alternative specifications. Our student-t likelihood performs somewhat better than a normal likelihood in predicting certain parts of out data, but is preferred mainly because it is more robust to outliers due to its longer tail than the normal, and because it effectively adjusts for a particular model of heteroskedastic normal errors in our context (Arnold 2019). Heteroskedasticity is modelled explicitly through our varying-coefficients approach, with each group in our model having its own variance parameter, in addition to the pooled (firm-level) error (Sims 2010; Gelman and Hill 2006). Our log-log specification for the investment-Q relation in our model further reduces heteroskedasticity dramatically.[35] The log-log specification also helps improve the normality of the relevant distributions. Different priors have almost no impact on our coefficient estimates. This is to be expected given the large amount of data which we have. We explore different random effect coefficients on the basis of different clusterings in the data, by industry and by firm size. This leads to variation being cut across clusters (firm sizes or industries) in a way which does not produce any clear results between units. While if we remove the country and/ or year group from the random effects then the variation in the data is misassigned to a different 'level' (Schmidt-Catran and Fairbrother 2015).

Most robustness measures for cash flow-Q papers concern endogeneity of some sort. When data has a natural clustering, especially with a time component, modelling the clustering directly helps correct for the unobserved correlation which occurs from unobserved shocks correlated within a country, a year, or a specific year within a country (Wooldridge 2010, chapter. 20).[36] In our case, our model has one error term common to all firms within each group of the model (plus the pooled regression level error), such that it assumes a degree of correlation across all firms within the same year; across all firms within the same country; and across all firms within the same year for a country.[37] Put differently, our model best deals with unobserved heterogeneity by directly modelling it through allowing slopes and intercepts

[35] This can be seen by running simple quantile investment regressions of Q on investment and plotting the fits across quantiles (Koenker and Hallock 2001).

[36] Though our panel being unbalanced complicates this.

[37] This induces correlation in our *nbyn* covariance matrix for the error terms (Gelman and Hill 2006). This is done explicitly by giving all firms within the same country, the same year, or same country:year cluster a common error term.

to vary across country and year clusters. Ignoring parameter heterogeneities among cross-sectional or time-varying units can lead to non-sensical parameter estimates if the average has no representativity across individual countries or years in our case (Hsiao 2014).

Endogeneity is a particular concern in firm-level regression for several reasons – especially when the dependant variable is the investment rate.[38] For one, right hand side variables in such regressions are invariably endogenous and an identification problem arises which can never be properly resolved due to the simultaneity present. Adding lagged dependant variables does nothing to deal with simultaneity bias, even though it is commonly believed to (Reed 2015). Adding a lagged dependant variable may control for other types of endogeneity and can help deal with serial correlation though (Hsiao and Tahmiscioglu 1997). Lagging the dependant variable, however, has significant data requirements and introduces other forms of survivor bias, excluding firms who do not conform to the balance panel (such as newer established firms). Instead, we include a lagged AR(1) error structure to deal with serial correlation and the dynamic structure of the model. This is measured very precisely in our model, with a 95% credible interval of $[0.57, 0.59]$. Adding a second autoregressive error does not improve model fit much, has a small coefficient, and adds significant computational time.

Secondly, endogeneity in cash flow-Q regressions are endemic if Q is mismeasured (Erickson and Whited 2012, 2006). Model estimation must take this into account (Whited 1992). In such cases Q might not fully capture firms' future investment opportunities, due to the firm being young with limited information, or if Q is measured with error due to average Q diverging from marginal Q (perhaps to the firm's market power). Measurement error in Q not only biases downward Q coefficients but complicates the interpretation of cash flow as measuring the cost of external financing. For if Q is mismeasured, and if cash flow also likely reflects unobserved future investment prospects, then cash flow may impact investment only because, like with mismeasured Q, it is correlated with the 'true' (perfectly measured) marginal Q used by firms to make their investment decisions. Correcting for measurement error in Q is, therefore, also vital in ensuring that cash flow can be measured and interpreted properly. Note that this impact persists even if the correlation is negative.

[38]See Robert Hall comment in Fazzari et al. (1988), pg.205.

It is commonly assumed that Q and cash flow rates are positively correlated. We find the relationship to be more complex in our data. For young and smaller firms a negative relationship exist, as negative cash flow correlates with higher valuations. For firms with cash flow rates (profitability) above 3% especially the correlation becomes strongly positive as cash flow increases along with valuations. In our coefficients we find a negative correlation between cash flow and Q. This makes sense: firms who are less financially constrained (lower cash flow coefficient) are more responsive to investment opportunities (higher Q coefficient). Our variance-covariance matrix finds -0.3 correlation between the cashflow and Q fixed effects (i.e. the global mean from which the random effects are drawn). Within the year random effect group there is no clear relationship between cash flow and Q, perhaps due to the loose prior we use, which assumes little correlation. However, for the country clusters we find a notable correlation between the two (even with a high estimated error), covering the 95% credible interval at $[-0.8, 0.07]$.

Care must be taken in what estimator to use in the context of measurement error. Some commonly used estimators, such as first differencing, will increase the size of the bias (Wooldridge 2016). A Bayesian approach to measurement error is computationally demanding but has several advantages. Firstly, the Bayesian estimator provides a posterior distribution that takes into account uncertainty due to estimating other parameters. In contrast, the classical estimator corrected for attenuation would require bootstrapping or some type of asymptotic approximation to account for this uncertainty. Secondly, Bayesian inference averages over plausible values of mismeasured Q in light of the data, rather than imputing a single best-guess and then proceeding as if this guess is correct. Uncertainty in estimation of Q is then propagated forward. Thirdly, we can integrate the measurement error with a more complex model: largely keeping our random effects structure, an autoregressive error structure, a student-t likelihood, and other deviations from a simplistic panel regression model (Carroll et al. 2006). A Bayesian approach to measurement error is formulated by treating the true quantities being measured as missing data (Clayton 1992; Sylvia Richardson and Gilks 1993; Gelman, Carlin, et al. 2013). The full model is detailed in Appendix D.

We conduct a sensitivity analysis in the Appendix to explore at what levels of measurement error our model results might change. Our cash flow random effect and fixed effect coefficients show little movement through various assumed levels of attenuation in Q. While only at very high levels of assumed attenuation bias in Q does it's fixed effect coefficient increase considerably ($\tau = 0.7$). Random effect Q coefficients do increase considerably at still high, but lower levels of attenuation bias ($\tau = 0.5$).

Moreover, even we assume very large levels of measurement error in our sensitivity analysis, the time-varying pattern of Q change does not change (nor the other variables). How likely are very high levels of measurement error in Q to occur? Erickson, Jiang, et al. (2014) find, using U.S. data, that the measurement quality of Tobin's Q to be quite low, approximately 45%. Evidence for developing economies appears not to be available though.

5 Deleveraging: Explaining estimated mean (intercept) investment rates

This section tries to explain reasons for the movement in the estimated mean investment rate (Figure 3), which displays cyclical variation, followed by the present deeper slump. Changes in this underlying impetus to invest can be understood theoretically as shifts in investors 'animal spirits' or in the exogenous marginal product of capital. In terms of our econometric model, this amounts to explaining variation *between* years in the random effects intercept coefficients using an additional set of 'macroeconomic' predictors which vary across years but not within each country or by firm. Adding predictors at the group level in a multilevel model corresponds to the classical method of contrasts in the analysis of variance (Gelman and Hill 2006).[39]

We use leverage as the main group-level predictor to predict the random effect intercept. In a world in which the Modigliani-Miller theorem does not hold, leverage matters to the investment decision of the individual firm – usually inversely (Ahn et al. 2006). In Jensen (1986) some leverage can, therefore, help the firm avoid over-investment. While in the model

[39]Group-level predictors are often interpreted as 'contextual effect' in the social sciences.

of Myers (1977) deleveraging can help the *individual firm* avoid having to pass up good investment opportunities, or invest less than the optimal amount if it reduces a company's risky debt.[40] These micro, firm-level, perspectives on leverage contrast with general-equilibrium and macroeconomic approaches in which more leverage can lead to more investment spending (Pintus and Wen 2013). When taken as a whole, deleveraging by the corporate sector can reduce aggregate demand and spending, with Japan being the classic case of this (Koo 2011).[41]

Empirically, leverage is known to be highly pro-cyclical (Caballero et al. 2019; Alter and Elekdag 2016), enabling a boom in investment rates as aggregate demand increases and finance constraints loosen. Mendoza and Terrones (2008) find a strongly positive association between leverage and the business cycle, including credit extensions, real exchange rate dynamics, and investment rates for industrial and emerging countries over the period 1960–2006. More recently some studies have, conversely, found leverage increasing among emerging market and developing economy firms even amidst the post-2008 downswing of the business cycle (Monitor 2014; Howell 2020).[42] Using Orbis data covering both public *and* private firms, Alter and Elekdag (2016) try show that emerging market corporate leverage increased dramatically between 2004 and 2014 . The authors note, however, that SMEs and other (non-listed) firms – firms not included in our sample – are likely the key drivers of aggregate emerging market corporate leverage dynamics. Moreover, their definition of leverage, as *total* liabilities over firm equity, shows only a moderate increase for the median firm from $\sim 59\%$ leverage in 2004 to $\sim 63\%$ in 2013.[43]

[40] Notes Myers 1977 (pg.3):"The argument is similar to Jensen and Meckling 1976 analysis of agency costs and optimal capital structure. The suboptimal investment policy is an agency cost induced by risky debt." In many respects this is what we see in our sample: firms are becoming more responsive to investment opportunities – not less – as deleveraging has occurred (as proxied by the time-varying Q coefficient in the previous section increasing).

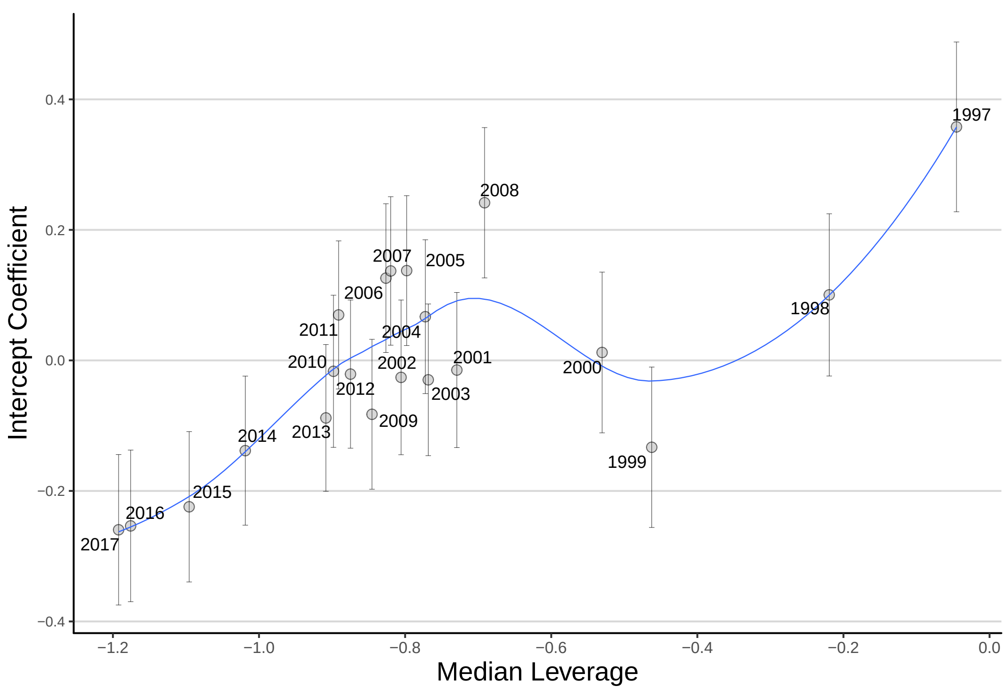
[41] In our data we do not see a big fall in asset values; and few firms with negative equity as expected from a classic 'balance sheet recession' (Koo 2011).

[42] Interest coverage ratios have deteriorated in advanced economies, where people now speak of 'Zombie firms' (using Worldscope data) (Banerjee and Hofmann 2020). This is confirmed in Compustat where in our advanced economy sample (Strauss and Yang 2020), interest expenses as a share of EBIT have been rising steadily since 2001 and by 2017 are at almost twice their 2000 level, 31% at the median. But evidence on this for developing economy firms is weak.

[43] Developing economy firms using low interest rates to deleverage (or to reduce total debt burden through refinancing at lower rates) is consistent with their estimated external financing constraints diminishing, as the time trend of our random effect cash flow coefficient shows. Studies have also tended to focus on the rise of *public* debt in emerging markets since 2008 (M. A. Kose, Nagle, et al. 2020). This is not inconsistent with the deleveraging of firms: tax revenue falls for government if firms spend less through deleveraging (all else being equals). Governments have also migrated bad private debt to public balance sheets to enable corporate deleveraging, especially in advanced economies. On international bond issuance by developing and emerging economies see Feyen et al. (2015).

We define leverage as total debt (short-term plus long-term debt) relative to the firms' total equity value (preferred stock plus common equity). We use median log leverage of our pooled sample within each year to try and account for changes in the underlying impetus of firms to invest (our time-varying random effects).[44] To do this we use the previously estimated random effects intercept coefficients as our investment rate 'data' to now be predicted by our new macroeconomic leverage predictor. This extended econometric model is detailed in Appendix B.2. In a classical regression, the group-level coefficients to be predicted and the group-level predictors would be collinear, and so must be run as two separate regressions (as in Hsiao and Tahmiscioglu 1997). This problem is avoided in a Bayesian model because of the partial pooling of the random group-level coefficients toward the estimated group-level population mean.

Figure 7. Estimated Mean Group Investment Rate Plotted against Median Leverage Group Predictor, 1997-2017, Log Scale.



Note: *Fitted local polynomial regression ('LOESS') line between the intercept coefficients – the regression data to be explained – and leverage, the group-level variable used to account for differences in pooled mean investment rates over time. 90% credible interval shown as vertical line. Median leverage is defined as total debt relative to total equity value of the median firm,* (dltt + dlc)/seq.

Figure 7 shows a clear positive relationship between the random effects intercept and

[44] Aggregate leverage also has predictive power but is less robust to outliers and amounts to using the mean of the sample. This is why we use the median.

median leverage within each year (of our pooled sample). Overall, there has been a shift from a high-leverage, high investment dynamic, to a relatively low-leverage, low investment one for developing country firms. Median leverage declines by 40% from 0.5 in 2008 to 0.3 in 2017. These leverage dynamics closely track other supporting metrics in our data, such as the inverse interest coverage ratio (IICR), defined as interest and related expenses over earnings before interest and taxes, (xint/ebit) – Appendix Figure 13.

After adding the median log leverage group-predictor to our baseline regression, all regressions are re-run concurrently as part of a single model. We find that a large portion (33%) of the variation between our random effects intercepts is statistically explained by median leverage within each year in our globally pooled sample. Formally, this amounts to the $\mathsf{SD}(\mathsf{intercept}_{year})$ declining from SD(0.17) to SD(0.12), with the uncertainty in this estimate remaining the same at 0.03.[45]

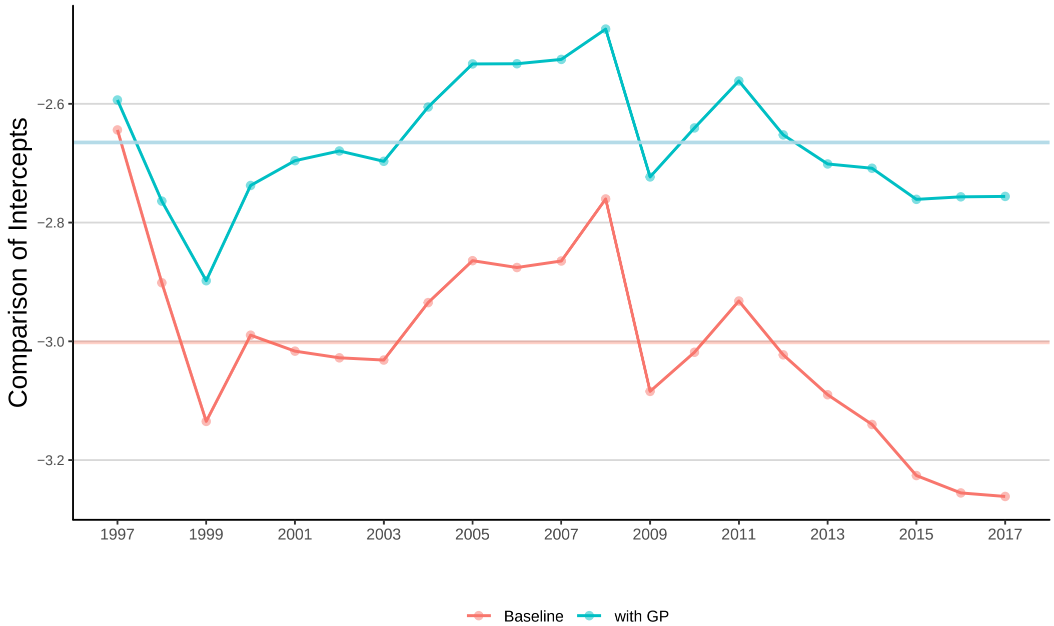
Next, in Figure 8 below, we plot the new random effects intercepts (top blue line) and compare it to the old random effects intercepts (bottom red line) to see which parts of the estimated investment cycle are best explained by the new median macroeconomic leverage predictor. We note the periods of the old random effects which change the most following the introduction of the new predictor: these are the uptick in estimated investment rates since 2001 and the decline in investment rates since 2013. In particular, a large portion of the dramatic drop in 'animal spirits' of firms since around 2011 can be accounted for by developing economy firms' deleveraging increasing. After accounting for this deleveraging in fact (top blue line), estimated investment rates now stay constant and even increase marginally between 2014-2017 (Figure 8).

Our findings on the role of leverage in explaining one third of the estimated underlying investment cycle ('animal spirits), including the more recent downturn, is somewhat at odds with Alter and Elekdag (2016), who appear to find leverage increasing strongly until 2013. We, however, cover a slightly different time period and use different data.[46] Magud and Sosa

[45] The 90% posterior credible interval for the variation in the random effects declines, therefore, from [0.12, 0.25] to [0.8, 0.18].

[46] They use Orbis data which covers small & medium sized enterprises (SMEs) and private firms, which the authors note are likely to be the main drivers of aggregate emerging market corporate leverage dynamics. Moreover, leverage among firms in their sample does not actually increase greatly past 2008. According to their Appendix: median firm *total* liabilities relative to total equity increases from around 56% in 2009 to approximately 60.5% in 2013, an 8% increase.

Figure 8. Predicted Investment Intercept With and Without Leverage Group Predictor



Note: *Plotting time-varying random effects plus fixed effects intercepts, with random effects population mean as a horizontal line. Using median log leverage as a group predictor sees the predicted time-varying random effects intercept investment rate shift up, as they are drawn from a distribution with a new higher population mean parameter (horizontal thick blue line). This group predictor helps account for much of the uptick in investment rates in the 2000s and especially the decline since 2013.*

(2015) instead find leverage negatively associated with emerging market investment rates at the firm-level. This runs counter to the notion that leverage is pro-cyclical.

What does this deleveraging association reflect though? Statistically, the data shows that it is due to a combination of strong equity issuance (growing denominator) coupled with a sharp fall in long-term debt (but only outside of china), plus a shift towards shorter-term debt, which increases in most countries still. Theoretically, our leverage finding is consistent with the theoretical lead-lag relationship between asset prices and investment in the 'financial accelerator', since median asset prices in our sample do fall following 2008 – and stagnate outside of China after years of rapid growth in the build-up to the 2008 GFC. It is also consistent with the finding of Li et al. (2015a), that firms with lower cash flows or more leverage reduce their investment more aggressively in response to greater financial market volatility (or higher interest rates). But given that U.S. interest rates fell post-2008; that external financing constraints decline in our sample; and that firms were able to issue new equity in most countries to reduce leverage, the above explanations are likely only partial interpretations of what our deleveraging predictor captures. Equally possible is that given slowing global growth, firms decided that deleveraging was a more optimal use of funds at the margin, either to maintain their return on capital, or given the increased cost of default in their eyes – as in a trade-off model of capital structure (Fama and French 2002). This is consistent with the Ozkan et al. (2020, p.234), who find that: "the incentives to attain target investment (leverage and cash holdings) got much weaker (stronger) in the aftermath of the financial crisis of 2008", such that the speed of adjustment to leverage and cash-holdings targets increases significantly. This in turn may be driven by slowing global and regional growth creating a relative constriction in aggregate demand, thereby limiting good investment opportunities, as with advanced economies (Strauss and Yang 2020).

6 Conclusion

Between 1997-2017 raw investment rates of developing economy firms show cyclical variation, declining steeply once Chinese investment rates fall after 2011, especially for the top half of the investment rate distribution. However, estimation of firms' 'cash flow-Q' investment demand function, using a Bayesian hierarchical model, indicates that investment demand may actually have slowed far more dramatically than raw investment rates suggest. Evidence from our time-varying intercept coefficients, reflecting the underlying mean impetus of firms to invest (their 'animal spirits'), show a sharp fall since the 2008 GFC to the lowest levels seen in our sample, with only a short-lived recovery between 2008-2011.

This collapse in the intercept of firms' investment demand function has occurred despite developing economy firms becoming less financially constrained over time, as cash flow coefficients have declined since 2008 amidst easy global monetary conditions; and despite developing economy firms becoming increasingly more responsive to investment opportunities. The latter is reflected in developing economy firms' time-varying Q coefficient values increasing since around 2012. Greater responsiveness of developing economy firms to investment opportunities is not necessarily a positive development though (Scott Richardson 2006), and may reflect a growing dearth of good investment opportunities facing firms relative to plentifully available financing post-2008 GFC (Howell 2020). This would also indicate that market power has not dulled firms' appetite for investment. Note though that this is only one channel through which this may operate and so we do not view this as definitive evidence of market power not dampening investment spending. This could instead operate through making firms move along their investment demand curve, or through creating a growing wedge between average and marginal Q (Abel and J. C. Eberly 1993).

Extending our hierarchical model, one-third of the variation in the underlying impetus of developing economy firms to invest is explained by the corporate sector's changing leverage behaviour, which increased at the median during the early 2000s and then fell considerably after 2008. Private sector deleveraging has historically risked creating a deflationary environment unless offset by a large increase in government spending and public debt accumulation, as was the case in Japan (Koo 2011). Growing leverage among advanced economy firms (Banerjee and Hofmann 2020) may to some extent be offsetting developing economy firms' deleveraging. But these cross-country private sector dynamics only risk creating further unsustainable global imbalances. This offset is likely only partial given weak wider economic conditions in advanced economies post-2008, especially in Europe. Weakening aggregate demand in advanced economies since 2008 is likely to have contributed to the fall in 'animal spirits' of developing economy firms in our sample. These negative spillovers we have not been able to estimate though.

China to some extent appears to act as an alternative centre of economic gravity for developing economy firms and so works to offset the deflationary impact of slowing demand growth from advanced economies. This is somewhat evident in our sample by their investment rate peak extending into 2011, thereby offsetting firm's underlying impetus to offset from falling further from 2008. A separate analysis might tell us what exactly the changing contribution of Chinese investment is to driving wider developing economy investment rates.

Finally, our study is not representative of all firms in developing economies, but as larger firms our sample reflects an important – if not always the primary – driver of private investment, innovation, and employment. As publicly listed firms, our sample probably faces fewer financing constraints than the majority of firms in developing economies, which are small & non-listed, and so our findings on financing constraints stand with that important caveat in mind. SME growth may reflect the dynamism and churn of the private sector, while our study focuses on firms who are already at the frontier of domestic production and so who macroeconomically have the largest present direct impact on the total quantum of fixed capital investment expenditure. Further studies might explore if our findings hold for SMEs and private firms, as separate rather than pooled samples (Alter and Elekdag 2016). As well as even the interaction between these sub-samples through a hierarchical model.

Our study has tried to show the considerable flexibility and predictive potential of a mixed effects Bayesian approach to micro-data; not only for small samples as in Meager (2019), but also for exploring variation in large datasets, which are increasingly common in academic research and which traditional econometric approaches may over-fit and under-explore.

Funding

No funding was received for this project. We have no conflicts of interest to declare.

Acknowledgements

Data availability

The data underlying this article cannot be shared publicly due to it being proprietary. The data comes from S&P's Compustat Global and downloaded via Wharton's WRDS - a paid subscription data interface. For those with existing paid access to the Compustat Global database the data can be shared. The data can also be shared on a case by case basis if permission is granted by S&P.

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Appendices

For Online Publication. This Appendix draws on Strauss and Yang (2020).

A Model

Following the formulation in J. Lewellen and K. Lewellen (2016), the value of the firm V_t is maximized with respect to the control variable investment I_t, given the capital stock K_t in period t and subject to the net present value of its profits $\Pi(K_t, s_t)$, less adjustment costs related to investment $C(I_t, K_t, \lambda_t)$, and less investment expenditure I_t. Profits are a function of a state variable s_t, reflecting past investment decisions and the firm's capital stock K_t. Quadratic investment adjustment costs are related to an exogenous stochastic parameter λ_t. The recursive Hamiltonian is:

$$V_t = \Pi(K_t, s_t) - I_t - C(I_t, K_t, \lambda_t) + \beta E_t[V_{t+1}]. \tag{5}$$

The first order condition (FOC) taken with respect to the control variable investment I_t in period t is (Romer 1996):

$$1 + C_I(I_t, K_t, \lambda_t) = \beta E_t[V_k(K_{t+1}, s_{t+1}, \lambda_{t+1})] \tag{6}$$

$$= q_t. \tag{7}$$

Equation 6 states that the firm invests until the purchase price of capital (fixed at 1), plus the marginal adjustment cost, equals the marginal value of capital. q_t is the present discounted value of future marginal revenue products of an additional unit of capital. This makes q the market value of an additional unit of capital. With a purchase price of capital fixed at 1, q is the ratio of the market value of an additional unit of capital to its replacement cost, if $\Pi(K_t, s_t)$ is homogeneous of degree 1 (Abel and J. C. Eberly 1993). We proxy this by the book-to-market value of the firm.[47] Next, quadratic investment adjustment costs for $C(\cdot)$ are assumed. Substitution of this into the FOC leads to the following - with subscript

[47]We use market value of equity plus book value of debt for the numerator (market value) and total assets as the denominator (book value). This keeps the variable strictly positive, despite some loss of interpretation.

I referring to the partial derivative with respect to investment:

$$\mathrm{C}_t = \frac{1}{2}a\left(\frac{I_t}{K_t} - \lambda_t\right)^2 K_t, \tag{8}$$

$$\mathrm{C}_I = a\left(\frac{I_t}{K_t} - \lambda_t\right), \tag{9}$$

$$\frac{I_t}{K_t} = -\frac{1}{a} + \frac{1}{a}q_t + \lambda_t, \tag{10}$$

where λ becomes the error term in the investment regression, a is a time-invariant adjustment cost parameter, and q_t is a sufficient statistic to explain the firm's investment rate. To get the firm's present cash flow into regression equation 10, assume that external finance is more costly than internal finance due to financial market imperfections, thereby creating a 'Pecking Order' of preferred sources of financing for the firm (Myers 1984; Myers and Majluf 1984). Assume external financing demand of the firm is roughly proportionate to $I_t/K_t > \Pi_t/K_t$, with quadratic external financing (EF) cost:

$$\mathrm{EF}_t = \frac{1}{2}b\left(\frac{I_t}{K_t} - \frac{\Pi_t}{K_t}\right)^2 K_t, \tag{11}$$

$$\mathrm{EF}_I = b\left(\frac{I_t}{K_t} - \frac{\Pi_t}{K_t}\right). \tag{12}$$

The cost of external financing is assumed to be $b \geq 0$. Plugging the above into the Equation 5 leads to the following final regression specification which we estimate:

$$\frac{I_t}{K_t} = -\frac{1}{a+b} + \frac{1}{a+b}q_t + \frac{b}{a+b}\left(\frac{\Pi_t}{K_t}\right) + \frac{a}{a+b}\lambda_t. \tag{13}$$

Equation 13 estimates firms' investment demand schedule, with a slope of q in investment-Q space. The q coefficient declines in proportion to $1/(a+b)$, such that an increase in a, the time-invariant adjustment cost parameter, and/or in b, the cost of external financing, should reduce the coefficient size of q. As can be seen, cash flow Π_t/K_t enters directly into the regression equation.

B Bayesian Hierarchical Model

B.1 Technical Model Specification

Equation 3 can formally be written in a hierarchical form as:

$$\log(y_i) \sim \mathrm{t}_\nu(\mu, \sigma_y^2, \nu_y), \tag{14}$$

$$\mu_{[i]} = X_i^0\beta^0 + X_i\beta_{t,c,j[i]} + \rho\epsilon_{i,t-1}, \qquad \text{for } i \in 1:n \tag{15}$$

$$\beta_{t,c,j} \sim \mathrm{MVN}(M_\beta, \Sigma_{t,c,j}^\beta), \qquad \text{for } t,c,j \in 1:T,C,J, \tag{16}$$

Equation 14 shows that our regression model is specified in log-level form. By making our dependant variable roughly normal, this dramatically improves sampling efficiency and reduces heteroskedasticity.[48] We use a symmetric student-t distribution t_ν, with the degree of freedom ν, as our likelihood function.[49]

The mean of the investment function (eq.15) is the location parameter μ of the t-likelihood, and estimated as the combination of the fixed effect and random effect coefficients. X_i^0 are the fixed effect predictors, with parameter estimates β^0 from the pooled, population-level regression. X_i are the 3 random, group-level, predictors with parameter estimates $\beta_{t,c,j[i]}$, varying for each 'cluster' within each group of countries and years (and country:years). The time- and country-level group regressions contain 24 and 18 clusters, respectively, such that $T = 24$ and $C = 18$, and the country:year level contains $J = 24$ x $18 = 432$ clusters. The country:year group coefficients are country-specific time effects (or equivalently time-specific country effects).[50] For each of the three groups (t, c, j), $\beta_{t,c,j}$ is a vector of length 3 random effects corresponding to the t^{th} c^{th} or j^{th} row of β. Finally, $\epsilon_{i,t-1}$ is the error term at time $t-1$, where ρ represents the estimated AR(1) error process. This estimates the degree of auto-correlation in the error term, and, therefore, the state-dependence of the investment

[48] This can be seen by running simple quantile investment regressions of log(Q) on investment, and plotting the fits across quantiles (Koenker and Hallock 2001; Deaton 1997).

[49] Although the student-t distribution becomes 'normal' shaped as $\nu_y \to \infty$, its longer tails allow it to accommodate outlying observations. A 't-likelihood' also effectively adjusts for a particular model of heteroskedastic normal errors (Arnold 2019).

[50] This structure implies that firms are 'cross-classified', with each firm belonging to only a single country, but to more than one year, and more than one 'country:year' cluster. We describe this as a non-nested model. However, 'country-country' clusters are nested *within* year clusters and country clusters (rather than the other way around), in the same way as students are nested within classes.

rate over time.[51]

For each group t, c, j, eq. 16 estimates the 3 random effects of our model $\beta_{t,c,j}$, as deviations around $M_\beta = \{\mu_\alpha, \mu_q, \mu_{cf}\}$, the grand mean of each of our 3 random effect predictors, drawn from a common multivariate normal (MVN) distribution.[52] The variance-covariance matrix Σ_β, is estimated separately for each t, c, j group of random effect parameters, with the 3 variance parameters in each group $\sigma_{\alpha,q,cf}$, determining the extent of variability in parameter estimates across countries, years, or country:years.

As the key quantities of interest of our investment model, *cash flow*, Q (Market-to-book or MTB ratio), and the *intercept* are estimated as both *fixed effects* and *random effects*, as recommended by Schmidt-Catran and Fairbrother (2015), among others. They are included in every level of our model and are the only predictors for the country, year, and country:year group regressions. In our 'fixed' population regression level, we also include a firm size dummy, an industry dummy, and a capacity utilization dummy (a capital-output ratio).[53]

B.2 Extension for Inclusion of Group-Level Predictors

When including log leverage as a group predictor, we select the median value of leverage within each year. This allows it to explain variation between years, while being constant within each country.

This amounts to our hierarchical model being extended to also predict the mean of the

[51]For computational reasons, we do not apply the error structure to the covariance matrix. This is also why we do not use a higher order AR process, since model improvement, judged by Bayesian R^2, is minimal while computational time increases considerably. Also, note that this auto-correlation structure is not independent from the random effects components, even though they are defined in separate parts of the model specification. This is because the fixed effects, random effects, and auto-correlation components all go into the same regression for Y, and so are estimated together.

[52]Later we use group predictors to model $\mu_\alpha = \gamma_0^\alpha + \gamma_1^\alpha \mu$, where μ will vary for each group $\{t, c, j\}$. X_i matrix is, therefore, able to contain group-level predictors too.

[53]For computational purposes, the actual model is implemented and estimated using a non-centered parameterization to improve convergence and reduce bias. It does not affect the interpretation of parameters, and so is not discussed further. Under a non-centered parameterization, our population means μ_α enter the population regression, leaving the prior on the random effects with a mean of zero. The random effects are also transformed into z-scores, $Z_{t,c,j}$, giving them a fixed prior that is unit normal. As a result the estimated population-level fixed effect parameters of cash flow, Q, and the intercept, $\beta^0_{cf}, \beta^0_q, \beta^0_\alpha$, would be indistinguishable from their estimated population means in the random effects distribution $\mu_\alpha, \mu_q, \mu_{cf}$. As a result, $X^0_i \beta^0$ only contains the fixed effects that have no random effect counterpart. For details see: Betancourt and Girolami (2015).

intercept coefficient distribution M^{α}_{β} for each year group t:

$$\beta_t \sim \mathrm{MVN}(M^{\alpha}_{\beta}, \Sigma_{\beta_t}) \tag{17}$$

$$M^{\alpha}_{\beta} \sim \mathrm{N}(\gamma_0 + \gamma_1 \mu, \sigma_{\alpha}). \tag{18}$$

μ is estimated just for the year group t, using data points running from 1 to 21, i.e. the number of estimated random effect intercept coefficients within the year group.

B.3 Hierarchical Priors and Variance-Covariance Structure

Below we write our variance-covariance structure more explicitly, beginning with the random effects being drawn from a wider population distribution, governed by hyper-parameters $(M_{\beta}, \Sigma^{\beta}_{t,c,j})$:

$$\begin{pmatrix} \alpha_{t,c,j} \\ \beta^{q}_{t,c,j} \\ \beta^{cf}_{t,c,j} \end{pmatrix} \sim \mathrm{MVNormal} \left[\begin{pmatrix} \mu_{\alpha} \\ \mu_{q} \\ \mu_{cf} \end{pmatrix}, \quad \Sigma^{\beta}_{t,c,j}, \right], \tag{19}$$

Each group t, c, j has its own variance-covariance matrix (though we do not write it out 3 times). Within each group, the variance-covariance matrix (eq. 20) is $\Sigma^{\beta} = \mathrm{D}(\sigma)\,\Omega\,\mathrm{D}(\sigma)$, where $\mathrm{D}(\cdot)$ has the standard deviation of each of the 3 random effect variables along the diagonal:

$$\Sigma^{\beta}_{t,c,j} = \begin{pmatrix} \sigma_{\alpha_{t,c,j}} & 0 & 0 \\ 0 & \sigma_{\beta^{q}_{t,c,j}} & 0 \\ 0 & 0 & \sigma_{\beta^{cf}_{t,c,j}} \end{pmatrix} \Omega \begin{pmatrix} \sigma_{\alpha_{t,c,j}} & 0 & 0 \\ 0 & \sigma_{\beta^{q}_{t,c,j}} & 0 \\ 0 & 0 & \sigma_{\beta^{cf}_{t,c,j}} \end{pmatrix}. \tag{20}$$

Ω shows the correlation between the random effect coefficients for different variables, such that we have:

$$\Omega_{t,c,j} = \begin{pmatrix} 1 & \rho_{\alpha_{t,c,j},\beta^q} & \rho_{\alpha_{t,c,j},\beta^{cf}_{t,c,j}} \\ \rho_{\alpha_{t,c,j},\beta^q_{t,c,j}} & 1 & \rho_{\beta^q_{t,c,j},\beta^{cf}_{t,c,j}} \\ \rho_{\alpha_{t,c,j},\beta^{cf}} & \rho_{\beta^q_{t,c,j},\beta^{cf}_{t,c,j}} & 1 \end{pmatrix}. \tag{21}$$

B.4 Priors

Priors

We put a loose LKJ prior on the covariance matrix of the multivariate *normal* distribution, with $\eta = 5$, such that prior independence between coefficients — a diagonal co-variance matrix — is the default. Our list of hyper-priors are:

$$M_\beta \sim \mathrm{N}(0, 0.5), \tag{22}$$

$$\sigma_{\alpha_{t,c,j}},\, \sigma_{\beta^q_{t,c,j}},\, \sigma_{\beta^{cf}_{t,c,j}} \sim \mathrm{Cauchy}(0, 2), \tag{23}$$

$$\Omega_{t,c,j} \sim \mathrm{LKJcorr}(5)\,. \tag{24}$$

The prior for the variables' population means M_β, follows a normal distribution centered at zero with a reasonably informative standard deviation of 0.5. This allows for an equal probability of negative and positive parameter values. Our model is not sensitive to the priors chosen. This is because our priors are only informative enough to help aid in the convergence properties of the model. Our other priors are:

$$M_\beta \sim \mathrm{N}(0, 0.5), \tag{25}$$

$$\alpha^0 \sim \mathrm{N}(0, 1.5), \tag{26}$$

$$\beta^0 \sim \mathrm{N}(0, 0.5), \tag{27}$$

$$\log(Q)^0 \sim \mathrm{N}(0.3, 0.3), \tag{28}$$

$$\nu \sim \mathrm{Gamma}(2, 0.1), \tag{29}$$

$$\sigma_y,\ \sigma_{\alpha,q,cf\in t},\ \sigma_{\alpha,q,cf\in c},\ \sigma_{\alpha,q,cf\in j} \sim \mathrm{Cauchy}(0, 2), \tag{30}$$

$$\mathbf{R} \sim \mathrm{LKJcorr}(5)\,. \tag{31}$$

On the LKJ prior: The multivariate normal density and LKJ prior on correlation matrices both require their matrix parameters to be factored. This is achieved by parameterizing the model directly in terms of Cholesky factors of correlation matrices using the multivariate version of the non-centered parameterization. The Cholesky decomposition is: $\Sigma^\beta = \mathrm{LL}^\mathbf{T}$, where L is a lower-triangular matrix. Inverting Σ^β is numerically unstable and inefficient. This is the preferred modern Bayesian prior (Stan Development Team 2019). The LKJ distribution for correlation matrices is $\mathrm{LKJcorr}(\Omega|\eta) \propto \det(\Omega)^{\eta-1}$, where $\eta > 0$ determines the degree of correlations (Lewandowski et al. 2009). The LKJ distribution behaves similarly to the beta distribution for scalars. $\eta = 1$ is a special form of a non-informative uniform distribution on correlation, $\eta > 1$ leads to less correlation between group-level coefficients, with more mass concentrated around the identity matrix, while $\eta < 1$ leads to stronger prior correlation between group-level coefficients as more mass is concentrated in the other directions. We use a loose LKJ prior with $\eta = 5$, such that prior independence between coefficients — a diagonal co-variance matrix — is the default. This helps with convergence for some of the models we run, such as the measurement error model. For robustness we run the models with $\eta = 1$, and the results are essentially the same.

C Data and Variable Description

Familiarity with IFRS accounting models can help one understand differences and similarities in variables across countries (for example PWC 2018). Our variables are reported gross, i.e. before amortization and depreciation, but after tax, unless stated otherwise. All dates and plots are for the fiscal year rather than the calendar year. We first look at and clean the combined sample of Compustat North America and Compustat Global before selecting our developing economy sub-sample.

C.1 Data Cleaning

Assets values and capital expenditure values less than or equal to zero we replace with 'NA'. We replace 'NA' values found in intangibles, goodwill, and exchange rate adjustments (cash-flow statement) with zero. For intangibles this follows Peters and Taylor (2017).

The first round of data processing limits the dataset to firms with positive values for all three of the following: gross capital stock, capital expenditure, and revenue. We exclude firms working in gardens, zoos, museums, non profit organisations, and utilities, but keep gas production and distribution. We remove financial companies but keep real estate and certain other related companies. This amounts to removing SIC codes 491, 84, 86, 493-499, 60-64, and 66-69.

The second round of data processing: We trim (i.e. remove) the bottom 0.5% of observations by capital stock. This sets a minimum capital stock value of 0.299 and is done because capital stock serves as the denominator for the key quantities of interest. We trim the bottom 0.5% of observations by capital expenditure. Next we keep only observations with values greater than or equal to zero for key variables RECT, CHE, XINT, and DLC and strictly greater than zero for LCT. We then trim the top 0.1% of the quick ratio variable (defined as ACT/LCT), and we trim the top and bottom 0.5% of cash flow rate observations.

C.2 Variable Definitions and Discussion

Key ratios we tend to modestly winzorise and trim. Ratios are sensitive to the denominator.

Capital Stock: Is defined gross (i.e. before depreciation and amortisation) as PPEGT + INTAN + INVT which is the sum of gross property, plant and equipment, intangible assets, and inventories. Our preferred capital stock measure includes intangibles and inventories, though our findings are not dependant on them. The BEA measure of capital stock now includes intangible assets (including software, R&D, and some intellectual property). Studies tend to include intangibles in their capital stock measure or at least adjust for it now (Fernald et al. 2017; Peters and Taylor 2017). See also: Haskel and Westlake (2018). However, intangible assets are measured net. Various simple methods of adjustment can be undertaken but did not appear to materially impact the results. More complex adjustment can be found in Peters and Taylor (2017), who notes a positive impact on Q coefficient values from the inclusion of intangible assets. Gross investment rates are recommended rather than 'net' for cross-country comparisons for national accounts and firm-level data (Lequiller and Blades 2014). GAAP and IFRS contain important differences in depreciation rules, implied by how development costs are capitalized differently, and also differences in how impairment losses and component depreciation are treated.

'Rates' and Capital-Output Ratio: all 'rates' are defined over the firms (gross) capital stock as the denominator. This includes the following variables: investment rate, cash flow rate, profit rate, and the capital-output ratio (which is defined as sales over the firms capital stocks).

Cash Flow: is defined as OANCF off the cash flow statement. The variable is measured gross, after taxes and interest payments, after making adjustments for changes in working capital and other non-operating income. See Compustat Balancing Models excel documents for a moderately detailed definition. Cash flow rates on fixed capital will be exaggerated in Compustat since OANCF includes dividends received by the firm, for example, but does not deduct dividends made.

Profit: We define profit from the income statement as OIBDP - TXT - XINT or gross operating income before depreciation and amortization after deducting taxes, interest payments and income.

Binned Variables and Dummies: All binned variables are made using the *cut2()* function in R. This ensures that an equal number of observations are in each bin unless this would not be ideal for the optimisation algorithm. The mean value in each bin is used as the bin label.

Leverage: is defined as total debt relative to total equity value, (DLTT + DLC)/SEQ.

Inverse Interest Coverage Ratio: is defined as interest and related expenses divided by earnings before interest and taxes, XINT/EBIT.

Tobin's Q: We calculate the firm's market-to-book ratio (MTB). Books values, the denominator, is calculated in the same manner across all countries in our sample. Market value calculations differ, however, between Compustat Global and Compustat North America. *For Compustat North America* this calculation is relatively easy, and is equal to the market capitalization of the firm's equity plus the book value of the firms debt: (CSHO * PRCC_F * AJEX) + (DLC + DLTT), while the book value of assets is AT. We adjust (i.e. multiply) CSHO by AJEX, which accounts for stock splits and stock dividends.

For Compustat Global, from which our sample in this paper comes from, the process of calculating the 'equity market capitalization' component is somewhat more involved and requires making additional assumptions. Data is downloaded for the last available month of the year ('end of month' filter) and when 'earnings participation flag' is equal to 'yes'. The company may have market values on several exchanges globally. Market capitalization is calculated across each exchange before being aggregated across, whereby we have QCSHOC = ((CSHOC*QUNIT)/1,000,000), marketcap = PRCCD*QCSHOC and $\mathsf{marketcap}_T$ =sum(marketcap), across all exchanges, where shares outstanding are CSHOC, and PQUNIT represents the size of the block in which the shares are quoted on the exchange. In particular see Compustat (2009) for further details. Our calculation excludes non-traded shares.

The literature tends to define Q as Market Value of Fixed Capital / Book Value of Capital. Erickson and Whited (2006) finds this performs better than other measures, such as market-to-book value of the firm, but not by much. We use the firm's market-to-book ratio (MTB) as our proxy for Tobin's Q. MTB likely captures average rather than margin Q though, which is only equal under restrictive assumptions (Hayashi 1982). Damodaran (2013) notes in particular that non-traded shares, management options, non-traded debt, off-balance sheet debt, trapped cash, and convertible securities can all lead to measurement error in enterprise value which ideally one should adjust for. In particular, cross-holdings in other companies may upwardly bias the (consolidated market) value of the enterprise.

From a computational perspective, using a variable which can only take on positive has considerable benefits too - especially in a Bayesian model. This allows us to log the variable which makes the sampling process several times quicker. Secondly, it helps reduce heteroskedasticity considerably. This can be seen by running simple quantile investment regressions of Q on investment and plotting the fits across quantiles (Koenker and Hallock 2001). See also (Deaton 1997). Thirdly, Q becomes lognormal when logged. This is related to Q being roughly log-normal. Finally, a log interpretation of Q is empirically more sensible since in general Q values tend to have quite a high variance (rather than in theory, where they are assumed to generally be between zero and one). A firm with a Q value of 20 we would expect to react differently to a one unit change in its value than a firm with a Q value of 0.5 or 1.

C.3 Country Selection and Categorisation

Country location of firm is based on foreign incorporation code (FIC) rather than country of headquarter or country of listing. We have 11 countries in total across 21 years. Country inclusion is based first on average GDP per capita (nominal) US$ between 1997-2017 of $15,000 or less. To be included in the fina sample the country then needed to have 1,400 or more observations in the Compustat file between 1997-2017. This gives us 11 developing economies in our sample covering the majority of GDP of developing economies. This includes: Brazil ("BRA" - 1,475 observations), China ("CHN" - 24,486), Indonesia ("IDN" - 2,729), Korea ("KOR" - 12,579), Malaysia ("MYS" - 8,832), Pakistan ("PAK" - 2,254), Poland ("POL" - 1,601), Thailand ("THA" - 5,212), Taiwan ("TWN" - 15,411), and South Africa ("ZAF" - 2,196).

Table 2. Data Sample Summary

Country Group	1997-2002	2003-2008	2009-2017
AFC	5,767	8,461	15,124
China	1,779	6,206	16,501
Others	2,820	10,828	23,583

Note: *Showing number of data points in our sample, by year and country grouping.*

C.4 Developing Economy Firm Sample Compared to Advanced Economy Firm Sample in Compustat

Below we compare our sample of firms to a sample of developed economy firms from Compustat. They both cover the same years, 19978-2017, and come from the sample combined sample, in effect prepared together with the same trimming and imputations. Developed economy firms include: "USA", "JPN", "GBR", "CAN", "AUS", "CYM", "FRA", "DEU", "SGP", "BMU", "SWE", "ISR", "CHE", "ITA", "NLD", "NOR", "DNK", "FIN". 182,062 observations are in the advanced economy sample and 91,069 in the developing economy sample.

Table 4. Size of Developing Economy Firms Compared to Developed in Compustat

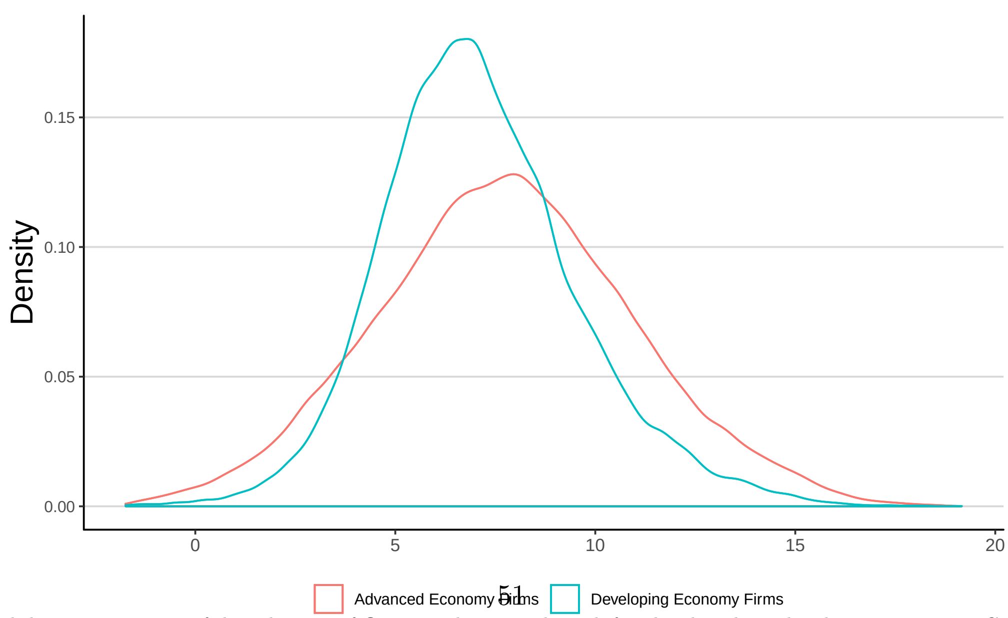
Country Group	Median	MAD	P10	P30	P70	P90
Advanced Economy Firms	215	296	12	68.2	676	3914
Developing Economy Firms	122	143	18.8	55.1	291	1275

Note: *Size is the gross capital stock, defined as property, plant, and equipment, inventory, and intangible assets. MAD stands for median absolute deviation.*

Table 3. Detailed Data Sample Summary by Country and Year

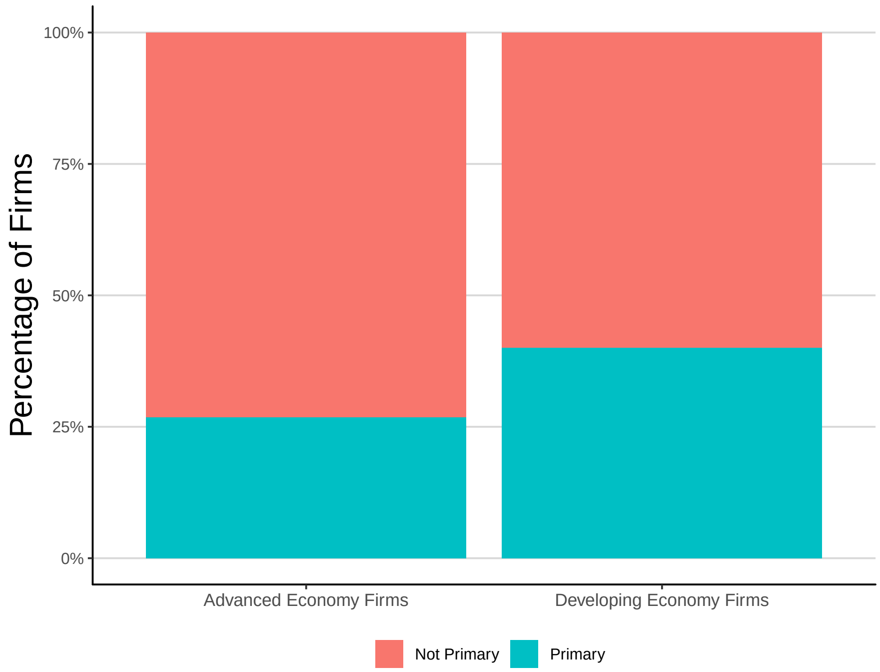
Year	BRA	CHN	IDN	IND	KOR	MYS	PAK	POL	THA	TWN	ZAF
1997	2	8	139	92	203	377	54	1	189	86	52
1998	6	17	148	103	201	366	56	7	173	97	54
1999	7	19	142	97	216	369	61	9	185	121	61
2000	10	22	135	103	214	374	70	6	135	140	75
2001	18	811	150	215	301	396	59	8	179	173	74
2002	23	902	166	283	315	484	45	11	210	455	86
2003	26	995	176	347	351	545	63	21	252	647	84
2004	38	1094	175	409	377	602	67	36	253	696	98
2005	44	1078	161	497	411	647	92	58	296	758	125
2006	61	1126	145	619	447	565	102	77	241	967	130
2007	108	915	86	857	611	450	117	89	247	963	130
2008	112	998	94	949	679	416	109	102	234	1104	126
2009	118	844	88	978	628	379	119	99	221	1082	131
2010	127	1522	100	1102	672	391	111	82	257	1164	131
2011	125	1725	121	1147	835	387	124	101	257	1221	133
2012	125	1788	105	1187	897	363	159	113	274	1229	119
2013	117	1778	125	1130	975	343	165	128	297	727	125
2014	110	1908	118	1068	977	354	173	154	312	917	120
2015	108	2098	113	1081	1053	347	162	176	319	958	116
2016	94	2261	109	1010	1085	341	168	166	333	950	117
2017	96	2577	133	1020	1131	336	178	157	348	956	109

Figure 9. Density of Firm Size by Sample: Developed vs. Developing Economy in Compustat



Note: *Kernel density estimate of distribution of firm size by capital stock for developed vs. developing economy Compustat firm samples for the period 1997-2017.*

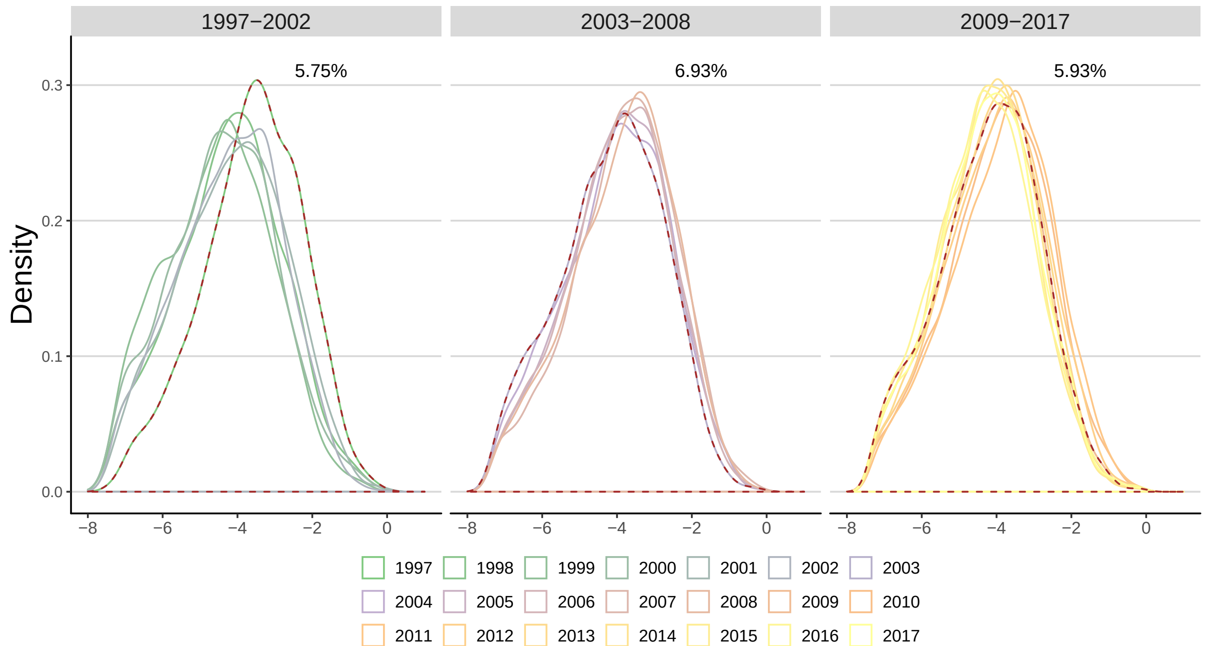
Figure 10. Industry Structure of Firms by Sample: Developed vs. Developing Economy in Compustat



Note: *Showing percentage for the period 1997-2017 based on SIC2 codes. Codes: 01, 02, 07, 08, 09, 10, 12, 13, 14, 20, 22, 28, 29, 30, 32, 33, 34 are for the "Primary Sector", while all other codes are for the "Not Primary" sector.*

C.5 Movement of Key Variables by Time and Country Group

Figure 11. Distribution of Developing Economy Firm-Level Investment Rates, By Time Period, 1997-2017



Note: *Kernel density approximation of log2() firm gross investment rates for 11 advanced economies. Black-orange dashed line is for the first year in each year group (1997, 2003, 2009). For the first time period (smaller sample size): sharp shift inward to the left after 1997, and then somewhat back out as investment recover from the 1997 Asian Financial Crisis. For the second time period: investment rates extend outwards to the right after 2003, increasing (becoming darker). For the final time period: we see a positive shift to the right after 2009 (orange lines) as some initial recovery occurs assisted by China, before shifting inwards to the left (yellow lines) since around 2014/2015. Median investment rate for each year group written above.*

Table 5. Investment Rate by Country and Year Group

Country	Time Period	Min.	P25	P50	Mean	P75	Max.	MAD
AFC	1997-2002	0.01	0.02	0.05	0.08	0.10	0.89	0.05
AFC	2003-2008	0.01	0.03	0.06	0.08	0.11	0.89	0.05
AFC	2009-2017	0.01	0.03	0.05	0.07	0.09	0.89	0.04
China	1997-2002	0.01	0.04	0.09	0.12	0.15	0.89	0.08
China	2003-2008	0.01	0.04	0.08	0.10	0.14	0.89	0.07
China	2009-2017	0.01	0.04	0.07	0.10	0.13	0.89	0.06
Others	1997-2002	0.01	0.03	0.06	0.09	0.12	0.89	0.06
Others	2003-2008	0.01	0.04	0.08	0.11	0.14	0.89	0.07
Others	2009-2017	0.01	0.03	0.06	0.08	0.10	0.89	0.05

Note: *Investment rates are cyclical, declining after the 2008 global financial crisis for most countries, years, and percentiles.*

Table 6. Cash Flow Rate Percentiles by Country and Year Group

Country	Time Period	Min.	P25	P50	Mean	P75	Max.	MAD
AFC	1997-2002	-3.79	0.01	0.07	0.08	0.14	1.86	0.10
AFC	2003-2008	-3.54	0.01	0.07	0.07	0.14	1.85	0.10
AFC	2009-2017	-3.89	0.02	0.08	0.09	0.16	1.85	0.10
China	1997-2002	-2.17	0.02	0.08	0.07	0.14	1.20	0.08
China	2003-2008	-2.69	0.02	0.08	0.08	0.14	1.67	0.08
China	2009-2017	-3.86	0.01	0.07	0.07	0.14	1.77	0.10
Others	1997-2002	-3.29	0.03	0.09	0.11	0.17	1.84	0.10
Others	2003-2008	-3.81	0.03	0.10	0.13	0.20	1.83	0.12
Others	2009-2017	-3.52	0.04	0.10	0.12	0.18	1.84	0.10

Note: *Cash flow rates increase for most countries and most years.*

Table 7. Q (Book) Value Percentiles by Country and Year Group

Country	Time Period	Min.	P25	P50	Mean	P75	Max.	MAD
AFC	1997-2002	0.08	0.54	0.72	0.85	0.94	14.54	0.28
AFC	2003-2008	0.09	0.54	0.73	0.94	1.04	18.16	0.33
AFC	2009-2017	0.08	0.62	0.86	1.23	1.34	33.35	0.44
China	1997-2002	0.08	1.40	1.96	2.27	2.83	10.35	0.98
China	2003-2008	0.09	0.89	1.24	1.63	1.87	20.71	0.63
China	2009-2017	0.09	1.17	1.85	2.41	2.99	33.60	1.20
Others	1997-2002	0.08	0.55	0.74	1.10	1.12	25.43	0.35
Others	2003-2008	0.08	0.68	0.94	1.29	1.47	27.89	0.48
Others	2009-2017	0.08	0.68	0.92	1.33	1.45	33.02	0.46

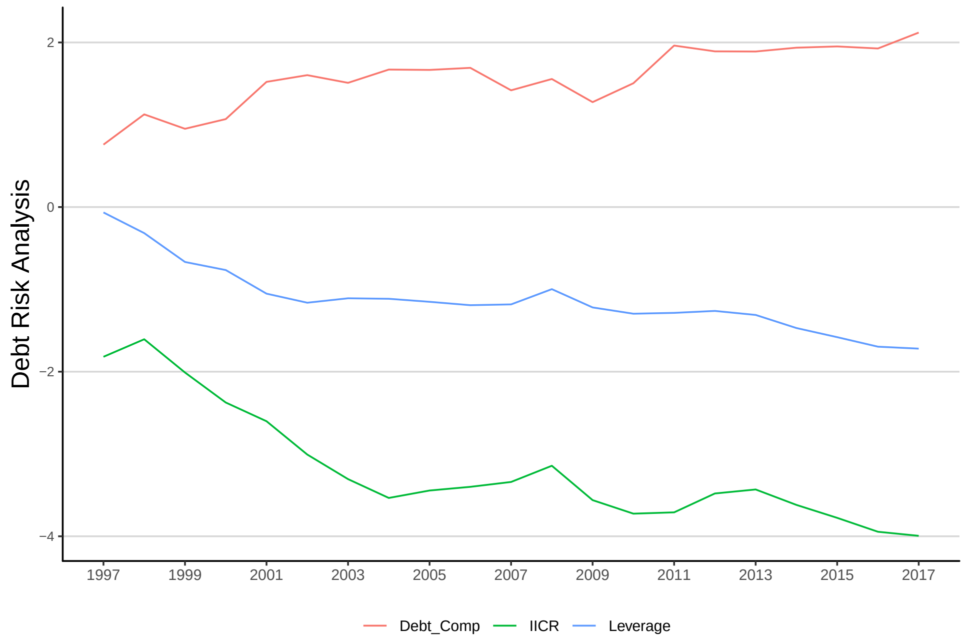
Note: *Q values are increasing for most of our sample for most years.*

Table 8. Quick Ratios by Country and Year Groups

Country Group	1997-2002	2003-2008	2009-2017
AFC	0.755	0.962	1.02
China	0.941	0.726	1.05
Others	0.810	0.958	1.01

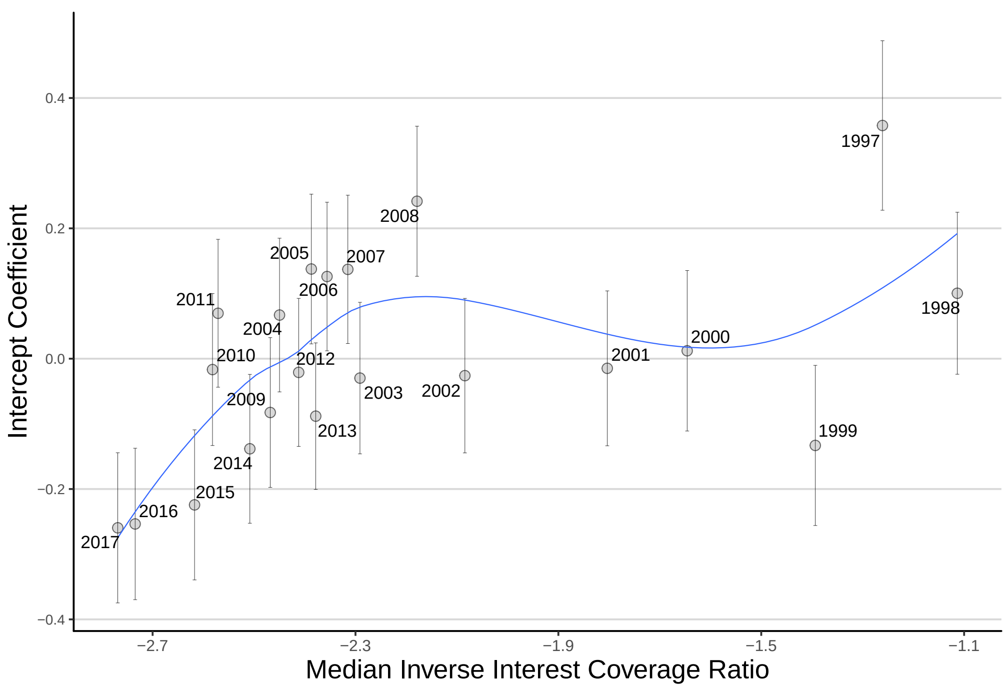
Note: *Quick ratio is defined as short-term assets over short-term liabilities, using Compustat terminology* (che + rect)/(lct). *China's sample prior to 2001 is small and so estimates are less reliable for it prior to then.*

Figure 12. Key Debt Measures (Median), Pooled Sample, Log2 scale, 1997-2017



Note: *Debt composition is proportion of short-term debt relative to long-term debt –* median(dlc)/median(dltt)*. This shifts away from long-term debt and towards short-term debt since 2009. At lower interest costs and lower total relative debt levels (leverage) this sees a decline in the inverse interest coverage ratio (interest costs relative to* EBIT*), such that interest payments account for a declining portion of earnings. Leverage is total debt over total equity.*

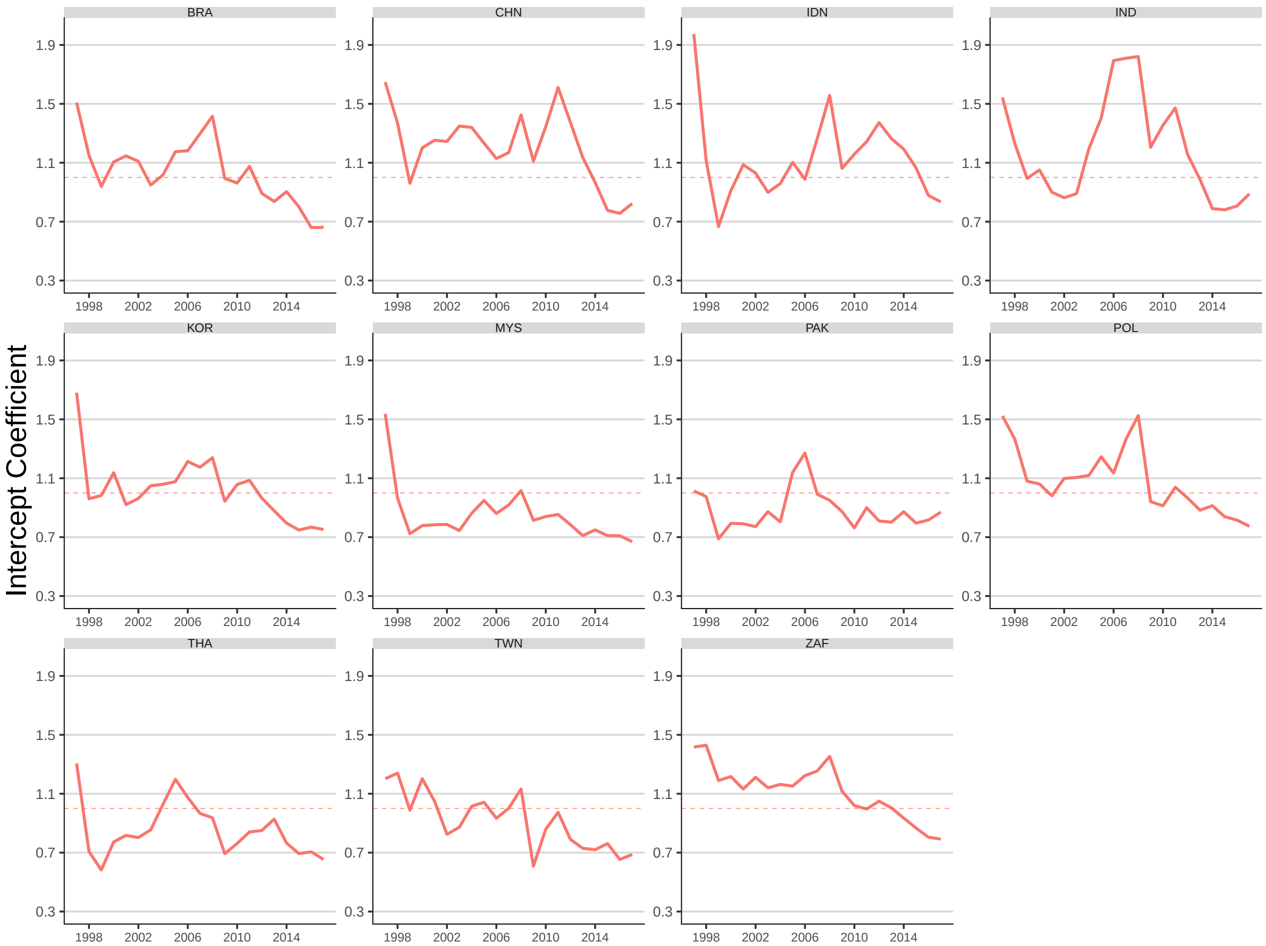
Figure 13. Estimated Mean Group Investment Rate Plotted against Inverse Interest Coverage Ratio, 1997-2017, Log Scale.



Note: *Fitted LOESS line between the intercept coefficients – the regression data to be explained – and median IICR. Explains 1997-1999 poorly. 90% credible interval shown as vertical line. Inverse interest coverage ratio (IICR) is defined as interest and related expenses divided by earnings before interest and taxes,* xint/ebit

C.6 Further Model Results and Fit

Figure 14. Intercept Coefficients of All Random Effects Combined, 1997-2017



Note: *Plot the exponentiated random effects intercepts from all three levels of our model combined. Investment rates decline for advanced economies as a secular tendency. When random effects intercept dips below one (dotted pink line) indicates declining investment rates.*

Table 9. Model Fit: Bayesian R^2 by Country and Year Groups

Year	R2	Est.Error	Q2.5	Q97.5
1997	0.07	0.01	0.05	0.09
1998	0.10	0.01	0.08	0.12
1999	0.11	0.01	0.09	0.13
2000	0.09	0.01	0.07	0.11
2001	0.12	0.01	0.11	0.14
2002	0.12	0.01	0.11	0.14
2003	0.11	0.01	0.10	0.13
2004	0.09	0.01	0.08	0.11
2005	0.08	0.01	0.07	0.09
2006	0.12	0.01	0.11	0.13
2007	0.12	0.01	0.11	0.13
2015	0.08	0.00	0.07	0.09
2016	0.08	0.01	0.07	0.09
2008	0.10	0.01	0.09	0.12
2009	0.13	0.01	0.11	0.14
2010	0.11	0.01	0.10	0.12
2011	0.12	0.01	0.11	0.13
2012	0.13	0.01	0.12	0.14
2013	0.11	0.01	0.10	0.12
2014	0.09	0.01	0.08	0.10
2017	0.09	0.01	0.08	0.10

Country	R2	Est.Error	Q2.5	Q97.5
IND	0.36	0.00	0.35	0.36
CHN	0.33	0.00	0.33	0.34
TWN	0.34	0.00	0.34	0.35
MYS	0.32	0.00	0.32	0.33
KOR	0.30	0.00	0.30	0.31
THA	0.35	0.00	0.35	0.36
IDN	0.35	0.01	0.34	0.36
POL	0.33	0.01	0.31	0.34
PAK	0.30	0.00	0.29	0.31
ZAF	0.40	0.01	0.39	0.42
BRA	0.40	0.01	0.38	0.42

Note: *The mean (R^2), Standard deviation (Est.Error) and the 90% credible interval are reported for each Bayes R^2. We see that R^2 for the year-level prediction is substantially lower than for the country-level. This is reflected graphically in wider credible intervals at the year level.*

D Robustness: Measurement Error Model

Attenuation bias is a common concern in investment regression specifications and has shown to be significant: materially impacting the size and significance of cash flow coefficients (downwards) and Q coefficients (upwards) (Erickson and Whited 2000).

We apply a Bayesian measurement error correction to both the fixed effects and the random effects of observed Q. This draws on the detailed analysis in Strauss and Yang (2020) and the model details are not repeated here. The results are shown in Table 10.

As expected the size of the fixed effect value of Q (β^q) increases as the value of τ increases. Of interest is that the measurement error corrected model with assumed weak measurement error ($\tau = 0.1$), produces a smaller Q coefficient at 0.09, than our non-measurement error

Table 10. Sensitivity Analysis of Hierarchical Model to Differing Degrees of Attenuation Bias

	Variable	**Non ME** Est.	**Non ME** Est.Err.	**ME .1** Est.	**ME .1** Est.Err.	**ME .3** Est.	**ME .3** Est.Err.	**ME .5** Est.	**ME .5** Est.Err.	**ME .7** Est.	**ME .7** Est.Err.
Fixed Effect	α	-3.00	0.08	-3.00	0.08	-3.01	0.08	-3.03	0.08	-3.15	0.09
	β^{cf}	0.19	0.04	0.19	0.04	0.19	0.05	0.19	0.05	0.20	0.04
	β^{q}	0.25	0.03	0.09	0.01	0.11	0.01	0.20	0.03	0.66	0.09
Country Random Effect	σ_{α_c}	0.15	0.04	0.14	0.04	0.14	0.04	0.15	0.04	0.20	0.05
	$\sigma_{\beta_c^{cf}}$	0.11	0.04	0.11	0.04	0.12	0.04	0.12	0.04	0.10	0.04
	$\sigma_{\beta_c^{q}}$	0.09	0.02	0.09	0.03	0.13	0.03	0.26	0.07	0.82	0.23
Year Random Effect	σ_{α_t}	0.17	0.03	0.17	0.03	0.18	0.03	0.18	0.03	0.14	0.03
	$\sigma_{\beta_t^{cf}}$	0.07	0.03	0.07	0.03	0.07	0.03	0.07	0.03	0.06	0.03
	$\sigma_{\beta_t^{q}}$	0.02	0.01	0.02	0.01	0.02	0.01	0.13	0.03	0.38	0.08
Country:Year Random Effect	σ_{α_j}	0.14	0.01	0.14	0.01	0.14	0.01	0.14	0.01	0.16	0.01
	$\sigma_{\beta_j^{cf}}$	0.13	0.02	0.13	0.02	0.13	0.02	0.14	0.02	0.15	0.02
	$\sigma_{\beta_j^{q}}$	0.04	0.01	0.04	0.01	0.05	0.01	0.12	0.01	0.37	0.03
Student-t Parameters	σ	0.68	0.00	0.68	0.00	0.67	0.00	0.63	0.00	0.54	0.01
	ν	8.24	0.24	8.23	0.24	8.04	0.23	7.21	0.21	6.15	0.19

Note: *Comparison of posterior estimates for baseline mixed hierarchical model (but with only one level of random effects) and with the addition of a measurement error model for Q. Three different values of τ are tested. For each coefficient, the mean (Est.) and the standard deviation (Est.Err) are reported. As τ increases the size of the fixed effects and random effects Q coefficients increase, but non-linearly.*

baseline model, at 0.25. Only with $\tau > 0.5$ does the measurement error model fixed effect estimate of Q overtake the non-measurement error value. The effects of assumed attenuation bias on the estimate of Q are strongly non-linear, as β^q more than triples in size from 0.2 ($\tau = 0.5$) to 0.66 ($\tau = 0.7$).

The variation in all the random effects of Q, $\sigma_{\beta_j^q,t,c}$, increases strongly too as τ increases, indicating that the lack of variability in Q across time and country might be an artifact of measurement error.

Of interest is that the fixed effect and random effects cash flow coefficients show no real movement downward, as would be the case if Q and cash flow were correlated. This is probably due to only a weak correlation existing between cash flow and Q.[54]

[54] In a related paper for advanced economies this is not the case.