Empirical Evidence on the Slowing in Developing Economy Firms' Investment Rates

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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 the investment slowdown using a Bayesian 'mixed effects' model consisting of time-varying and country-varying coefficients to fully explore variation in financing constraints and investment behaviour. Firms' estimated underlying impetus to invest (or exogenous 'animal spirits') shows a steep and persistent decline since 2008, falling to record lows after a modest recovery till 2011. Investment rates appear to have increasingly been sustained through a relaxing of the external financing constraint and firms gradually becoming more responsive to investment opportunities, reflected in the slope of the investment demand curve – approximated by time-varying Q regression coefficients – increasing over time.

JEL Codes: D22, D25, E22, F23, O16.
Keywords: Developing Economy Firms, Emerging Markets, Investment Rates, Finance Constrained, Tobin's Q, Bayesian Econometrics.

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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 incredible 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 developing economy investment slowdown using publicly listed firms from 11 key developing economies.[1]

We focus on three types of causes for declining investment rates. 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)?[2]

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 increasingly subject to competitive pressures 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 these factors can depress investment spending is through making firms *less* responsive to investment opportunities (Gutiérrez and Philippon 2017a,b, 2018; Döttling et al. 2017).[3] On the other hand, increasingly unfettered access to capital markets for developing economies may have seen firms become *more* responsive to investment opportunities (M. A. Kose, Nagle, et al. 2020), thereby sustaining investment rates through borrowing even if they may have not been good investment opportunities.

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. These are exogenous shifts in firms' marginal product of capital or 'animal spirits', and includes spillover effects from weakening aggregate demand growth in advanced economies since 2008 or slowing investment rates in China since 2011. These

[1] Our sample uses non-financial publicly listed firms with a minimum capital stock size of US$0.29 million. 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] Although publicly listed firms are less financially constrained than smaller firms, by virtue of having already issued equity to the public, their importance in high quality investment, coupled with their larger financing needs, makes access to efficient external financing vital for economy-wide growth rates and not guaranteed.

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

may in turn be driven ultimately by ageing populations, slowing technological change, or increasing levels of inequality slowing aggregate demand growth (Summers 2015).

A focus on the above factors follows from the fact that large, often publicly listed, firms now make up a significant share of production and employment in developing economies, even if they account for less than 10% of total enterprises (Tsebe et al. 2018, p. 10).[4] Since 2018 China even has more listed public companies than the U.S.[5] These firms face structural "middle-income traps" (Qureshi et al. 2014), arising from declining fertility rates (Jones 2020; Harding 2020),[6] growing income inequality, and slowing capital accumulation creating a vicious cycle of low innovation and income growth (IMF 2014; A. Kose et al. 2017; M. A. Kose and Ohnsorge 2019). This follows from major emerging markets in Asia and Central and Eastern European Union member states transiting to middle-income status and higher.[7] While exogenous factors still matter as domestic demand remains relatively small outside of China and India, commodity price movements do not drive exports for the countries in our sample apart from Brazil and South Africa to some extent (UNCTAD 2019) (Appendix C.4).

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 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 somewhat restricted by the availability of internally generated profits. Such 'finance constrained' models allows for cash flow coefficients to vary by firm type, rather than being held fixed across all firms.[8] Some of the models also allow for Q coefficients to vary across firms.[9]

[4] 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 economies.

[5] 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).

[6] Africa's demographics are different.

[7] For our sample: 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). Using World Bank definition of GNI per capita between \$3,996-\$12,375, calculated using World Bank Atlas method for 2019.

[8] According to whether the firm is categorised, *a priori*, as financially constrained or not.

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

Extending the approach of finance-constrained models, 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).[10] 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).

Use of a mixed fixed and random coefficients Bayesian model, combined with a large cross-country panel dataset we assemble, 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. In contrast, existing evidence on the causes of the investment slowdown among developing economies is not always that meaningful, either because of the narrow time period or region which they cover (Anand and Tulin 2014; Qureshi et al. 2014; Islamaj et al. 2019), or because of a reliance on the mean of national accounts data for descriptive statistics (A. Kose et al. 2017).[11] And while firm-level studies do provide more granular evidence, they suffer from coefficient estimates being highly unstable owing to their fixed effect estimation being sensitive to sample size changes when estimating multiple interaction effects (Magud and Sosa 2015; Gelman 2019).

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. We find that:

1. Raw investment rates by developing economy firms are cyclical with evidence of a gradual though notable decline since 2012 to pre-2002 levels or below.

2. The decline in the underlying impetus of firms to invest (all else being held equal) shows a much clearer and steeper decline since 2008, to the lowest levels we see. This fall is temporarily offset until 2011, most likely by temporarily higher rates of Chinese investment.

3. Their is considerable variability in the degree of external financing constraints and the responsiveness of firms to investment opportunities in different countries. 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.

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

[11] National accounts studies of investment rates are limiting for other reasons to owing to what they include and exclude (Ruggles 1993).

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

5. After the 2008 global financial crisis (GFC) investment rates by developing economy firms appear to increasingly have been sustained through firms becoming gradually *more* responsive to investment opportunities and through a relaxing of the external finance constraint, mostly like as access to cheap financing has grown. This indicates that 'financialization' and growing market concentration have not depressed how responsive firms are to investment opportunities. But it does pose questions around the sustainability of investment rates.

To the extent that the combination of increasing responsiveness to investment opportunities and declining external financing constraints might reflect over-investment by firms (Jensen 1986), as they clamour to find 'good' investment opportunities[12] amidst slowing global growth yet easy financing conditions, then these development may be undesirable and risk leaving developing economy firms' balance sheets exposed in the event that global financing conditions change.

Our findings are related 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 forecasts 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 1 and 2, Table C.5). Plotting raw investment rate data, however, is probably less informative than estimating econometrically the underlying change in the impetus to invest among firms. This 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.

Our paper is closest to Magud and Sosa (2015) who, using an even larger firm-level panel, estimate

[12] With positive net present rates of return.

'cashflow-Q' investment regression coefficients which vary by region and firm type.[13] They also find that coefficients, including financing constraints, vary significantly by region and firm type (Magud and Sosa 2015); 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.[14] We overcome sample size sensitivity issues partly through estimating our coefficients jointly, which allows for a 'borrowing of strength' across countries and years.[15] While uncertainty in coefficients 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. While Hsiao and Tahmiscioglu (1997) use a classical version of a mixed fixed and random coefficients model in estimating 'cashflow-Q' regressions.

Section 2 which follows describes our 'cash flow-Q' investment model. Section 3 then provides a brief overview of our data and empirical movements in raw investment rates by developing economies. Section 4 describes our regression equation, which we estimate using a Bayesian mixed effects hierarchical model with 'partial pooling' (detailed further in Strauss and Yang 2020). Section 5 reports the model's key findings and Section 6 concludes. Online Appendices explains our Bayesian model priors and fit (Appendix B), dataset and variables (Appendix C), descriptive statistics on key variables (Appendix C.5), and measurement error model (Appendix D).

2 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:

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

Assuming quadratic adjustment costs $C(\cdot)$, and positive external financing costs $b \geq 0$, leads to the

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

[14] Our model is also effectively a combination of interaction effects (Gelman 2006).

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

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 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. 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.

3 Data

This section provides a brief overview of the key features of our data. Please see the Appendix for further details.

3.1 Data Construction

Our sample covers non-financial publicly listed firms constructed by merging S&P's Compustat Global and Compustat North America databases and then, after cleaning and trimming, selecting our sub-sample.[16] 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.[17] 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 not country of listing.

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).[18] The countries in our sample are based on where they are legally

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

[17] 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).

[18] 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.

incorporated (rather than where they are publicly listed). The countries chosen are not commodity-dependant according to UNCTAD's classification (UNCTAD 2019), except Brazil and to some extent South Africa.[19] 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).[20]

Variable definitions differ somewhat by country, even though most use IFRS accounting standards (with China following something similar). Values are in nominal US$, converted into a common currency using the Compustat Global currency file. Our variables are reported gross, before amortization and depreciation, but after tax, unless stated otherwise.

Capital stock is the denominator used for the variables in our regression, including cash flow rate, investment rate, and capital-output ratio. We define the capital stock as gross $\mathsf{PPEGT} + \mathsf{INTAN} + \mathsf{INVT}$, the sum of gross property, plant, and equipment, intangible assets, and inventories. Our findings are not dependant on this definition though. 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 certain countries in particular. The procedure for calculating Q values in Compustat is discussed further in our Appendix.

3.2 Initial Data Description

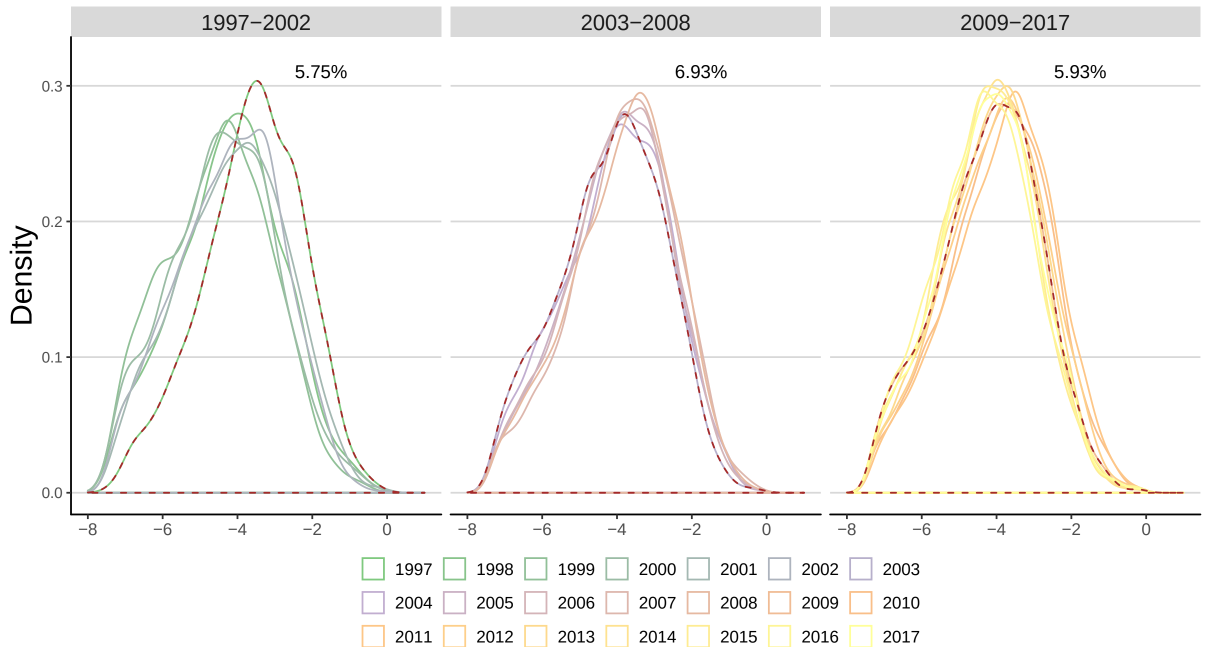
Figure 1 shows the distribution of developing economy firm-level investment rates by time period, with the median value for each period written above. Developing economy firms show a largely cyclical movement in their investment rates. After the 2008 global financial crisis (GFC) investment rates begin to fall in developing economies, declining to their pre-2002 levels – or lower in the case of China. The

[19] 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 countries with a sizeable energy sector (UNCTAD 2019).

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

cyclical movement in investment rates has been accompanied by median investment opportunities — Q values — and cash flow rates (profitability) being stable or increasing (see Appendix C.5).

Figure 1. Distribution of Developing Economy Firm-Level Investment Rates, By Year Group, 1997-2017

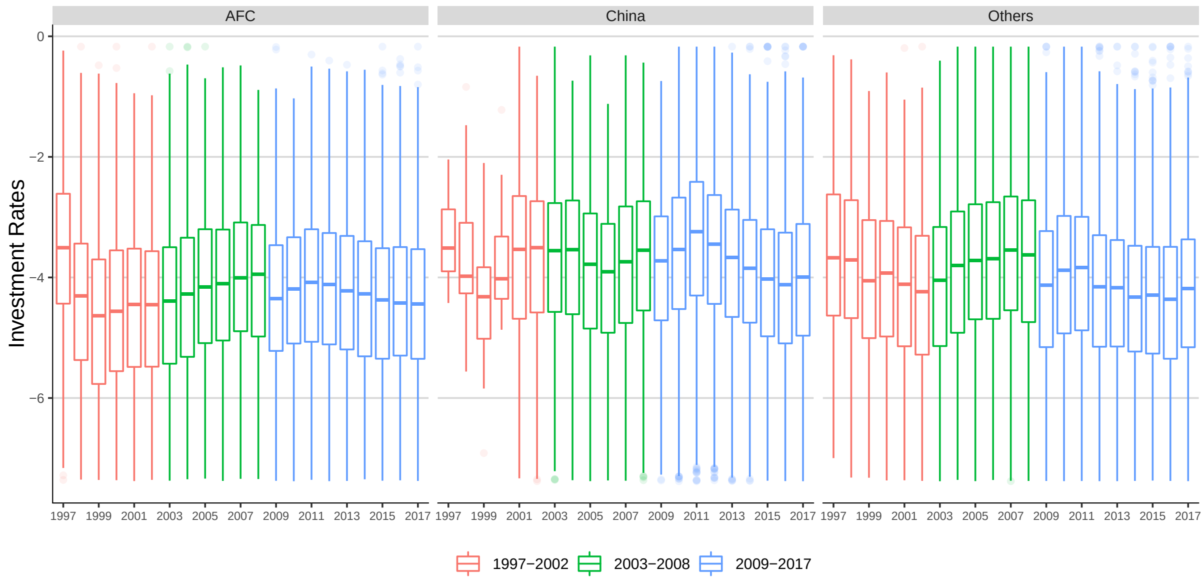


Note: *Kernel density approximation of log2() firm gross investment rates for 11 advanced economies. Black-orange dashed line is for the first year in each year group (1997, 2003, 2009). 'Other' consists of Brazil, India Pakistan, Poland, South Africa, and Taiwan. 1997 Asian Financial Crisis (AFC) countries' consist of Thailand, Korea, Malaysia, and Indonesia. For first year group (smaller sample size): sharp shift to the left and then somewhat back out as investment rates decline and then slowly recover for the 1997 AFC countries' firms. For second year group: investment rates extend outwards to the right, increasing (becoming darker). For final year group: we see a positive shift to the right (orange lines) as some initial recovery occurs assisted by Chinese growth, before shifting to the left, as investment rates contract (yellow lines). Median investment rate for each year group written above.*

Compared to advanced economies (Strauss and Yang 2020), the fall in raw investment rates is more muted for developing economy firms, at least until 2011/2012, owing to Chinese investment rates only peaking in 2011. China's 2011 investment peak is evident in Figure 2 which shows box plots for each country group for each year.[21] In comparison, the rest of our sample shows an investment peak around 2007. The investment boom upswing also 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 more heterogeneous countries of Brazil, India, Pakistan, Poland, South Africa, and Taiwan, it bottoms in 2002 before picking up for the next cycle in 2003. These differing dynamics across firms in different

[21] 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 firm-level investment rates with 'outlier' dots and the median as the bold short horizontal line. 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.*

countries makes neat periodizations and group categorizations difficult.

4 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 we do not repeat it here. Our priors are listed in the Appendix.

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 within each group (complete pooling), or by assuming no relatedness between countries or years within each group (no pooling, complete independence).[22] The parameters for the group of countries (and the group of years) are drawn from a common prior distribution and estimated together, allowing the inferences for one country (or year) to potentially 'learn' (or 'borrow strength') from another, rather than estimated in isolation from each other (McElreath 2018). The extent to which one country learns from another is based partly on how similar their observations are to one another for any given variable and on the

[22]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).

relative sample sizes.[23] This is particularly useful for developing economy studies where sample sizes can be small for any individual country or firm type. This joint estimation approach produces a lower *total* mean squared error for the sum of the parameters than a maximum likelihood estimator which estimates each parameter separately (James and Stein 1961; Kreft and De Leeuw 1998; Lehmann and Casella 1998).

Following the investment demand function specification in eq. 13, the firm's investment rate is determined by Q and *cash flow* rates ('cash flow' for short). Our hierarchical regression model focuses on the intercept of the investment demand function, the slope of Q, and the slope of *cash flow*, by allowing for these (firm-level) coefficients to vary by year and country - in addition to being 'fixed'. In varying across country or year clusters within each group these three variables become our 3 'random effects'. Denoting $y_{c,t[i]}$ as the investment rate of firm i in country c and time t, our baseline regression which we estimate 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 $11 * 21 = 231$ clusters), which serves largely as a control group and so is not included 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 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 (10 bins), and 1-digit NAICS industry code. ϵ is an error term discussed further in Strauss and Yang (2020), where a more technical overview of the model as a whole is provided. We include an AR(1) error process to account for the panel nature of our data.[24]

[23] The more similar they are, the tighter and more 'informative' the adaptive prior becomes, such that each observation 'regularizes' the other more considerably.

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

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

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

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

where y, θ, and ϕ denote the data, parameters of the likelihood function, ϕ is the parameters of the prior distribution on group-varying components of θ. $p(\boldsymbol{M}_{\boldsymbol{\beta}}, \boldsymbol{\Sigma}^{\boldsymbol{\beta}})$ is the prior distribution on the parameters of the prior distribution, also called the *hyper prior* distribution.

5 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:

5.1 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 is declining since the 2008 GFC, reflecting a continuous fall in the underlying impetus to invest, despite countervailing policy measures in force.

ii **Moderate external financing constraints becoming weaker 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 increasing (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.

5.2 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.[25]

Table 1 reports the fixed effects coefficients and the variation in the random effect coefficients for each group (year, country, and year:country control group). The variation in the random coefficients within each group c, t, j is captured in the standard deviation of that group's random effect, such that σ_{α_t} shows the variation in the random effect intercept across years. 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), 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 $\text{cor(logQ, cash flow)} = -0.43(0.23)$, 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

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

Table 1. Summary of Hierarchical Model Regression Results

	Variable	Estimate	Est.Error	l-95% CI	u-95% CI	$\hat{\mathbf{R}}$
Fixed Effects	α	-3.00	0.08	-3.16	-2.85	1.00
	β^q	0.25	0.03	0.20	0.31	1.00
	β^{cf}	0.19	0.04	0.10	0.28	1.00
Country Random Effects	σ_{α_c}	0.15	0.04	0.09	0.25	1.00
	$\sigma_{\beta_c^q}$	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.*

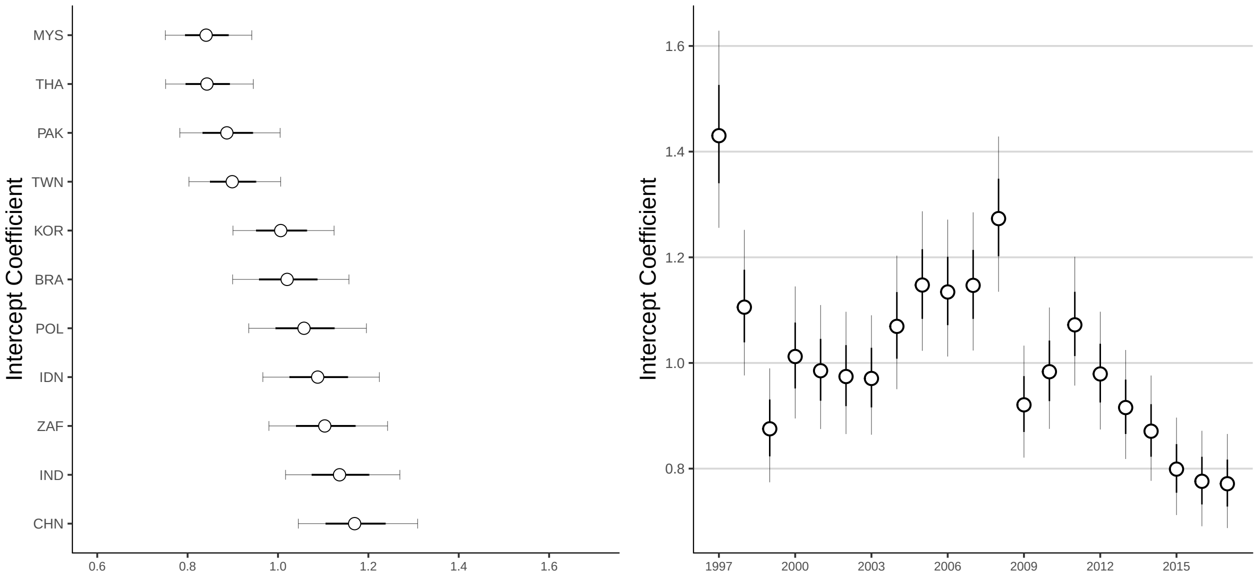
cash flow coefficients, the opposite is true and Q coefficients are lower as firms are less able to respond to investment opportunities.

Several key findings stand out. Firstly, as shown in Figure 3, the slowdown in developing economy estimated investment rates shows signs of 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 effect intercept coefficients over time, which captures the underlying impetus of firms to invest, all else being held equal.[26] Figure 3 shows that the attempted recovery in baseline investment rates among developing economy firms collapses after 2011, 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.

Secondly, developing economy firms remain responsive to investment opportunities: more so than

[26]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.

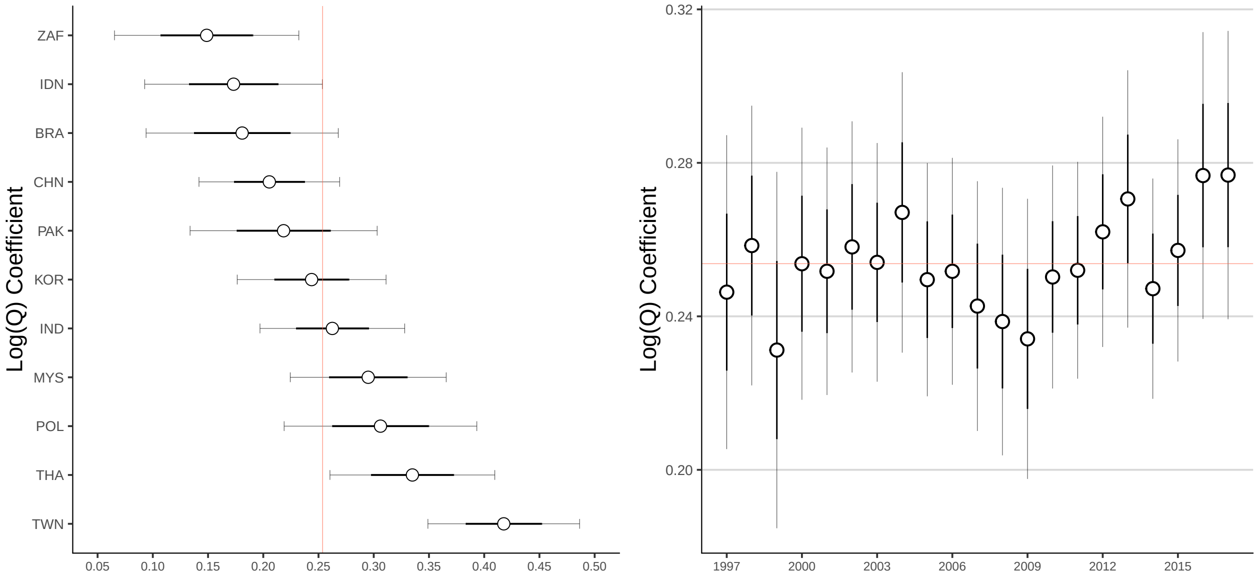
Figure 3. Intercept Coefficients by Country and Year, 1997-2017



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 time trend of the intercept (right hand side graph) shows clear cyclical fluctuations marked by a persistent fall in the trend after the 2008 GFC, falling continuously after a modest recovery lasting until 2011. The intercept falls greatly after the 1997 AFC, 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.*

developed economy firms (where Q coefficients are lower - see Strauss and Yang 2020), and increasingly so over time as the coefficient for 2016 and 2017 (at least) moves above the previously established cyclical pattern. 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_c^q or β_t^q). 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).

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



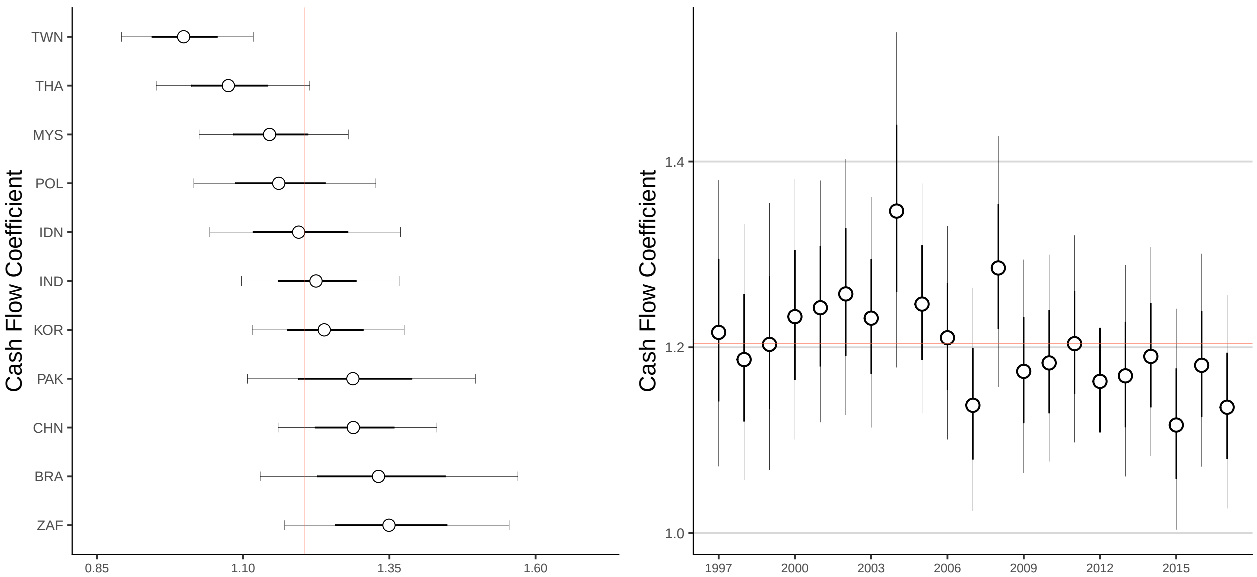
Note: *Q coefficient shows strong cyclical movements with no clear tendency to increase or decrease over time, except in the past few years. This upswing indicates that firms are not less responsive to investment opportunities, despite lower investment rates, but in fact the opposite. The Q coefficient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

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 economies 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 effects and random effects cash flow coefficients).

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. These random effects are for net external releasers of finance (the least constrained group of firms).*

The vertical red line is the fixed effect cash flow, 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 much lower external financing constraints.[27] 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 effects 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 negligible 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 which we noted earlier.

[27] Though with more relative variation given an estimated error of 0.04.

Despite some moderate to low levels of external financing constraints existing, financing constraints appear to be declining over time for developing economy firm. This makes sense. Apart from global monetary easing – which has greatly reduced borrowing costs for developing economy firms and governments (United Nations 2015) – cash flow rates (profitability) has tended to be stable or increasing post-2008 GFC for developing economy firms (Appendix C.5).[28]

5.3 Discussion

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 in the investment demand function since 2008 (notwithstanding a modest recovery until 2011) – and the 'raw' investment rates which we plotted in Section 3.2, 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 was evident from the above, developing economy firms' responsiveness to investment opportunities, and the degree of external financing constraints which they face, have both been changing over time.

Another difference between our estimated intercept coefficients and the raw investment rates is that our econometric estimator produces a 'partially pooled' estimate for each coefficient which allows for one year's data to inform another year's; whereas the raw investment rates do not such thing. 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.

Large declines in estimated (intercept) investment rates, despite diminishing external financing constraints, and firms being somewhat more responsive to investment opportunities, poses questions of the sustainability of higher developing economy firms' investment rates. If such investments have been made in projects with negative net present returns then this risks creating a deterioration in the balance sheet of developing economy firms. Leverage in emerging markets firms, perhaps from this, may have risen in recent years (Alter and Elekdag 2016), though our sample finds mixed evidence of this (Table 9).[29]

Weak demand expectations are, of course, influenced by domestic policy, and can be addressed with

[28] 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.

[29] Median quick ratios have increased in our sample, but leverage ratios have declined across all percentiles.

more aggressive aggregate demand management. Even a given macroeconomic stance can be made more investment-friendly by changing the composition of public budgets (more public investment spending) or the incentives for investment given by the tax system (more favourable deductibility for capital spending, wealth taxes that favour higher-productivity assets).

6 Conclusion

Raw investment rates of developing economy firms between 1997-2017 show cyclical movements in investment rates, declining persistently once Chinese investment rates (and related derived demands) fall after 2011. However, estimation of firms' 'cash flow-Q' investment demand functions, using a Bayesian hierarchical model, indicates that investment demand may actually be slowing more dramatically than raw investment rates suggest though. Time-varying intercept coefficients, reflecting the underlying impetus to invest, show a sharp fall among developing economy firms since the 2008 GFC to the lowest levels seen in our sample, with only a short-lived recovery between 2008-2011. This has occurred despite developing economy firms becoming less financially constrained over time, as cash flow coefficients have declined amidst easy global monetary conditions; and despite developing economy firms becoming increasingly becoming more responsive to investment opportunities. The latter is reflected in the more recent uptick in developing economy firms' time-varying Q coefficient values.

Greater responsiveness to investment opportunities is not necessarily a positive development (Richardson 2006) and may reflect a growing dearth of good investment opportunities relative to plentiful available financing post-2008 GFC. If this leads to over-investment then the economic outcomes from relatively higher rates of investment are unlikely to be optimal. Further research is required to assess if this finding does in fact point to over-investment by developing economy firms, since we do not know if the projects which they have invested in more recently have negative net present values and reflect managers behaving badly (Jensen 1986).

A concern is that without policies to better sustain aggregate demand in advanced economies the negative spillovers from them to developing economies, including through lower investment rates, may continue to be considerable. The extent to which China can increasingly act as an alternative centre of economic gravity for developing economies, and so make such a policy less relevant, seems very salient since our data shows that such a relationship already exists to some extent. A separate analysis might tell us what exactly the changing contribution of Chinese investment is to driving wider developing economy investment rates. 'Recoveries which die in their infancy', as Hansen opined (Hansen 1939), may become applicable to developing economy firms too then if the forces of stagnation – from within and without – override any potentially positive internal dynamics within developing economies.

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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.[30] 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 respect to

[30] 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.

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 Hierarchical Model: Additional details and findings

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:

$$M_\beta \sim \mathrm{N}(0, 0.5), \tag{14}$$

$$\sigma_{\alpha_{t,c,j}},\ \sigma_{\beta^q_{t,c,j}},\ \sigma_{\beta^{cf}_{t,c,j}} \sim \mathrm{Cauchy}(0, 2), \tag{15}$$

$$\Omega_{t,c,j} \sim \mathrm{LKJcorr}(5)\,. \tag{16}$$

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. The full list of priors can be found in Appendix B. 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:

$$M_\beta \sim \mathrm{N}(0, 0.5), \tag{17}$$

$$\alpha^0 \sim \mathrm{N}(0, 1.5), \tag{18}$$

$$\beta^0 \sim \mathrm{N}(0, 0.5), \tag{19}$$

$$\log(Q)^0 \sim \mathrm{N}(0.3, 0.3), \tag{20}$$

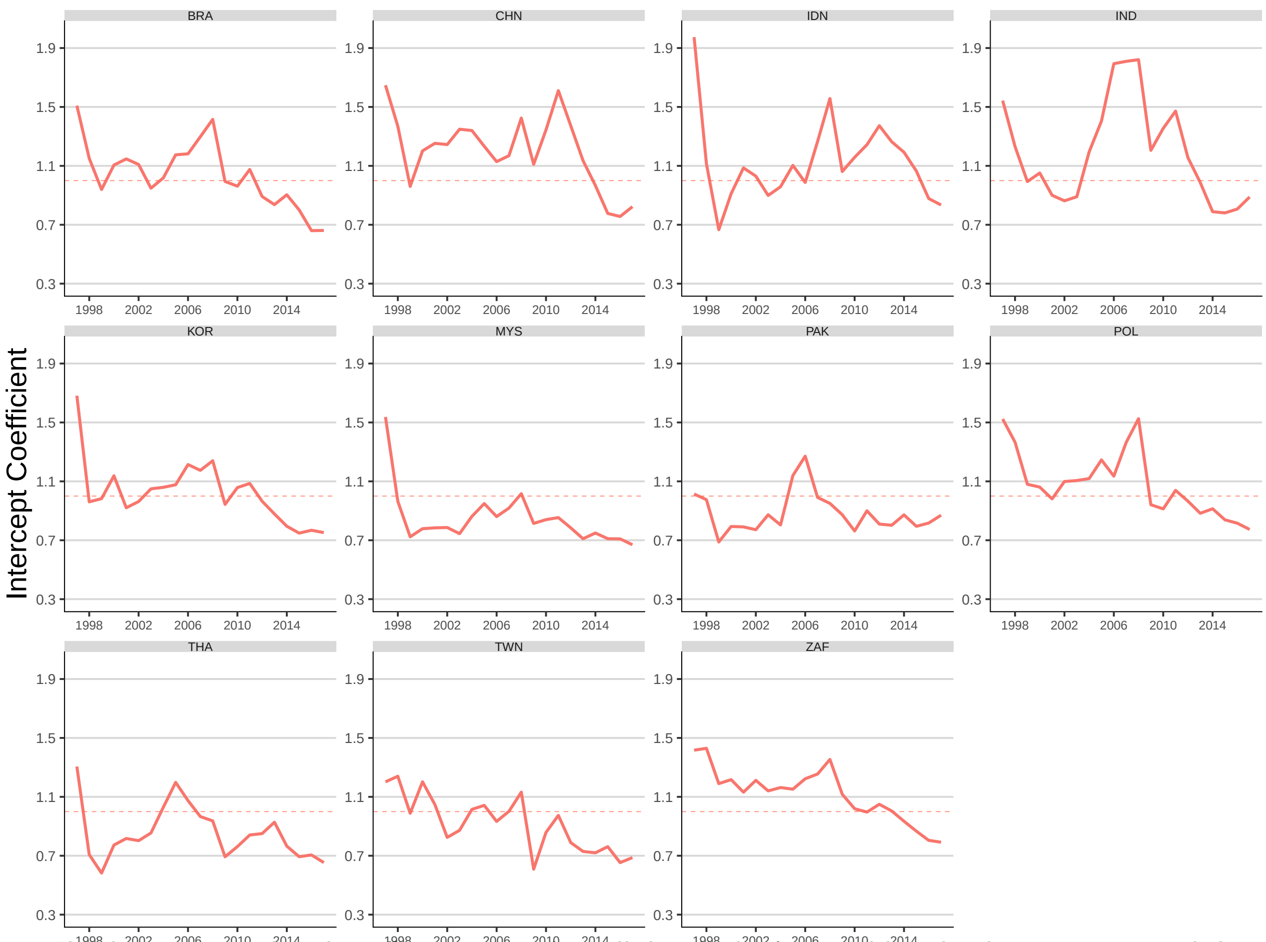
$$\nu \sim \mathrm{Gamma}(2, 0.1), \tag{21}$$

$$\sigma_y,\ \sigma_{\alpha,q,cf\in t},\ \sigma_{\alpha,q,cf\in c},\ \sigma_{\alpha,q,cf\in j} \sim \mathrm{Cauchy}(0, 2), \tag{22}$$

$$\mathbf{R} \sim \mathrm{LKJcorr}(5)\,. \tag{23}$$

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

Figure 6. 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 2. 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.*

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.

The third round of data processing: revolves around FINCF. We remove the top and bottom 0.1% of FINCF/cash flow ratios, and the top and bottom 0.5% of FINCF/sales ratios. We test to see if firm's derived cash flow identity of CHECH = IVNCF + OANCF + FINCF + EXRE is within an arbitrary range of accuracy of the given change in its cash flow (CHECH). We remove 1,093 observations.[31] *The fourth round of data processing:* revolves around fixed capital investment expenditure and Q. We winzorise the top 0.1% of investment rates setting it equal to 0.88 (the top 0.99% percentile). We trim the bottom 0.5% of investment rates. Next we trim the top and bottom 0.5% of Q observations. Lastly we remove any duplicate observations. This is introduced via Compustat Global owing to how we choose to download the data through the WRDS portal.

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 mea-

[31] If firms calculated value of CHECH is more than 200% bigger or smaller than the actual value of CHECH then they are removed.

sure 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.

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: $(\mathsf{CSHO} * \mathsf{PRCC}_F * \mathsf{AJEX}) + (\mathsf{DLC} + \mathsf{DLTT})$, 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 $\mathsf{QCSHOC} = ((\mathsf{CSHOC*QUNIT})/1{,}000{,}000)$, $\mathsf{marketcap} = \mathsf{PRCCD*QCSHOC}$ and $\mathsf{marketcap}_T = \mathsf{sum(marketcap)}$, 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 3. 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 5. Size of Developing Economy Firms Compared to Developed in Compustat

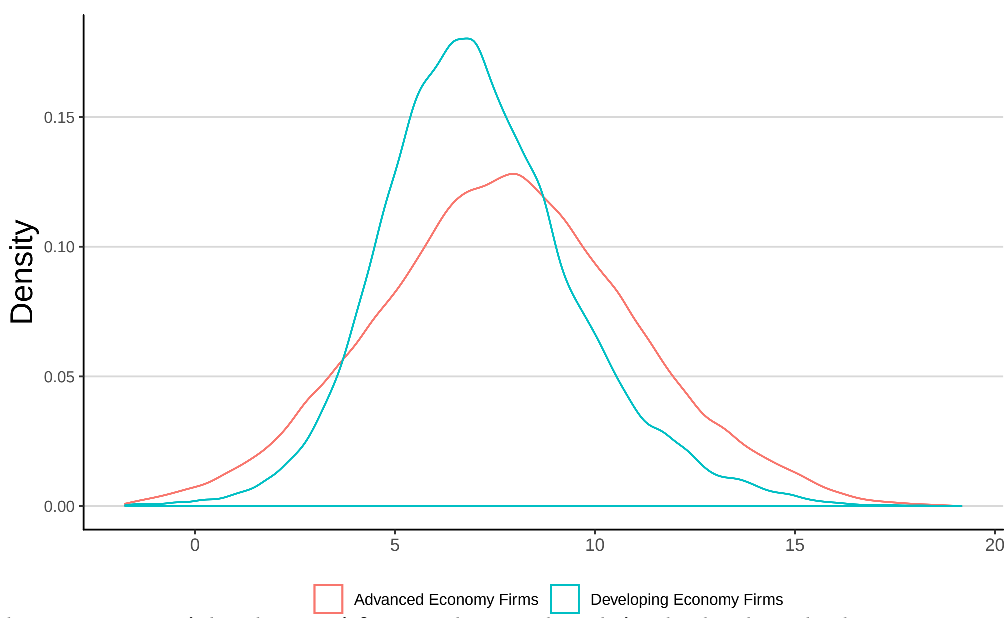
Country Group	Median	MAD	P10	P30	P70	P90
Advanced Economy Firms	215	296	12	68.2	676	3914
Developing Economy Firms	122	143	18.8	55.1	291	1275

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

Table 4. Detailed Data Sample Summary by Country and Year

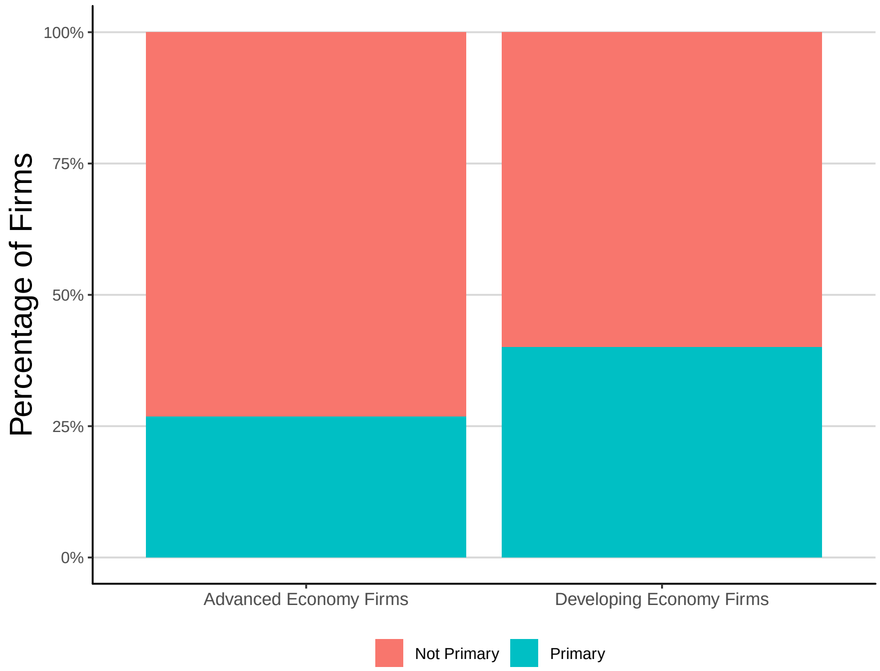
Year	BRA	CHN	IDN	IND	KOR	MYS	PAK	POL	THA	TWN	ZAF
1997	2	8	139	92	203	377	54	1	189	86	52
1998	6	17	148	103	201	366	56	7	173	97	54
1999	7	19	142	97	216	369	61	9	185	121	61
2000	10	22	135	103	214	374	70	6	135	140	75
2001	18	811	150	215	301	396	59	8	179	173	74
2002	23	902	166	283	315	484	45	11	210	455	86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

Table 6. 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 7. 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 8. 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 9. 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.*

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 the non-measurement error value. The effects of assumed attenuation bias on the estimate of Q are strongly non-linear, as β^q

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
	$\sigma_{\beta^{cf}_c}$	0.11	0.04	0.11	0.04	0.12	0.04	0.12	0.04	0.10	0.04
	$\sigma_{\beta^{q}_c}$	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
	$\sigma_{\beta^{cf}_t}$	0.07	0.03	0.07	0.03	0.07	0.03	0.07	0.03	0.06	0.03
	$\sigma_{\beta^{q}_t}$	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
	$\sigma_{\beta^{cf}_j}$	0.13	0.02	0.13	0.02	0.13	0.02	0.14	0.02	0.15	0.02
	$\sigma_{\beta^{q}_j}$	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.*

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.