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

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Abstract

Using a large panel of publicly listed firms covering 11 developing economies between 1997-2017 we detail a notable slowdown in investment rates post-2008. We test competing explanations for slowing investment rates using a Bayesian 'mixed effects' model consisting of time-varying and country-varying coefficients. Firms' investment rates have increasingly been sustained through 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. Firms' estimated underlying mean impetus to invest (their 'animal spirits') declines steeply from 2008, falling to record lows by 2017. One third of this variation is explained by the corporate sector's changing leverage, which declines considerably during this period.

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1 Introduction

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). This paper investigates the nature and causes of the investment slowdown for publicly listed firms from 11 key developing economies.[1] 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).[2] While in the universe of public firms, developing economies are of growing importance, with China overtaking the U.S. in number of listed firms (OECD 2018; Wigglesworth 2019).[3]

We focus on three types of causes for declining investment rates among publicly listed firms. The first consists of external financing constraints: are financing constraints for publicly listed developing economy firms severe or becoming worse (Love 2003; Love and Zicchino 2006; Magud and Sosa 2015; Li et al. 2015)?[4]

The second type of cause we estimate includes anything which changes firms' responsiveness to investment opportunities. Growing global integration of capital and product markets (Grahl 2001) has seen publicly listed developing economy firms subject to growing competitive pressures, including ones similar to those facing developed economy firms. This might reasonably lead 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, as firms focus on maximizing short-term shareholder returns (Lazonick et al. 2014; Bortz and Kaltenbrunner 2018). One way growing market concentration and 'financialization' can depress investment spending is through making firms *less* responsive to investment opportunities (Gutiérrez and Philippon 2017a,b,

[1] Our sample uses non-financial publicly listed firms. 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] 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.

[3] 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).

[4] 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).

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 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' changing, and includes spillover effects from weakening aggregate demand growth in advanced economies since 2008 or slowing investment rates in China since 2011. These in turn may ultimately be driven by ageing populations, slowing technological change, or increasing levels of inequality slowing aggregate demand growth (Summers 2015).

A focus on the above factors is relevant for developing economy firms, especially those in our sample, as the economies in which they predominately operate have transitioned to middle-income status and above.[6] 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, apart from firms in Brazil and to some extent South Africa (UNCTAD 2019) – see Appendix C.4 for the industry composition of our sample.

Our evidence is based on estimating 'cash flow-Q' investment demand equations. The Q theory model of investment is widely used to try and explain observed movements in firms' investment rates (Summers et al. 1981), where marginal Q summarises the firm's investment opportunities, subject to adjustment costs. 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 be determined exclusively by marginal Q – which we proxy by the market-to-book value

[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] 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.

of the firm's assets – but also on the availability of internal funds for investment financing. If the firm's investment spending is sensitive to changes in its internal funds – proxied by present cash flow – then that firm is 'financially constrained' since their investment decision is tied to their internally generated profits. This implies that access to external bank-based and/or market-based finance is inefficient and expensive. These 'finance constrained' investment demand models allow for cash flow coefficients to vary by firm type, rather than being held fixed across all firms. Some of the models also allow for Q coefficients to vary across firms.[7]

Extending this approach, we allow for firms' responsiveness to investment opportunities and their degree of external financing constraints to vary by country and year in order to assess if the restrictions which they face differ across these contexts (Gelman and Hill 2006; Gelman, Carlin, et al. 2013).[8] This helps avoid nonsensical inferences which can arise when fixing coefficients to be equal across countries, years or other categories when they should not be (Barcikowski 1981; Pesaran and Smith 1995; Pepper 2002; Wooldridge 2003; Hsiao 2014).

Our use of a mixed fixed and random coefficients Bayesian model, combined with a large cross-country panel dataset, allows us to provide robust cross-country and time-varying evidence on the existence and nature of the slowdown in developing economy firms' investment rates. Our sample consists of 91,069 observations on 11,812 unique firms, across 11 major developing economies for 21 years between 1997-2017. This detailed firm-level data helps us to overcome some of the deficiencies in the existing literature that stem from their use of an overly narrow time period or geographic region (Anand and Tulin 2014; Qureshi et al. 2014; Islamaj et al. 2019), or a reliance on fixed effects models for accounting for country effects (A. Kose et al. 2017). From a methodological point of view, our Bayesian mixed effects model addresses the well known issue with the fixed effects estimator, namely that coefficient estimates from multiple interaction effects become highly unstable due to its sensitivity to sample size (Magud and Sosa 2015; Gelman 2019). We overcome this issue through estimating our time-varying and country-varying coefficients 'jointly'. This allows for a "borrowing of strength" across clusters while still permitting multiple comparisons across unique sub-samples in the data.[9] We can also apply measurement error correction to this model – a common problem in cash flow-Q regressions – to ensure that our core results are not driven by

[7] For a critique of these models and their interpretation Strebulaev, Whited, et al. (2012).

[8] This effectively models the conditional heteroskedasticity (Sims 2010).

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

attenuation bias (Appendix D). Moreover, as a Bayesian model, we are able to explain 'macroeconomic' variation between estimated random effects coefficients through the inclusion of 'group predictors', and estimate this variation concurrent to the firm-level variables explaining variation between firms.

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. Raw investment rates by 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 investment distribution.

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.

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.

4. There is considerable variability across countries in the degree of external financing constraints facing firms and in firms' responsiveness to investment opportunities. In general, we see an inverse correlation such that firms who are in countries which are less financially constrained are also more responsive 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) investment rates by developing economy firms appear to 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.

Our findings relate to the recent literature on the precise timing of the investment slowdown among developing economies. Using national accounts data, Magud and Sosa (2015) find that private investment rates post-2008 global financial crisis (GFC) "remains close to pre-crisis trends". A. Kose et al. (2017), ostensibly using similar data, instead find a sharp decline in investment rates since 2010, to well below both the pre-crisis and long-term averages, and forecast investment weakness to persist. Movements in our firm-level data accord more with A. Kose et al. (ibid.) as raw investment rates decline to at or below pre-2002 levels (Figures 10 and 2, Table C.5). However, plotting raw investment rate data is less informative than estimating econometrically the underlying change in the impetus of firms to invest, as we do.[10]

Our findings on the role of leverage in explaining one third of the estimated underlying investment cycle, including the more recent downturn, is somewhat at odds with Alter and Elekdag (2016) who find leverage to be increasing through the 2008 GFC – though we cover a slightly different time period to them. In addition, 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 in their sample does not actually increase greatly, according to their Appendix: median firm *total* liabilities relative to total equity increases from around 59% in 2004 to around 63% in 2013, a 6.7% increase.

Our paper is closest to Magud and Sosa (2015) who estimate 'cash flow-Q' investment regression coefficients which vary by region and firm type.[11] They also find that coefficients, including financing constraints, vary significantly by region and firm type, but in their regression model coefficients are estimated in isolation from one another, often with highly unstable three-way interaction terms, such that we are left wondering if their coefficients changing back and forth in significance is due simply to changes in their sample size. As mentioned above, our Bayesian model overcomes this

[10] The latter approach help show that part of the (quickly exhausted) recovery between 2008-2011 was due to firms becoming more responsive to investment opportunities and being less finance constrained, with only a partial contribution from the underlying impetus to invest mildly recovering.

[11] They cover a different time period and two dozen more countries than us.

issue through estimating coefficients jointly, while uncertainty in estimates is reflected in posterior Bayesian credible intervals (Gelman and Loken 2013; Wasserstein, Lazar, et al. 2016). Our econometric estimation is a more developed version of the Bayesian hierarchical model used by Meager (2019) for a meta-analysis. Hsiao and Tahmiscioglu (1997) is a classical forerunner of applying this approach in estimating 'cash flow-Q' regressions.

Section 2 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).

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 Hamiltonian is:

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

Assuming quadratic adjustment costs $C(\cdot)$, and positive external financing costs $b \geq 0$, 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. 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. 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 finance (Myers 1984; Myers and Majluf 1984). 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.[12] 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.[13] 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 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).[14] The countries chosen are not commodity-dependant exporters, according to UNCTAD's classification (UNCTAD 2019), except Brazil and

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

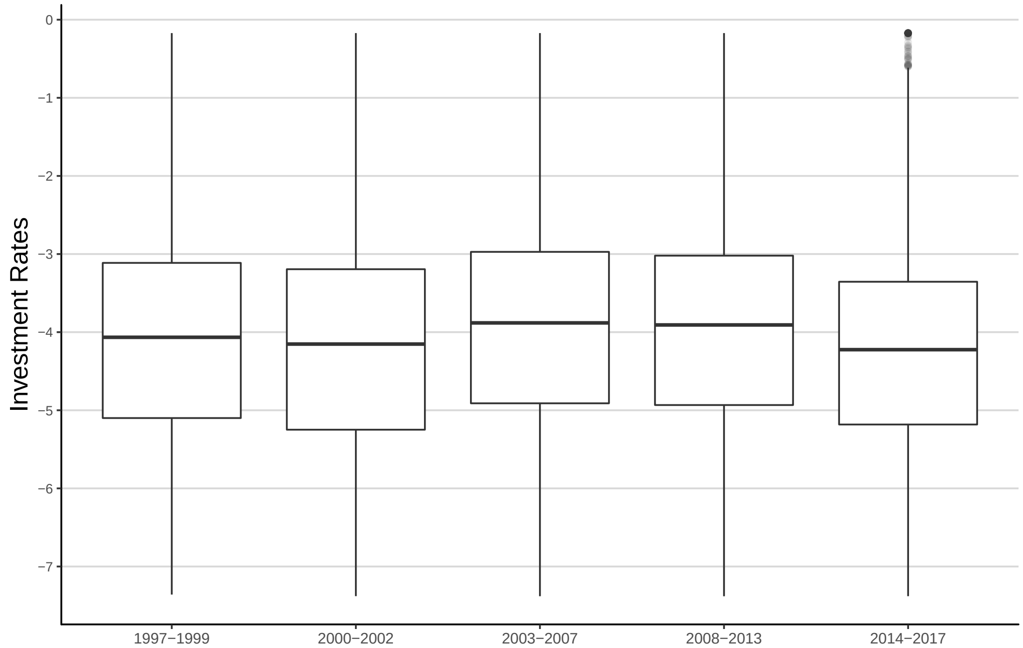
[13]Vietnam was excluded due to erratic behaviour in its capital stock. The countries in our sample account for the vast majority of investment spending for all developing and emerging markets on a population or GDP weighted basis (with Saudia Arabia, Mexico, Turkey, and Russia notable omissions).

[14]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.

to some extent South Africa.[15] 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).[16] Variable definitions differ somewhat by country due to differing implementations of IFRS accounting guidelines.[17] 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).[18] 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 $\mathsf{PPEGT} + \mathsf{INTAN} + \mathsf{INVT}$, 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 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.

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.*

2.3 Initial Data Description

Figure 1 shows the boxplot[19] for log investment rates over five consecutive time periods on our pooled sample (see also Figure 10 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

[15]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).

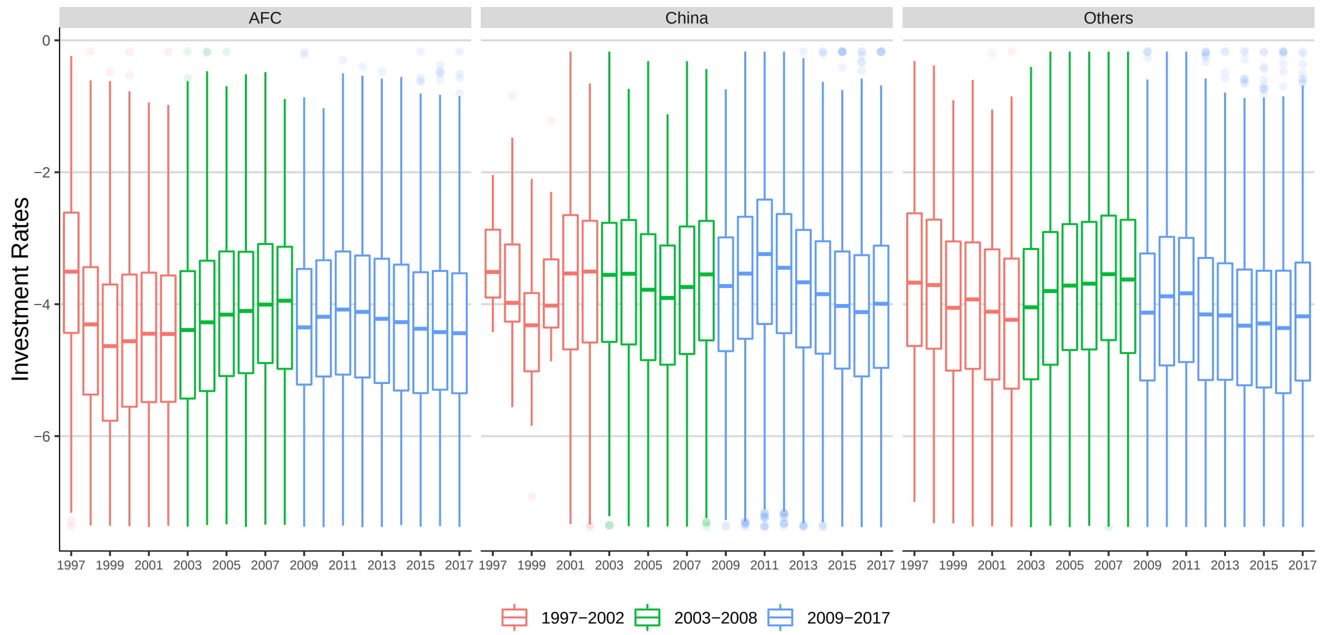
[16]Accounting guidelines for capitalizing intangible expenditure is much stricter under U.S. GAAP than IFRS.

[17]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`.

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

[19]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.

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.*

Appendix C.5).

Compared to advanced economies (Strauss and Yang 2020), the fall in raw investment rates for developing economy firms 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).

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).[20] 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 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).[21]

Following the investment demand function specification in eq. 2, the firm's investment rate is

[20] 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).

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

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:

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

$\mathrm{Q}_{c,t[i]}$ 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 x 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 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.[22]

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

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

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:

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

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. $p(\boldsymbol{M_\beta}, \boldsymbol{\Sigma^\beta})$ 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:

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.[23] Our core findings are robust to measurement error (Appendix D).

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
	$\sigma_{\beta_c^q}$	0.09	0.02	0.05	0.15	1.00
	$\sigma_{\beta_c^{cf}}$	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
	$\sigma_{\beta_t^q}$	0.02	0.01	0.00	0.04	1.00
	$\sigma_{\beta_t^{cf}}$	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
	$\sigma_{\beta_j^q}$	0.04	0.01	0.02	0.05	1.00
	$\sigma_{\beta_j^{cf}}$	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.*

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

[23] 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.).

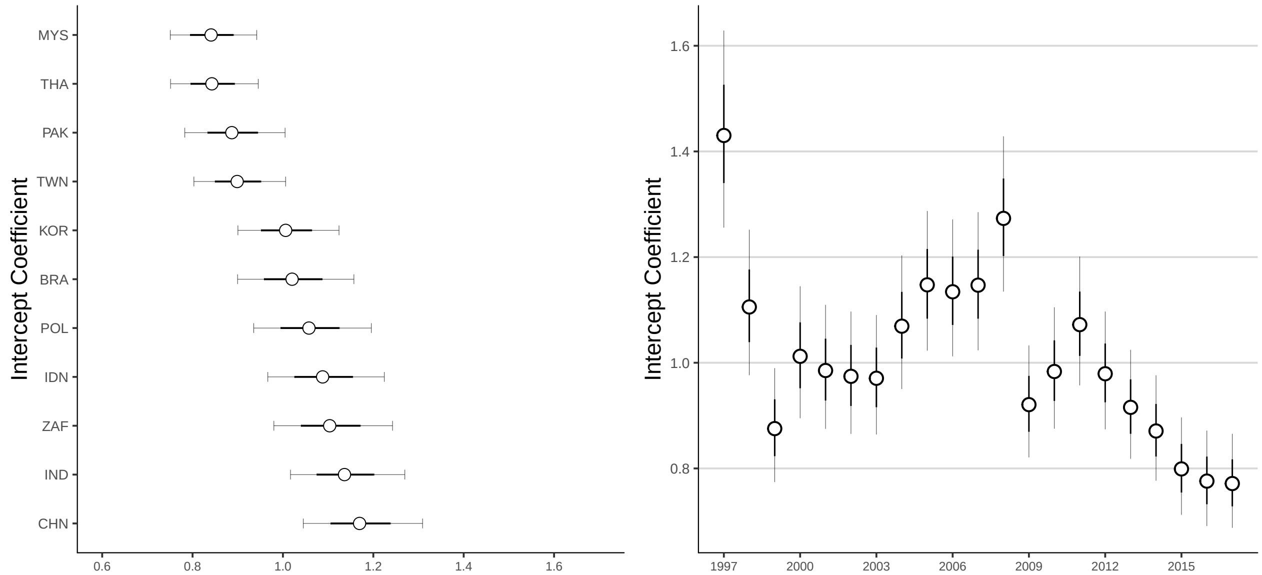
within each group c, t, j is captured in the standard deviation of that group's random effect, such that σ_{α_t} shows the variation in the random effect intercept across years.

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.[24] 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 sinks 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.

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 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

[24] 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

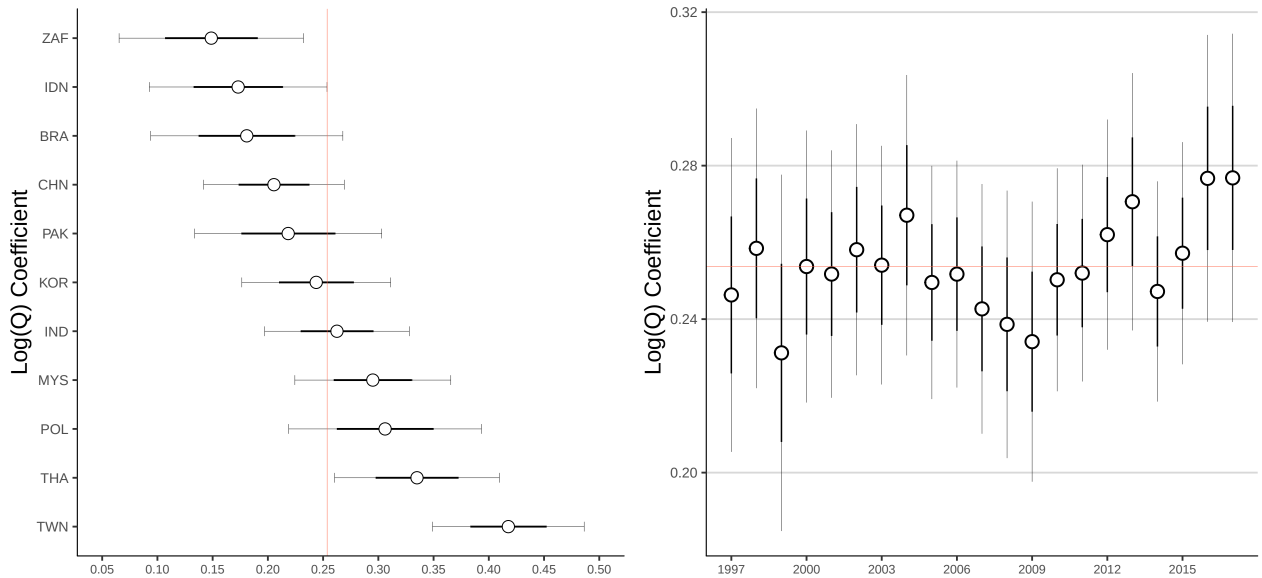


Note: *This shows the exponentiated random intercept coefficient, i.e the predicted mean/median investment rate. An exponentiated intercept coefficient of above (below) 1 shows an increasing (decreasing) mean-centred investment rate from the global average. The intercept falls greatly after the 1997 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.*

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



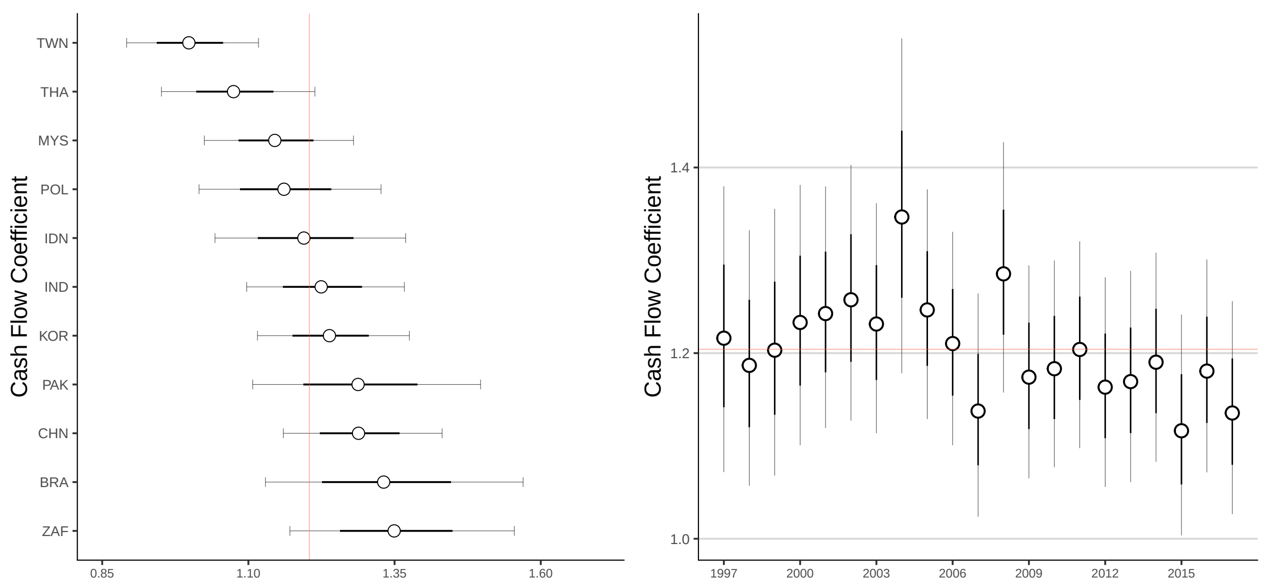
Note: *Q coefficient shows strong cyclical movements with no clear tendency to increase or decrease over time, except in the past few years. This upswing indicates that firms are not less responsive to investment opportunities, despite lower investment rates, but in fact the opposite. The Q coefficient 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).

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. 2015). 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).[25]

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.*

[25]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.

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%) 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 a 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.[26]

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.

[26]Although we do not report it 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* only 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.

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).[27]

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 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.[28] 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).[29]

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).[30] 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

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

[28] 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).

[29] 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).

[30] 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.

from $\sim 59\%$ leverage in 2004 to $\sim 63\%$ in 2013.[31]

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).[32] 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 6 shows a clear positive relationship between the random effects intercept and 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 12.

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 $\mathsf{SD}(0.17)$ to $\mathsf{SD}(0.12)$, with the uncertainty in this estimate remaining the same at 0.03.[33]

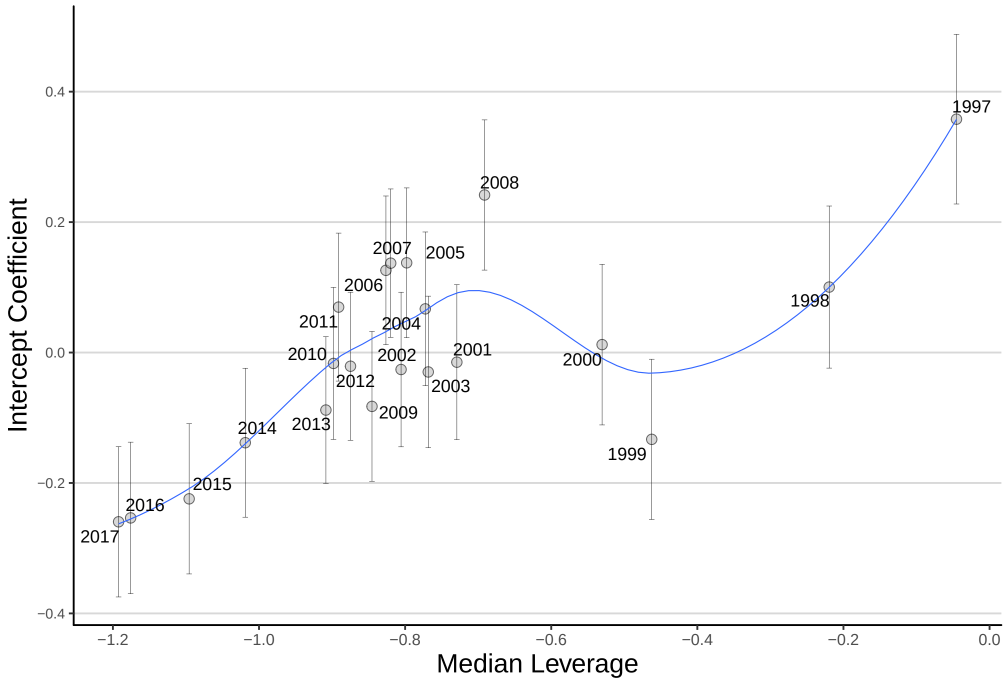
Next, in Figure 7 below, we plot the new random effects intercepts (top blue line) and compare it to the old random effects intercepts (bottom red line) to see which parts of the estimated investment

[31] 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).

[32] 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.

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

Figure 6. Estimated Mean Group Investment Rate Plotted against Median Leverage Group Predictor, 1997-2017, Log Scale.

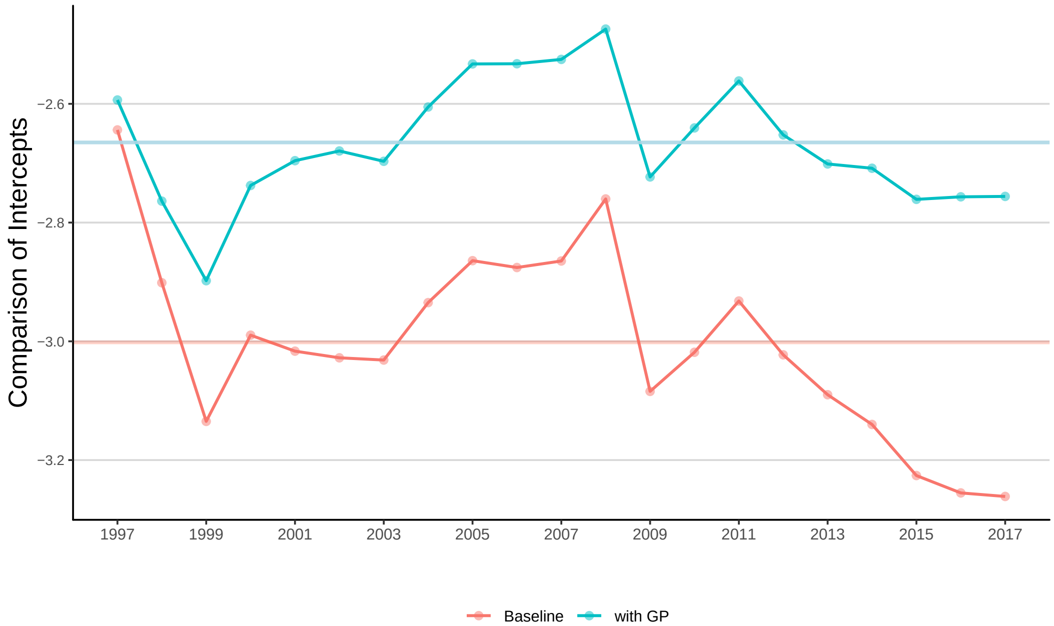


Note: *Fitted local polynomial regression ('LOESS') line between the intercept coefficients – the regression data to be explained – and leverage, the group-level variable used to account for differences in pooled mean investment rates over time. 90% credible interval shown as vertical line. Median leverage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

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 7).

Given that financing constraints have been declining at the firm-level (shown previously), and monetary conditions globally have been easing, this deleveraging may be driven by slowing growth creating a relative constriction in aggregate demand growth.

Figure 7. 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.*

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 (Richardson 2006), and may reflect a growing dearth of good investment opportunities facing firms relative to plentiful available financing post-2008 GFC (Howell 2020).

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 overfit and underexplore.

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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:

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

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

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

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

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. We proxy this by the book-to-market value of the firm.[34] Next, quadratic investment adjustment costs for $C(\cdot)$ are assumed. Substitution of this into the FOC leads to the following - with subscript I referring to the partial derivative with

[34]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.

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.[35] We use a symmetric student-t distribution t_ν, with the degree of freedom ν, as our likelihood function.[36]

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).[37] 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

[35] 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).

[36] 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).

[37] 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.

state-dependence of the investment rate over time.[38]

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.[39] 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).[40]

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 intercept coefficient distribution M_β^α for each year group t:

$$\beta_t \sim \text{MVN}(M_\beta^\alpha, \Sigma_{\beta_t}) \tag{17}$$

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

μ is estimated just for the year group t, using data points running from 1 to 21, i.e. the number

[38] 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.

[39] 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.

[40] 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, $\beta_{cf}^0, \beta_q^0, \beta_\alpha^0$, would be indistinguishable from their estimated population means in the random effects distribution $\mu_\alpha, \mu_q, \mu_{cf}$. As a result, $X_i^0 \beta^0$ only contains the fixed effects that have no random effect counterpart. For details see: Betancourt and Girolami (2015).

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 $(M_\beta, \Sigma^\beta_{t,c,j})$:

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

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 lowertriangular 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 $\text{LKJcorr}(\Omega|\eta) \propto \det(\Omega)^{\eta-1}$, 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 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 have 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

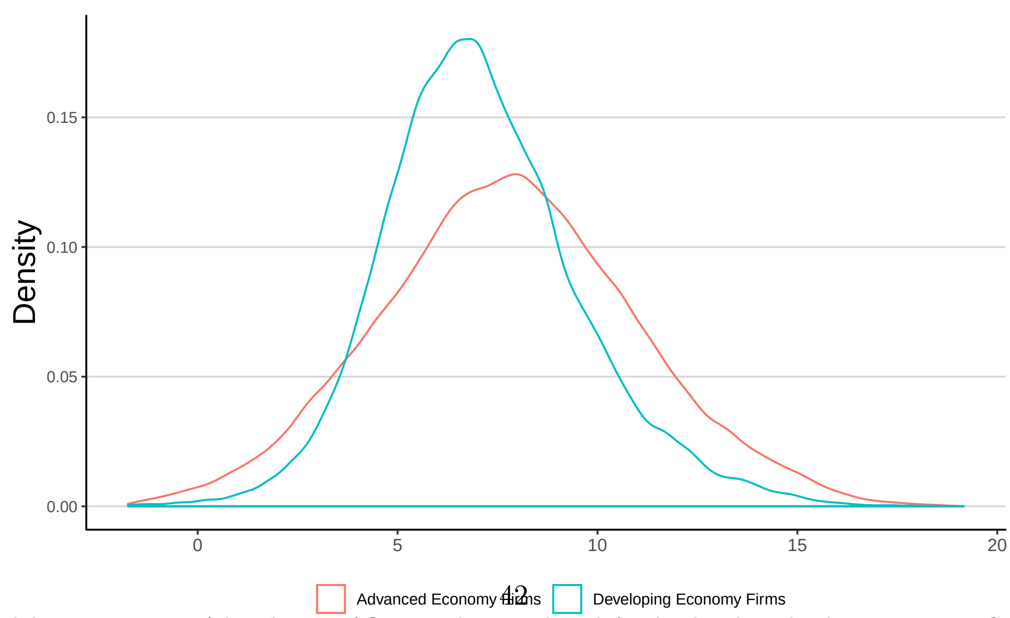
Country Group	Median	MAD	P10	P30	P70	P90
Advanced Economy Firms	215	296	12	68.2	676	3914
Developing Economy Firms	122	143	18.8	55.1	291	1275

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

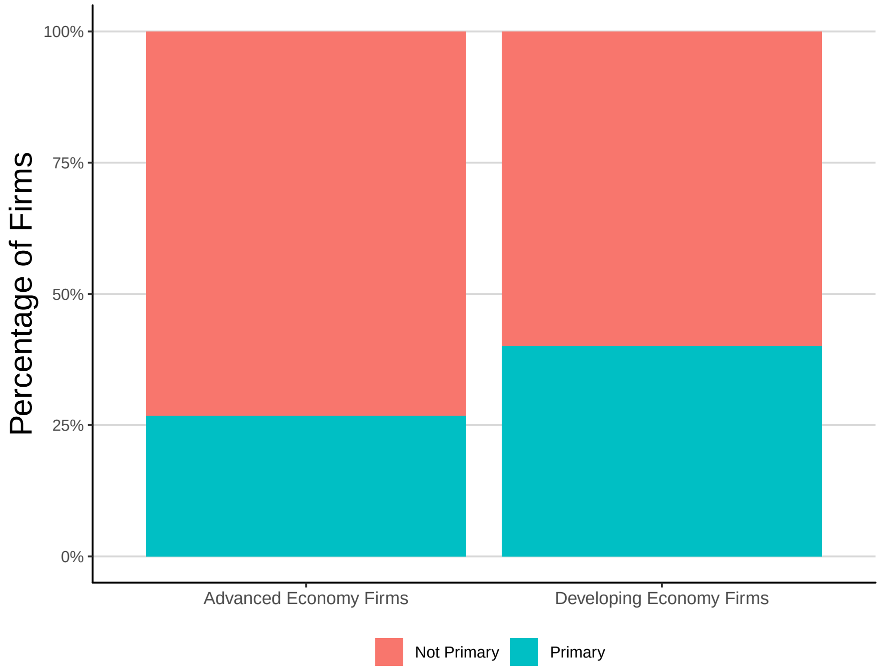
Year	BRA	CHN	IDN	IND	KOR	MYS	PAK	POL	THA	TWN	ZAF
1997	2	8	139	92	203	377	54	1	189	86	52
1998	6	17	148	103	201	366	56	7	173	97	54
1999	7	19	142	97	216	369	61	9	185	121	61
2000	10	22	135	103	214	374	70	6	135	140	75
2001	18	811	150	215	301	396	59	8	179	173	74
2002	23	902	166	283	315	484	45	11	210	455	86
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 8. 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.*

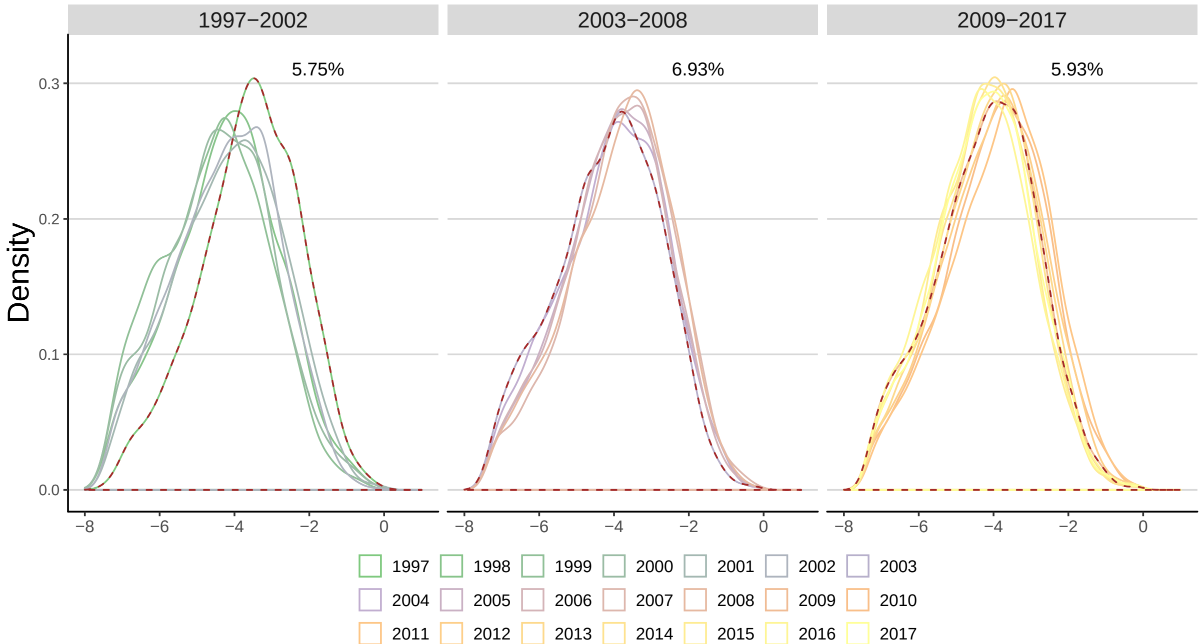
Figure 9. Industry Structure of Firms by Sample: Developed vs. Developing Economy in Compustat



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 10. 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 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 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

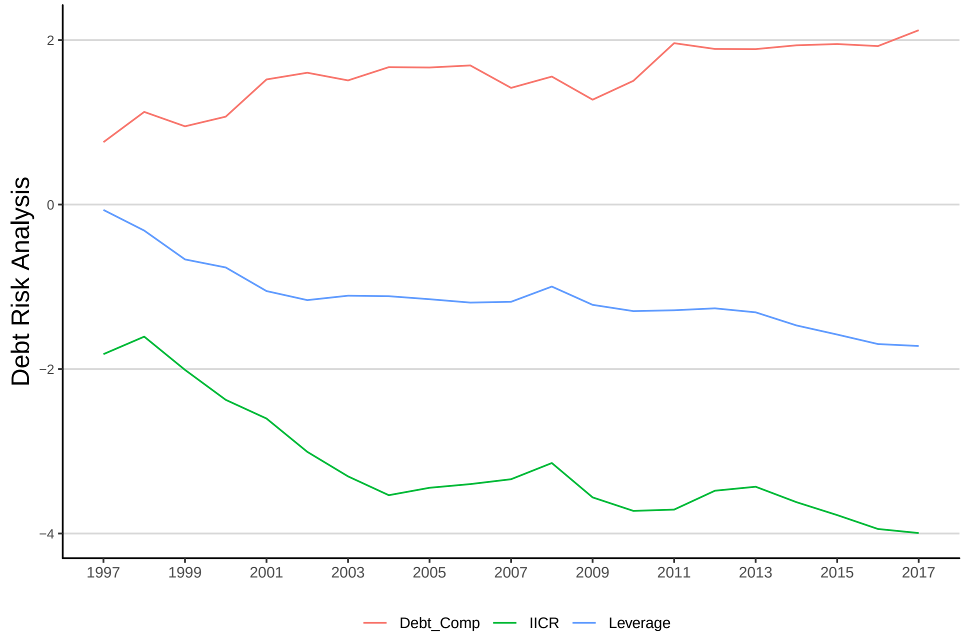
Note: *Q values are increasing for most of our sample for most years.*

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

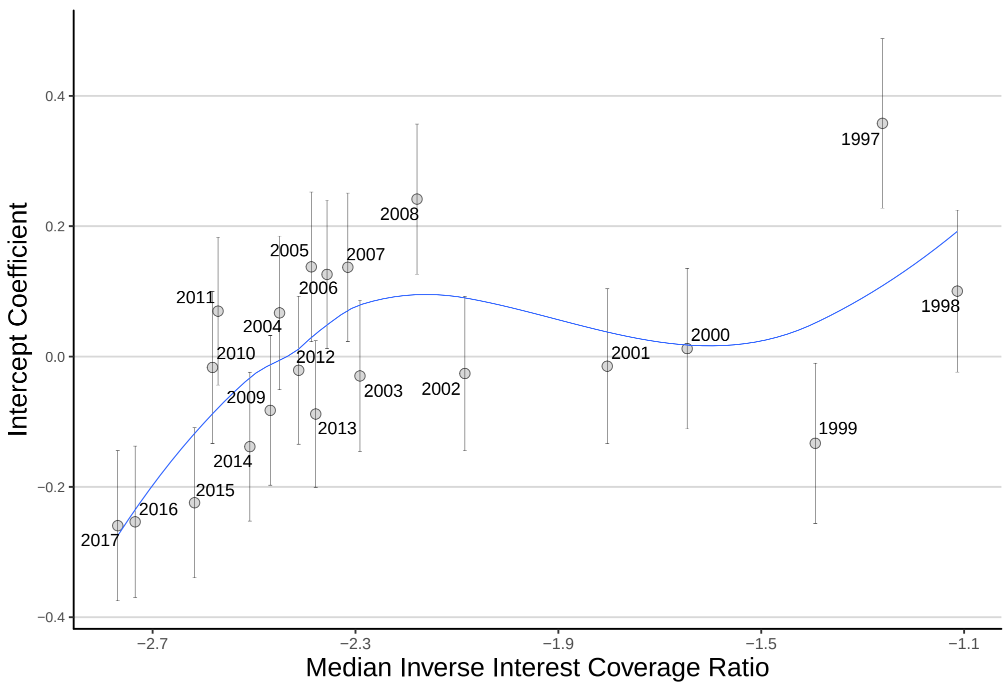
Note: *Quick ratio is defined as short-term assets over short-term liabilities, using Compustat terminology (che + rect)/(lct). China's sample prior to 2001 is small and so estimates are less reliable for it prior to then.*

Figure 11. Key Debt Measures (Median), Pooled Sample, Log2 scale, 1997-2017



Note: *Debt composition 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). Leverage is total debt over total equity.*

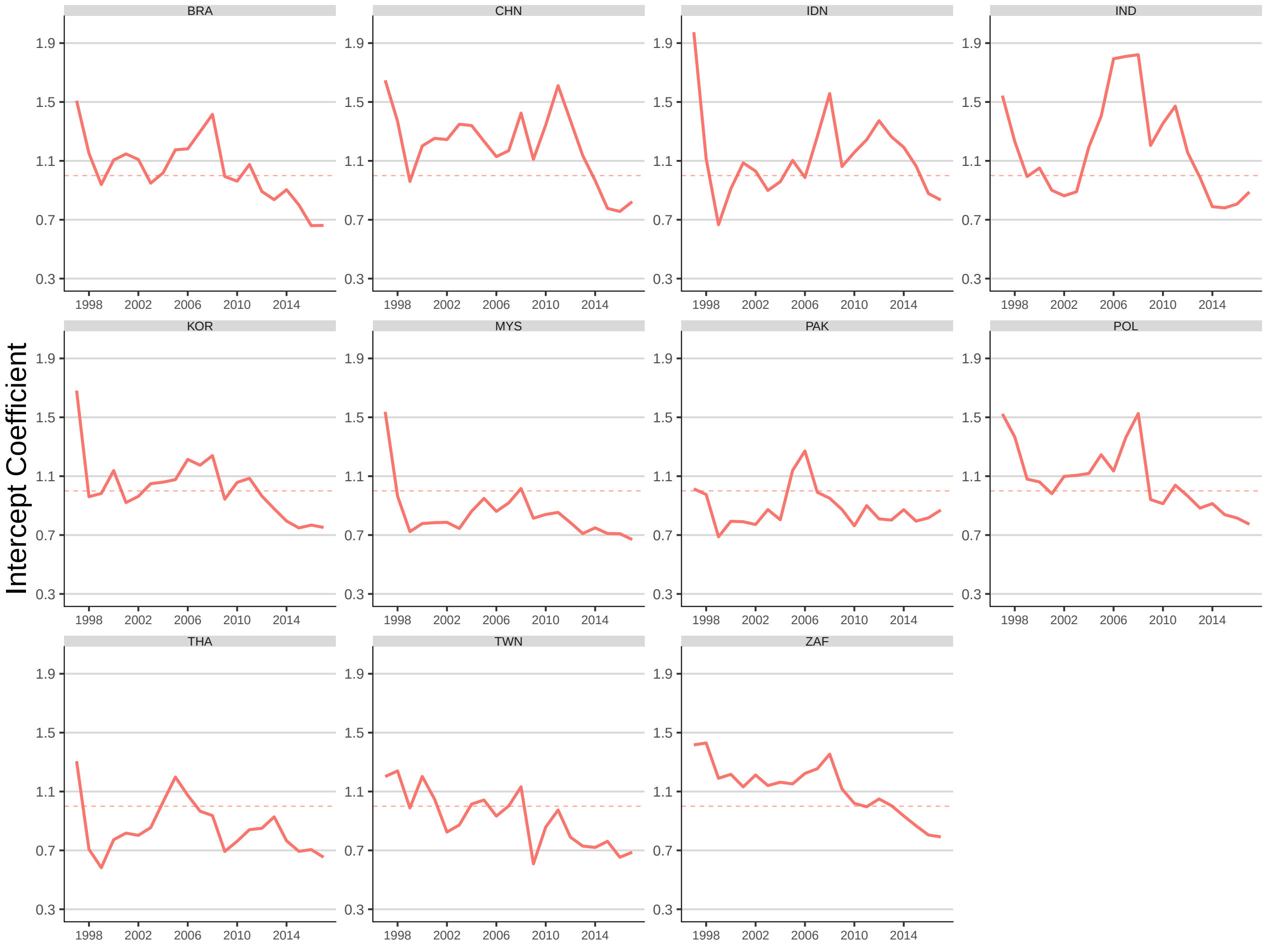
Figure 12. Estimated Mean Group Investment Rate Plotted against Inverse Interest Coverage Ratio, 1997-2017, Log Scale.



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 13. 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 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 baseline model, at 0.25. Only with $\tau > 0.5$ does the measurement error model fixed effect estimate of Q overtake

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

		Non ME		**ME .1**		**ME .3**		**ME .5**		**ME .7**	
	Variable	Est.	Est.Err.	Est.	Est.Err.	Est.	Est.Err.	Est.	Est.Err.	Est.	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.*

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, $\sigma_{\beta^q_j,t,c}$, 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 may be due to only a weak correlation existing between cash flow and Q; or due to the correlation between our random effects being modeled in advance; or due to us not including an 'exposure model' into our measurement error model, which explicitly models Q as a a function of cash flow. Correlation coefficients of various types and a generalised additive model (GAM) - a non-parametric spline fit - shows a poor relationship between log(Q) and cash flow across our sample and various sub-samples though.

From a Bayesian perspective, correcting for attenuation is only beneficial if it improves the model fit, which by definition is a predictive quantity. Higher `Q` coefficient values alone is not in itself an indication of an improved Bayesian model fit. Measurement error correction appears to help our model fit, as measured by Bayesian R^2, but not unambiguously.