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The Global Investment Slowdown: Corporate Secular Stagnation and the Draining of the Cash Flow Swamp*

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Abstract

Using a Bayesian ‘mixed effects’ model we estimate competing explanations for the investment slowdown on a large panel of firms with time-varying and country-varying coefficients. This allows us to explore both *microeconomic* (firm-level) and *macroeconomic* (country- and time-level) explanations. Evidence for key supply side, firm-level, impediments to investment rates are absent: advanced economy firms are financially unconstrained and remain responsive to investment opportunities. Instead, differences in firms’ investment rates across time and between countries can largely be explained by our secular stagnation predictor, proxied by the corporate sector’s ‘net external financing’ demand. This shows that firms, and the corporate sector as a whole across advanced economies, are increasingly net external ‘releasers’ of funds to shareholders, creditors, and bondholders, reflecting cross-cutting exogenous factors creating a chronic excess of cash flow over weakening investment opportunities.

JEL Codes: D22, D24, E12, E22, E23.

Keywords: Secular Stagnation, Investment Slowdown, Hierarchical Model, Finance Constrained, Tobin’s Q, Investment Rates, Corporate Savings, Bayesian Econometrics.

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1 Introduction

Have the investment rates of non-financial publicly listed firms declined?¹ And if so, why? Existing research agrees that investment rates have declined in the U.S. since around 2000 (Alexander and J. Eberly 2018; Gutiérrez and Philippon 2017b; IMF 2015). There is some disagreement, though, over whether the investment slowdown is cyclical or secular in Europe (Caselli et al. 2003; Döttling et al. 2017; Lewis et al. 2014). Post-2008, the slowdown has continued and spread to developing economies (Kose et al. 2017; Magud and Sosa 2015).² Figure 1 details a clear secular decline in gross investment rates since 2001 across U.S. firms *and* 14 other advanced economy and tax haven locations.³ Developing economy firms have only seen a notable slowdown since 2014 (and after the 1997 Asian financial crisis).⁴ This has been accompanied by median investment opportunities — raw Q values — declining or stagnating among advanced economy and U.S. firms, while increasing among developing economy firms (see Appendix C.4).

There is less consensus, however, on the causes of the investment slowdown. Country-specific explanations are often provided: These include the outsourcing of labour-intensive production, lower labour force participation rates, the bias of technological change, and reduced government spending (Alexander and J. Eberly 2018; Fernald et al. 2017). Not all of these explanations can easily be generalized across most advanced economies though, despite the slowdown being a cross-country feature (Figure 1).⁵

The investment slowdown is particularly difficult to explain given that it has gone hand-in-hand with increasing profitability. This is the opposite of what is expected. In Keynes’s *Treatise on Money*, an inexhaustible supply of corporate profits — a so-called ‘widow’s cruse’ — is supposed to follow from high, not low, corporate investment (Keynes 1930). Higher permanent profitability should entail higher Q values, and, in turn, higher temporary investment (Romer 1996).

Reconciling high profitability with weak investment rates has seen increasing emphasis placed on declining corporate competition (Gutiérrez and Philippon 2017a; Jones and Philippon 2016; Philippon 2019). This is sometimes linked to intangible assets (Alexander and J. Eberly 2018; Crouzet and J. C. Eberly 2019). Declining competition is also linked to U.S. specific trends in weaker antitrust enforcement,

¹We later define the ‘corporate sector’ as non-financial 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*.

²Our developing economy sample is defined further in Appendix C.

³See Appendix C for variable definitions and construction details.

⁴During 2004-2007 investment rates increased for all firms globally. 2011-2014 showed a modest recovery for advanced economy firms, and a strong one for U.S. firms. Developing economy investment rates fell below 6% at the median from 2014, though they slowed from 2012. Developing economy firms only surpass 1,000 observations in 1997.

⁵While productivity growth has also slowed in Europe, labour force participation rates have increased across Europe, Canada, and Japan. Government spending in GDP shows uneven movements between 1995-2017 for the U.S., Japan, Korea, France, and UK, and requires further investigation (OECD 2019a,b).

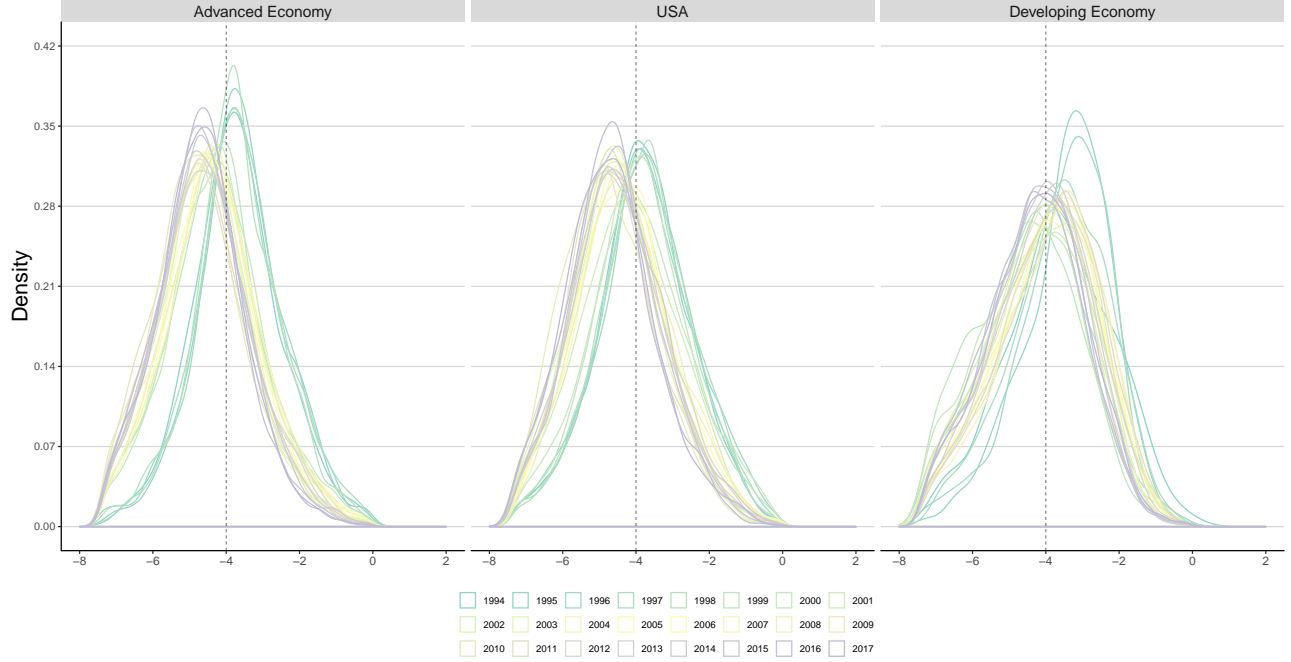
higher prices and profitability, and lower investment rates (Döttling et al. 2017; McAdam et al. 2019; Philippon 2019). As a U.S. specific explanation though, declining competition appears to fail (Bajgar et al. 2019; Freund and Sidhu 2017) – even if it remains relevant more broadly. In line with Autor et al. (2019), we find that trends in cash flow rates (profitability), investment rates, and raw Q values are similar *across* almost all advanced economies. Furthermore, we find no evidence in our regressions of the investment demand curve flattening over time as might be expected if market power was increasing. Several other arguments also rely implicitly on the slope of the investment demand curve *changing* and so are similarly unconvincing. These include the notion that firms have become *less responsive* to investment opportunities due to the ‘financialization’ of capital markets (Lazonick et al. 2014), or *more responsive* as previously profligate managers become disciplined by new institutional shareholders (Gutiérrez and Philippon 2018).

Instead, we draw on the ‘secular stagnation’ framework to understand slowing rates of investment (Backhouse and Boianovsky 2016; Hansen 1939). As formulated by Summers (2014), a chronic excess of (desired) savings over (desired) investment is depressing economy-wide economic growth. The supply of economy-wide savings has increased due to growing inequality, higher capital and collateral requirements, increasing intermediation costs, and large developing economy savings (Summers 2015). Concurrently, investment demand has shifted inwards due to slowing population and labour force growth, slowing technological change, the falling relative price of capital goods, and technology firms having much lower start-up and scale costs. A defining symptom of this is a surplus of uninvestable corporate cash. This symptom we use as a proxy for ‘secular stagnation’ causes. Its proper measurement, description, and statistical association with ‘true’ (estimated) investment rates is the focus of this paper.⁶

Our hypothesis for the *corporate* investment slowdown we call ‘corporate secular stagnation’ and is defined as *a chronic and increasing excess of corporate cash flow over weak investment opportunities*. It highlights a growing mismatch between investment and savings at the firm-level, in response to investment demand shifting inward and internal funds increasing. We take these shifts to be exogenous. The impact of ‘corporate secular stagnation’ is to make the corporate sector a major contributor to depressed real interest rates through its net external financing demand becoming increasingly negative. The tendency for any individual firm to experience secular stagnation, we summarize through a negative ‘net external financing’ position (FINCF), taken from the firm’s cash flow statement. FINCF responds endogenously to shifts in investment opportunities and internal funds, and so serves as a

⁶Damodaran (2015) argues that technology firms have a quicker, or more ‘compressed’, ‘life cycle’.

Figure 1. Distribution of Global Investment Rates Over Time



Note: Kernel density approximation of $\log_2()$ firm gross investment rates for 24 countries (U.S., 14 advanced economies, and 9 developing economies), shifting in sharply in 2001. Dotted line at $\log_2(-4) \approx 6\%$ investment rate. Median investment rates decline from 6% to 4% in advanced economies, and from 7% to 4% in the U.S. This is accompanied by an equally strong narrowing in the variability of advanced economy investment rates (not evident here).

proxy for underlying corporate secular stagnation (rather than as an independent, strictly exogenous, causal factor itself). As such this paper is, first and foremost, an empirical investigation, which finds little evidence in favour of key microeconomic, firm-level, supply side explanations for the investment slowdown; and instead that *secular stagnation* explanations, proxied by the FINCF variable, and acting at the macroeconomic level as common exogenous secular shocks affecting all advanced economy firms, are likely paramount (Ollivaud et al. 2016; Reifschneider et al. 2015; Summers 2015).

FINCF turns out to be an incredibly strong predictor of differences in firms' investment rates, because firms tend to release unneeded funds externally. For most advanced economy firms, FINCF has shifted from being positive (a net external 'borrower'), to negative (a net external 'releaser' of funds), as firms' investment demand has shifted in while internal funds have shifted out. This allows firms to finance all available investment opportunities using internal funds; leading to the external sector being used not for net 'borrowing', but instead as an outlet to 'drain' excess funds — the 'cash flow swamp' — which risks accumulating on firms' balance sheets. The other cash flow statement outlets for firms' excess funds are the net accumulation of financial assets, and internal cash retentions, and lack the predictive power of FINCF.

The results from our hierarchical 'cash flow-Q' regressions are consistent with corporate secular

stagnation as the primary cause of the investment slowdown. Supply side impediments (Caggese and Perez-Orive 2017; Goldin et al. n.d.; J. Lewellen and K. Lewellen 2016) of the type we investigate appear to be absent. We find that: (i) Firms who are net external ‘borrowers’ of funds invest 25% more than net external ‘releasers’. (ii) Intercept coefficients reflecting the investment demand curve decline over time. This is especially evident for advanced economy firms. (iii) The slope of the investment demand curve (approximated by the time-varying Q regressions coefficients) remains roughly constant and Q coefficients are reasonably high. (iv) Cash flow coefficients for advanced economy firms are negligible and reflect the absence of any meaningful finance constraint. (v) Differences in firms’ investment rates across time, and between countries, can largely be ‘explained’ by our secular stagnation predictor, and reflect common exogenous secular shocks generating a chronic excess of cash flow over investment opportunities across all advanced economy firms.⁷

The turn to firms releasing surplus funds externally (rather than retaining it), as summarized by FINCF, is unsurprising: Out of the 40,000 publicly listed companies analyzed by Aswath Damodaran in 2016, more than half generated aggregate returns on investment lower than their cost of capital. As such, these funds should, at least in theory, be returned to shareholders instead of reinvested or retained (Damodaran 2016). In contrast, the majority of the academic literature focuses on firms retaining funds – and increasingly so. This serves as the basis for an alternative set of largely supply side explanations for changing firm behaviour (Armenter and Hnatkovska 2017; Chen et al. 2017; Falato et al. 2013; Faulkender et al. 2019; Han and Qiu 2007). The tendency to retain, and the tendency to release, surplus funds appears to be two ends of the same cash flow swamp in our sample. However, the retention tendency out of cash flow is somewhat weaker in our estimation, and ultimately less connected to changes in investment rates across time and countries (Appendix E, Figure 11).

Our paper’s contributions are empirical and threefold: Firstly, we use FINCF (net external financing activities) from the firm’s cash flow statement as a proxy for the degree of ‘corporate secular stagnation’ conditions facing any individual firm, and all firms within a country or year. At the *microeconomic* level, firms’ who are net external ‘borrowers’ have structurally higher investment rates than net ‘releasers’ across the distribution. This is because the relative and absolute decline in investment demand manifests as a surplus of available financing, which is then released externally.

As a result, the non-financial corporate sector is a growing contributor to the depressing of real

⁷We put the word *explains* in inverted commas, since the relationship between FINCF and predicted investment rates (intercept coefficients) is to a large extent endogenous.

short-term interest rates (the focus of the contemporary secular stagnation literature) through firms borrowing less and releasing more funds externally. The explanatory power of FINCF persists even with the inclusion of Q in a regression. In addition, drawing on Fazzari, Hubbard, Petersen, et al. (1988), who use *gross* external distributions to shareholders to try and distinguish more financially constrained firms from less financially constrained firms, we use FINCF, a *net* variable, for this same purpose. A net variable is imperative to use since, under contemporary financial markets, even financially-constrained firms borrow funds and issue equity, while concurrently distributing earnings to shareholders (Denis and McKeon 2018; Lian and Ma 2019). At the *macroeconomic* level, aggregate FINCF is increasingly negative (net ‘releaser’ of funds), and implies that the corporate sector as a whole now serves as a source of net finance for the household and government sectors to draw on (Palumbo and Parker 2009). This follows from the definition of FINCF, as the sum of all cash inflows and outflows between the firm and its external shareholders, bondholders, and creditors.⁸

Secondly, we provide cross-country and time-varying evidence on the nature of the global investment slowdown for 24 countries between 1994-2017, using a merged Compustat Global and North America database. Distinct from existing studies, our hierarchical ‘mixed effects’ model allows us to estimate Q coefficients, cash flow coefficients, and regression intercepts that vary by year and by country (Gelman and Hill 2006; Hsiao and Tahmiscioglu 1997). This is important because noticeable differences in how these variables impact firms’ investment rates across time and country exist. For example, developed economy firms are unconstrained financially, having negligible cash flow coefficients, while developing economy firms remain constrained financially, having meaningful cash flow coefficients. In these circumstances, pooled estimates can be seriously misleading (Barcikowski 1981; Hsiao 2014; Pepper 2002; Pesaran and Smith 1995; Wooldridge 2003). In addition, existing investment slowdown studies do not account for the time-varying movement of coefficients. This makes the meaning of time-dummies in investment slowdown studies questionable (Gutiérrez and Philippon 2017b).

Thirdly, our hierarchical model allows us to use firm-level data to try and ‘explain’ ‘macroeconomic’ variation, defined as variation in firms’ (estimated) investment rates between country and time (Gelman and Hill 2006; Gelman, Shor, et al. 2007). This is achieved by first estimating ‘true’ firm-level investment rates. These are estimated as the sum of the fixed effect and random effect intercepts and hold constant key firm-level explanatory variables and controls. These estimated ‘true’ investment rates are then used

⁸Consisting of dividend payments made externally, short-term and long-term borrowing issuances, principal short-term and long-term debt repayments, share repurchases and share issuances.

as ‘data’, to be explained by a separate set of macroeconomic, ‘group-level’, predictors. This allows us to properly test the secular stagnation hypothesis, which by definition relates to common exogenous factors affecting all firms within a country or year. Aggregated versions of our secular stagnation variable, FINCF, are used as the group predictors and proxy for the factors which are decreasing investment demand and increasing cash flow across firms. In contrast, existing firm-level studies trying to explain country-level variation have used separate, additional, national-accounts data (Chen et al. 2017; Döttling et al. 2017).

Our econometric results show that macroeconomic variation in firms’ estimated investment rates (intercept coefficients), over time and between countries, is closely related to the shifting net external financing balance of the corporate sector as a whole (aggregate FINCF), as well as the proportion of firms that are net ‘releasers’ of funds in a given country or year.

Empirically, our findings are in line with Gruber and Kamin (2015), who link changes in the national accounts’ concept of ‘net lending’ to declining private investment expenditure and increasing corporate distributions. We also do not give this relationship a strict causal interpretation since the economy-wide, and global, net external financing balance is responding endogenously to weakening investment demand and higher profitability – the ultimate causes of which we do not seek to explain (Figure 2).

The paper’s empirical approach can be seen as an outgrowth of the capital structure literature (H. DeAngelo, L. DeAngelo, Skinner, et al. 2009; Fama and French 2001, 2005). Our use of the firm’s ‘net external financing position’ is similar to what Frank and Goyal (2003) construct for their ‘Pecking Order’ (i.e. costly external finance relative to internal finance) tests — also used by Gutiérrez and Philippon (2017b). Our variable is more comprehensive and includes short-term borrowing. Moreover, our corporate secular stagnation variable, FINCF, and its relationship to increasing profitability and declining investment opportunities, is similar to, and consistent with, the capital structure literature’s findings on the implications of Pecking Order and Agency Theories for firms’ gross distributions (Fama and French 2002). Our paper shows that fundamentals are driving this net ‘distribution’ (releasing) decision (Nohel and Tarhan 1998) rather than a pure capital structure motivation. Lastly, life cycle theories of the firm (H. DeAngelo, L. DeAngelo, and Stulz 2006), make similar predictions to ours: As firms mature, their investment opportunities dry up relative to increasing cash flow rates, leading to an increase in their tendency to release surplus funds. Our findings, however, cut across firms of all sizes, indicating a common exogenous shock (even if larger firms tend to have a higher probability of being a net ‘releaser’ of funds in our sample). While our sample is fairly robust to the decline in new listings in the U.S. by using a panel covering all major economies with very different listing tendencies.

The next section sketches our model and discusses our corporate secular stagnation variable (FINCF). Section 3 describes our Bayesian hierarchical model — a ‘mixed effects’ model with shrinkage. Section 4 reports the model’s microeconomic results. Subsection 4.2 extends the model by including two group-predictors to ‘explain’ macroeconomic variation in firms’ estimated investment rates between countries and years. Section 5 concludes. Our Appendix contains a detailed description of our dataset and variables, including further descriptive statistics on FINCF and a measurement error corrected version of our hierarchical model.

2 The Net External Financing Position and Secular Stagnation

2.1 Cash Flow-Q Investment Model

Following Fazzari, Hubbard, Petersen, et al. (1988), we use the now well-known cash flow-Q investment model (Romer 1996). The general derivation of this follows J. Lewellen and K. Lewellen (2016), and can be found in the Appendix A. 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 is subject to several constraints. We assume quadratic investment adjustment costs and quadratic external financing cost, with the latter in proportion to $I_t/K_t > \Pi_t/K_t$, where Π_t is cash flow. This leads to the following final regression specification:

$$\frac{I_t}{K_t} = -\xi + \xi * q_t + \beta * \xi * \frac{\Pi_t}{K_t} + \xi * \alpha * \lambda_t. \quad (1)$$

q_t is the present discounted value of future marginal revenue products of an additional unit of capital. As such, q is the market value of a unit of capital. With a purchase price of capital fixed at 1, q is the ratio of the market value of a unit of capital to its replacement cost. q is proxied by the book to market value of the firm.⁹

The q coefficient declines in proportion to $\xi = 1/(\alpha + \beta)$, such that an increase in α , the time-invariant adjustment cost parameter, and/or in β , the cost of external financing, should reduce the coefficient size of q . Cash flow, Π_t/K_t , enters directly into the regression equation. But, we can see it will be of little significance if the cost of external finance is $\beta \rightarrow 0$, or if the firm has no need to access external finance — i.e. $I_t/K_t < \Pi_t/K_t$. In our regression specification, we interact the ‘cash flow’ variable with FINCF to distinguish firms that are more (potentially) financially constrained from those who are less

⁹We use total assets as the denominator instead of capital stock. This keeps the variable strictly positive, despite some loss of interpretation.

(or not at all) financially constrained. Lastly, if q is measured incorrectly, this measurement error can bias downward our regression estimate of q . This is made worse if q is correlated with cash flow (which can also bias upwards the estimated cash flow coefficient) (Erickson and Whited 2000, 2012). We correct our baseline model for measurement error in the Appendix H using a Bayesian approach (Clayton 1992; Richardson and Gilks 1993).

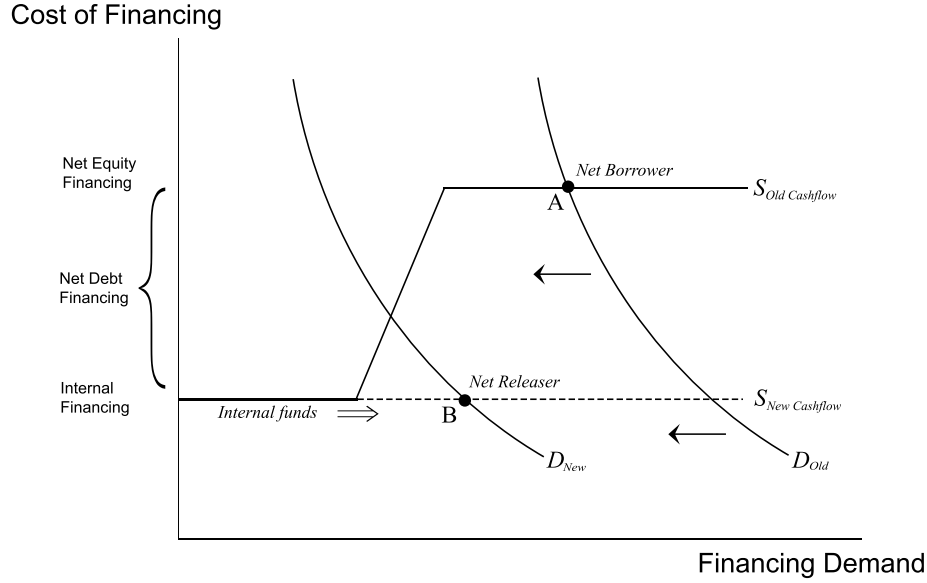
The cash flow-Q model is useful when we suspect firms are potentially finance *constrained*, arising from a combination of costly external finance and the firm’s internal funds being insufficient to cover all efficient investment needs. However, an increasing number of firms in our data appear, *a priori*, to be financially *unconstrained* and instead subject to corporate secular stagnation, such that $I_t/K_t < \Pi_t/K_t$. Their demand for (net) external financing is zero or negative due to their investment opportunities falling short of available internal financing. These firms are identified by a weakening of their net external demand for financing, so much so that they are increasingly net ‘releasers’ of funds externally. Our model needs to account for these firms too, even if only qualitatively, and in particular their tendency to release, rather than largely retain, unneeded surplus.

Extension of the cash flow-Q model to account for financially unconstrained firms subject to secular stagnation is reflected in Figure 2 (Fazzari, Hubbard, Petersen, et al. 1988). The investment demand curve declines for most firms, shifting in to the left, while firms’ horizontal supply of internal financing extends, or increases, outwards to the right as cash flow rates increase. As a result, most firms move from equilibrium point A to equilibrium point B. Empirically, we identify this movement using firms’ net external financing position, FINCF, and its shift from being a positive net external borrower of financing to a negative net external releaser of cash flow and cash, with no real reliance on the external sector except as an outlet to release surplus funds.

Though we do not formalize Figure 2 in a model, our thesis must explain why firms experiencing secular stagnation might release unneeded surplus — especially since it is this tendency that we take to be a proxy for secular stagnation.¹⁰ Pecking Order theory is ill suited for this (Appendix for further discussion) since it predicts an ingrained bias towards retentions – yet we see the opposite (H. DeAngelo, L. DeAngelo, and Stulz 2006). At the microeconomic level, Agency Theory (Easterbrook 1984; Jensen and Meckling 1976), and its models (Hart and Moore 1994; Stulz 1990; Tirole 2010), are much better suited to explaining when firms would disgorge unneeded cash under market imperfections. Moreover,

¹⁰Many ‘workhorse’ investment models do not allow for the possibility that a firm may concurrently borrow and lend, or distribute, in different markets — for example, through issuing equity and paying dividends concurrently (Fazzari, Hubbard, Petersen, et al. 1988; Poterba and Summers 1984)

Figure 2. Corporate Secular Stagnation



Note: The supply of firms' internal funds increases (double lined arrow) as cash flow rates increase, extending the horizontal dotted line out through Point B, as investment demand shifts in (a pure intercept shift with the slope remaining constant). As a result, most firms move from being net external 'borrowers' of finance (Point A) to net external 'releasers' (Point B). At B, firms invest less despite having more internal finance. Any 'free cash flow' at B tends to be released externally. The y-axis reflects a Pecking Order of financing costs, with internal financing the least costly.

'free' cash flow becomes the primary problem facing firms now. The literature assumes that the Agency Theory problem is more applicable to certain industries (Jensen 1989), or mature firms in their corporate life cycle (Brealey et al. 2011). Below, we show that it has now become *the* problem facing most advanced economy firms who are experiencing corporate secular stagnation and at risk of a cash flow swamp forming on their balance sheet. In response, advanced economy firms are releasing externally, in net, their cash flow in increasing quantities.

2.2 FINCF: Data Definition, Uses, and Empirical Content

FINCF serves two mutually supportive purposes in our study: First and foremost, it is used as an identifier of the extent of secular stagnation facing the individual firm and the economy as a whole. It highlights that the corporate sector as a whole in advanced economies are now a major contributor to depressed real interest rates through it's net external financing demand becoming negative. Secondly, following Fazzari, Hubbard, Petersen, et al. (1988), FINCF — as the firm's net external releasing or borrowing of funds — is used as our proxy for the extent of 'financing constraints' facing the firm. Firms that have large positive *net* external borrowing flow positions are more likely to encounter external financing constraints than firms that are net external 'releasers' of funds: they tend to be smaller, have higher investment

demand, less collateral, higher leverage, and *far lower* cashflow rates (tending towards negative too) (see Appendix).¹¹ For the economy as a whole, corporate secular stagnation is, similarly, a financially unconstrained environment, one that is ‘cash rich but investment opportunity poor’. Further descriptive evidence on FINCF and its relationship to our key variables can be found in the Appendix E. Before defining FINCF below, we first describe our dataset.

2.2.1 Dataset and Sample

Our sample covers non-financial, publicly listed, firms constructed through merging S&P’s Compustat Global and Compustat North America databases. The data is consolidated at the firm-level. Appendix C contains a full description of the data preparation and variable definitions. Our final sample consists of 283,702 observations on 35,805 unique firms across 24 countries and 24 years, between 1994-2017. This includes the U.S., 14 other developed economies (including the tax havens of the Cayman Islands and Bermuda), and nine developing economies. Our sample begins in 1994, since Compustat Global has little coverage prior to then. It should be noted, though, that developing economies in Compustat Global only contain a critical mass of observations from 1997. Values are in nominal US\$, converted into a common currency using the Compustat Global currency file. Variable definitions differ somewhat by country, based on differing accounting standards. In particular, the U.S. follows GAAP accounting standards, while the rest of the world tends to follow IFRS, with differences between countries following IFRS. Despite certain limitations, we chose to use an unbalanced panel, as a balanced design – with no gaps between any year – would exclude most of the largest firms in existence today and create considerable survivor biases.

2.2.2 FINCF Definition

FINCF is defined as ‘net external financing activities’ and comes from the firm’s cash flow statement. It records all cash inflows and outflows between the firm and its external creditors, bondholders, and shareholders. As such, it covers net equity issuances, dividend outflows (but not inflows),¹² net short-term credit flows, and net long-term debt flows, between the firm and the external sector. These include:

- *Long-term debt issuance and principal repayments*¹³

¹¹Median leverage is 0.49 for net external ‘borrowers’ compared to 0.29 for net external ‘releasers’, through borrowers have a higher MAD (0.61) compared to releasers (0.41).

¹²Dividend received is located in cash flow, for North America firms.

¹³FINCF excludes interest payments on debt. It includes the principal payments on capital (financial) lease liabilities, since a debt is being accumulated in order to gain an asset.

- *Current debt issuance and principal repayments*
- *Cash dividends Paid*
- *Purchase of common and preferred stock*
- *Sale of common and preferred stock*
- *Other: Debt and equity issuance costs, changes in stock options, minority shareholder dividends, dividends on subsidiary stock, and tax benefits of stock options.*

FINCF has the benefit of being widely-reported by all firms and covers a number of items that are difficult to obtain individually in cross-country firm-level datasets, such as share repurchases and share issuances. The above is the definition for firms following U.S. GAAP accounting standards. Compustast Global firms instead tend to use IFRS accounting standards and so, define FINCF differently.¹⁴ As a cash flow statement variable, FINCF is reported gross (i.e. before depreciation) and taxes and other cash expenses are also deducted. FINCF comes from the firms' cash flow identity:¹⁵

$$\Delta\text{Cash Stock} = \Delta\text{Operating \& Other cash flow} + \Delta\text{Fixed Capital Inv.} + \Delta\text{Net Financial Inv.} + \Delta\text{Net External Financing}, \quad (2)$$

$$\text{CHECH} = \text{OANCF} + \text{CAPX} + (\text{IVNCF} - \text{CAPX}) + \text{FINCF}.$$

The cash flow identity¹⁶ shows that, in theory, there are two channels other than FINCF and CAPX, through which changes in the firms' investment opportunities or internally generated cash flow rates can be manifested, namely changes in cash stocks (CHECH), and changes in the net purchase of financial assets (IVNCF less CAPX). Moreover, *increases* in cash flow can lead to *increases* in net external borrowing (FINCF) — rather than *decreases* as secular stagnation predicts — if the firm is currently financially constrained, or expects to be constrained in the future.

2.2.3 FINCF as a Proxy for Financing vs. Secular Stagnation Constraints

Given that FINCF reflects a surplus of available financing relative to investment opportunities, we also use it as a proxy for the extent to which the firm might face external financing constraints arising from imperfections in financial markets (Myers and Majluf 1984). Our approach can be seen as a generalization

¹⁴Firms listed in China, India, and Japan are not required to report using IFRS standards. IFRS permits interest and dividends received and paid, as well as bank overdrafts, to be classified as 'operating activities', or 'investing activities' or 'financing activities'.

¹⁵'Net' here refers to the nature of the aggregation process, summing sales and purchases of assets. We exclude exchange rate adjustments from this formula, EXRE.

¹⁶In the cash flow statement, fixed capital and financial investments come combined in one 'investing activities' variable, IVNCF. It is a net term, since it includes the sale of fixed capital assets and financial assets, mergers and acquisitions, etc. For our purposes, we disentangle fixed investment from financial investment, but only approximately, since we simply deduct (or technically 'add') CAPX from FINCF.

of Fazzari, Hubbard, Petersen, et al. (1988), who use *gross* dividend distributions undertaken by the firm for this purpose. FINCF by contrast is a *net* variable. Use of the latter as a proxy for financing constraints makes much more sense for advanced economy firms operating in highly-developed financial markets, where even finance-constrained firms borrow funds and issue equity while concurrently distributing earnings to shareholders (Denis and McKeon 2018; Lian and Ma 2019).¹⁷

Our use of FINCF as a proxy for the degree of the financing constraints can be illustrated using the U.S. company, Starbucks. In 2018, it announced that it intended to expand its capital returns program to shareholders through dividends and share repurchases, amounting to over a quarter of its market capitalization at the time (Cannivet 2019). It concurrently issued large amounts of debt, such that its debt-to-equity ratio increased from 59% in 2016 to 800% in 2019. This saw its bond credit-rating downgraded in 2018 from A–to BBB+ — S&P’s lowest investment grade level. Given Starbucks’s higher levels of debt, Starbucks was now (potentially) financially constrained according to some measures (Whited 1992), while according to other measures, it was not financially constrained since it was undertaking large gross distributions to shareholders (Fazzari, Hubbard, Petersen, et al. 1988). In contrast, our ‘financially constrained’ indicator, FINCF, says that in order to properly assess the nature and degree of the constraint, what matters is the *net* external two-way flow of funds between the firm and its shareholders, bondholders, and creditors. If Starbucks net equity raising position (including dividends undertaken, equity purchased, and equity issued), plus what it concurrently borrows from and repays in principal to its bondholders and creditors, is negative then this indicates that Starbucks has a negative net external money demand and is a net ‘releaser’ of funds externally. In the above case, we would expect FINCF to be negative. And in fact ‘Starbucks Corp’ has a negative FINCF position in our dataset between 2005-2017 (the years for which Starbucks is included in our sample). We propose that this implies that it has greater financial slack — proxied by its exceptionally high cash flow rates — than investment opportunities.¹⁸ As such, we would call Starbucks ‘financially unconstrained’ because its inability to access external financial markets on efficient terms is not the cause of any current financial distress.

Instead, our theory would predict that Starbucks, given its negative FINCF balance, is potentially

¹⁷In our case, only 17% of external ‘releasers’ of funds do not distribute earnings, following the approach in Fama and French (2001) and Skinner (2008) to constructing earnings distributions on Compustat. In comparison, 37% of net ‘borrowers’ do not distribute earnings. In both instances, the relative tendency not to distribute earnings is greater among developing economy firms in our sample, which are twice as likely not to distribute in both categories.

¹⁸Starbucks’ has cash flow rates consistently above 20% – even higher than its investment rates of around 10% and high, *but declining*, raw Q values.

subject to corporate secular stagnation constraints. As it happens, slow sales growth, despite high profit margins, was the stated reason for its capital returns program and, ultimately, for its credit rating downgrade. Its large increase in debt load is what Agency Theory might predict, under tight governance conditions, to be an optimal *response* – rather than cause – to ensure that Starbucks commits to releasing its surplus cash flow. Easy monetary conditions would have further incentivized a debt-financed capital returns program.

A similar version of our ‘net external financing activities’ variable is used by Frank and Goyal (2003) for a Pecking Order test of firms’ debt structure. Our variable is calculated differently, though.¹⁹ Gutiérrez and Philippon (2017b, Fig. 15), drawing on Frank and Goyal (2003), explore why the investment slowdown in the U.S. is most pronounced among firms with high credit ratings (those rated AA to AAA) compared to firms with lower credit ratings (those rated below AA).²⁰ They come up with several important empirical findings which support our conclusions.²¹

2.2.4 FINCF as Corporate Secular Stagnation

We begin by documenting the tendency for advanced economy firms to experience secular stagnation, as proxied by the ‘net external financing activities’ (FINCF variable from the cash flow statement) becoming increasingly negative. We explore in Appendix D alternative interpretations for our findings and movements in FINCF, as well as arguments in favour of focusing instead on cash flow statement items: CHECH (cash accumulation) or IVNCF less CAPX (net financial asset accumulation). We provide econometric evidence that FINCF reflects demand side corporate secular stagnation: responding strongly to movements in investment opportunities and cash flow rates. Our econometric findings build upon the capital structure literature, which notes that firms’ *gross* financing positions and distribution flows tend to correspond with their growth prospects and profitability characteristics (H. DeAngelo, L. DeAngelo,

¹⁹Frank and Goyal (2003) do not include dividends paid with net equity issuance though, as our variable does, following GAAP and IFRS guidelines. Dividends are instead part of the firm’s ‘financing deficit’, while changes in short-term debt — i.e. Compustat item DLCCH. — are entirely excluded.

²⁰They calculate the firm’s ‘financing deficit’ as roughly equal to (FINCF), but they do not include changes in short-term debt or dividends.

²¹They find: (1) More highly rated firms turned to an external financing surplus around 1990, while this happened much later (mid-2000s) for less highly rated firms; (2) The shift towards negative external financing — i.e. net ‘releaser’ of funds — has empirically been driven by negative net equity issuance (the sale and purchase of common and preferred stock), since long-term net debt issuance has remained positive; (3) Moreover, net debt issuances have been *positive* for firms with high credit ratings, and have run concurrently to large *negative* net equity issuance by this same group of firms since the mid-1980s. This is exactly what Agency Theory might recommend for cash-rich firms facing a secular stagnation environment; and (4) Even firms with worse credit ratings, and with large positive net debt issuance, have had negative equity issuance since the mid-1980s. This highlights the limitations of using gross distributions to shareholders as a measure of financial constraints. Together, these findings support our secular stagnation hypothesis, despite using a related definition only, since the trend towards disgorging cash externally is driven by financially healthier firms engaging in (negative) net equity issuance, even as their net debt issuance remains positive — and increasing.

Skinner, et al. 2009; Fama and French 2001, 2002, 2005).

Corporate secular stagnation is defined as a chronic excess of cash flow over stagnating or declining investment opportunities (for descriptive evidence see Appendix E). Figure 3 details corporate secular stagnation among advanced economy firms. This is proxied by the increasing proportion of firms becoming net external ‘releasers’ of funds, and the corporate sector as a whole shifting to a net external ‘releaser’ of funds position. For developing economy firms, the trend is largely downward after the 1997 Asian financial crisis.²² In addition, the propensity to release funds externally out of cash flow increases at the median across advanced economies and the U.S. (Appendix E, Figure 11). The argument that this simply reflects the natural life cycle (H. DeAngelo, L. DeAngelo, and Stulz 2006) of advanced economy firms maturing in our sample — or globally — is discussed in Appendix D.1.

The above shift is unlikely a pure capital structure (or ‘financing’) decision undertaken by firms in isolation from their investment decisions (Damodaran 2010).²³ Firms’ investment rates are closely tied to their net external financing positions: Firms that are net external ‘releasers’ of funds have a median investment rate of 4.2% (.032 MAD), compared to an investment rate of 7.1% (.065 MAD) for firms that are net external ‘borrowers’ (Appendix, Figure 13).

We explore in Appendix D alternative interpretations for movements in **FINCF**, as well as arguments in favour of focusing instead on cash flow statement items: **CHECH** (cash accumulation) or **IVNCF** less **CAPX** (net financial asset accumulation).

2.2.5 FINCF Empirical Estimation

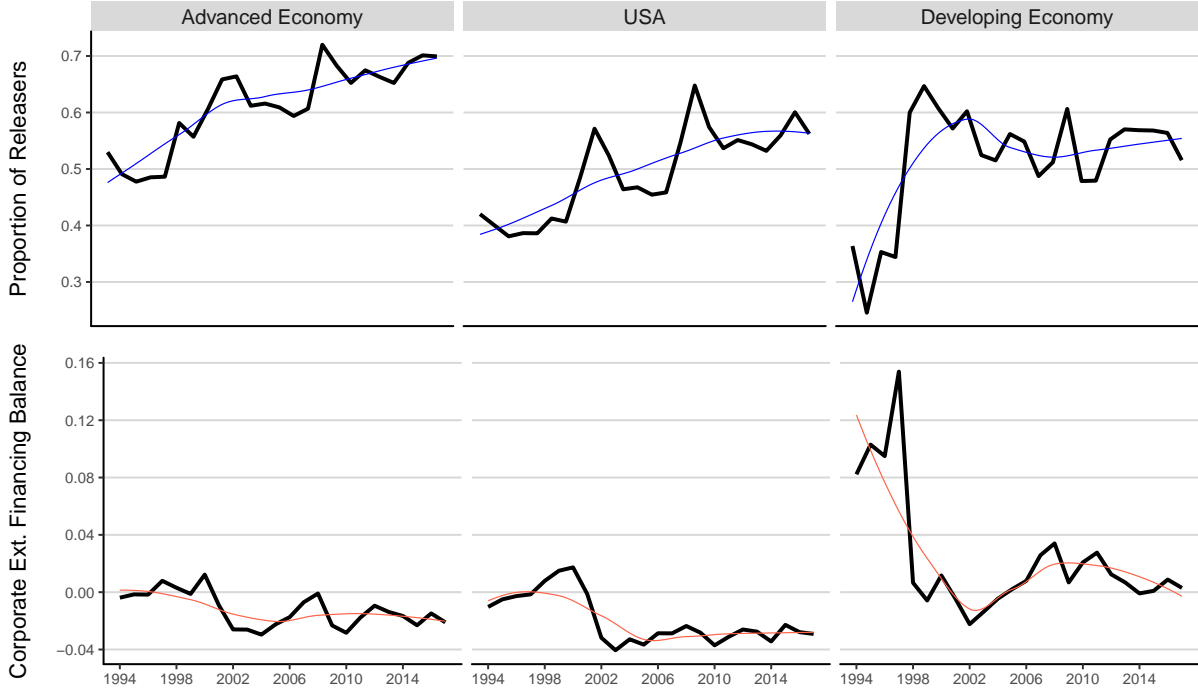
We run a simple regression to show the strong relationship between **FINCF**, and a firm’s cash flow and investment opportunities. This justifies our use of **FINCF** as a proxy for the degree of secular stagnation facing the firm. The results show a close correspondence to Agency Theory and Pecking Order findings for gross flows (Fama and French 2002). We first run differenced regressions for net external ‘borrowers’ and for net external releasers of funds, both normalized by sales. It is run on an unbalanced panel.²⁴ Subscript f and t indicate the firm and the time index, respectively.

²²At the 10th and 20th percentile of firms by **FINCF** position — amounting to the largest net ‘releasers’ of funds — developing economy firms show a decline in external releasing over time, while developed economies show a clear increase. Similarly, at the other end of the distribution (firms that borrow a lot in net), firms at the 80th and 90th percentile show large declines in their net borrowing in advanced economies, while only moderate declines in the developing economy group. In the U.S., net external releasing of funds increases at the 10th percentile of **FINCF** firms between our three time periods: From 7.9% of sales between 1994-2001 to 12.3% of sales by 2008-2017. Similarly, for the other advanced economies, this increases from 8.5% of sales to 10% of sales.

²³Use of a *net* variable also to some extent rules out decisions undertaken largely for capital structure engineering purposes. For example, share repurchases of 10million combined with debt issuance of 10 million would see a net **FINCF** balance of zero.

²⁴Since we have an unbalanced panel, we exclude observations with non-contiguous dates when differencing within each firm.

Figure 3. Corporate Secular Stagnation as Firms Become Net External ‘Releasers’ of Funds



Note: In advanced economies and the U.S., the corporate sector has shifted to an external net ‘releaser’ financing position (bottom graphs) since 2001, and it has gotten gradually worse until 2017. Developing economies have shown an upward trend since 2002, coming out of a negative balance. The top graphs show that an increasing proportion of firms in developed economies and the U.S. are net ‘releasers’ of funds externally. No such trend exists for developing economies, even if the level is fairly high. The impact of the 1997 Asian financial crisis stands out for developing economies in both instances.

$$\begin{aligned} \Delta \text{Log}(\text{FINCF})_{ft} = & \Delta \beta_1 \text{Cash Flow Rate}_{ft} + \Delta \beta_2 \text{Log}(Q)_{ft} + \Delta \beta_3 \text{Cash Flow Rate}_{ft} * \text{Log}(Q)_{ft} + \\ & \Delta \beta_2 \text{Log}(\text{Cash})_{ft} + \text{Year Dummy}_{ft} + \text{Error}_{ft}. \end{aligned} \quad (3)$$

It may appear obvious – even definitional – that a firm’s free cash flow, and in turn net external releasing of funds through FINCF, will increase whenever $I_t/K_t < \Pi_t/K_t$. Instead, a Pecking Order theory would predict that as cash flow *increases*, firms that are financially constrained will not only *invest more*, but also *borrow more* — rather than *less*. This is because as a firm’s cash flow increases it gets more collateral against which it can borrow (Almeida et al. 2004; Bernanke, Gertler, and Gilchrist 1999; Bester 1987). Evidence shows that most borrowing by U.S. firms relies on a cash flow collateral constraint, such that cash flow increases can directly relax borrowing constraints (Lian and Ma 2019). Instead, we see the opposite: Increases in cash flow rates lead to increases in the net dispensing of funds, *not* a decrease as a finance-constrained approach would predict. This relationship – as well as the very high levels of observed cash flow rates – is a key characteristic of corporate secular stagnation at the

Table 1. FINCF Regression Results

	Net ‘Releaser’	Net ‘Borrower’
Cash Flow Rate	0.6 (.03)***	-.67 (.028)***
Log(Q)	-0.029 (.015)*	0.16 (.017)***
Log(Q):Cash Flow Rate	-0.01 (.056)	-0.09 (.03)**
Log(Cash)	-0.03 (.004)**	0.13 (.005)***

*** $p \leq 0.01$, ** $p = 0.05$, * $p = 0.1$

Note: For both dependant variables, a positive value indicates more net ‘borrowing’ and more ‘net releasing’ of funds externally. Both *FINCF* and *cash* are normalized by sales. For net external ‘borrowers’ the panel is: $f = 20,227$, $t = 1 - 21$, $N = 57,600$. For net external ‘releasers’, the panel is: $f = 19,882$, $T = 1 - 23$, $N = 93,276$.

microeconomic level.

For net external ‘borrowers’, a one unit (i.e. 100%) increase in the cash flow rate is associated with firms borrowing 49% less (relative to sales).²⁵ Firms having more investment opportunities are associated with less net external ‘borrowing’, such that a 1% increase in investment opportunities leads to 0.16% decrease in net borrowing relative to sales.²⁶ Similarly, for net external ‘releasers’ of funds, more cash flow is associated with firms increasing their net external releasing of funds, while changes in investment opportunities have little impact even though the estimated sign is negative as expected (such that more investment opportunities lead to less net external releasing of funds). Interaction affects between $\log(Q)$ and *cash flow rate* are weak. For net ‘borrowers’, the negative interaction coefficient sign indicates that an increase in cash flow might counteract the positive impact of investment opportunities $\log(Q)$ on ‘net borrowing’.

Our findings also indicate that, in net, cash enables more net external borrowing. Higher normalized cash holdings are positively associated with more net borrowing and have little relation for net releasers. This makes sense: *Relative* cash stocks tend to be much higher for small, growth, firms with high investment rates (Denis and McKeon 2018). In these instances, cash acts as a proxy for investment demand, as well as supporting additional external borrowing through providing collateral for young, asset-poor firms (Lian and Ma 2019).

We run several variations of the specification for robustness. The above results are stable across

²⁵A one unit increase in the cash flow rate — amounting to a 100% — leads to a $\exp(0.67) = 0.511$, or a 49% decline in net external borrowing relative to sales at the geometric mean, rather than the arithmetic mean.

²⁶More precisely, these are conditional relationships due to the inclusion of an interaction. Such that each coefficient has an effect on FINCF conditional on the other variables being at their mean.

country groups and year groups, though some interesting differences exist.²⁷ ‘Leverage’ as a predictor is not significant economically or statistically, so we remove it. Removing the interaction term does not destabilize the results.

Finally, we use $\log(\text{CHECH})$, normalized by sales, as the dependant variable. Focusing on firms with positive CHECH, or cash accumulation, the key coefficients are *cash flow rate* = 0.56 and $\log(Q)$ = 0.10.²⁸ The *cash flow rate* coefficient varies considerably by country group and time. It increases over time, from 0.28 to 0.43 to 0.83, indicating an increasing propensity over time for changes in cash flow to be retained. This tendency to retain cash flow, as judged by the cash flow rate coefficient, is stronger in developing economies = 0.65, and advanced economies = 0.79, than in the U.S. = 0.35. As such, cash accumulation by the firm is closely tied to changes in firms’ cash flow rates — even if the retention tendency out of cash flow is not as closely tied to country groups as our other predictors.

3 Econometric Model

In this section, we detail the Bayesian hierarchical model — i.e. a ‘mixed effects’ model with shrinkage — that we use to estimate our cash flow-Q investment regressions. These are used to test several hypotheses regarding the causes of the global investment slowdown. Our hierarchical model allows for our firm-level coefficients — and in turn our hypotheses — to vary across time and country. Our coefficients and hypotheses could instead vary by industry or firm size (or other firm-level attributes), but we found these groups to be far less informative in capturing variation in our data (as estimated by the degree of variability in coefficients between clusters within these groups). As such we did not pursue these groupings further.²⁹

3.1 Microeconomic and Macroeconomic Explanations for the Investment Slowdown

Using our hierarchical regression model, we test the following three *microeconomic* (firm-level) hypotheses on the causes of the global investment slowdown. They are microeconomic since they look to explain variation *between* firms, while pooling across years and countries.

²⁷For ‘net external borrowing’ as the dependant variable, the coefficients on $\log(\text{Cash})$ = 0.56 and *cash flow rate* = -1.34 — both significant at the < 0.1% level — are much larger when run on the developing economy sub-group. This indicates that cash accumulation in developing economies may serve to reduce an external borrowing constraint to a far greater extent than in developed economies. The investment opportunities coefficient $\log(Q)$ is highest for the ‘developed economy’ group at 0.21, excluding the U.S.. The *cash flow rate* coefficient declines from -0.7 between 1994-2001, to -0.6 during 2002-2007, before increasing again to -0.73 between 2008-2017.

²⁸Both are statistically significant at < 0.01%.

²⁹Instead we control for them as ‘fixed effects’. Industry aggregation is too broad at the SIC 1 digit level while at the SIC 2 level we get too many industries, which are also difficult to handle from a cross-country perspective.

1. **Increasing financial constraints** (increasing *cash flow rate* coefficients): Firms are becoming more financially constrained over time due to external finance becoming more costly and/or relative demand for external financing increasing (Döttling et al. 2017; Gutiérrez and Philippon 2017b).
2. **Declining responsiveness to investment opportunities** (declining Q coefficients): Firms are becoming less responsive to investment opportunities over time due to either ‘financialization’ (Lazonick et al. 2014), or the increasing monopoly power of firms (Gutiérrez and Philippon 2017a). We might also expect Q coefficients to increase over time if previously profligate managers, who were investing in projects with a negative net present value, were now reigned in by the market (Gutiérrez and Philippon 2018).
3. **Advanced economy firms are investing less, other things being equal** (declining intercept coefficients): Over time and relative to developing economy firms too, potentially. This indicates that information not captured by Q, *cash flow rates* (‘*cashlow*’ here on in), and our other predictors, are causing mean-centred estimated investment rates to shift down over time.

The interpretation of our coefficients follows from the simple model outlined in Section 2. Other models provide different interpretations of the cash flow coefficient (Gomes 2001; Hennessy and Whited 2007; Moyen 2004; Rajan and Zingales 1998). For robustness we run the model with different priors, likelihood specifications, and with and without various predictors and countries. The findings do not change materially. We also run a smaller version of the model corrected for measurement error using Bayesian methods (Appendix H). Our key findings remain qualitatively the same.

After running and presenting our ‘microeconomic’ hierarchical regressions, we extend our model by adding two macroeconomic ‘group’ predictors to test the *macroeconomic* hypothesis that **corporate secular stagnation**, reflecting common exogenous shocks, ‘explains’ differences in firms’ estimated investment rates *between* countries and over time (Gelman, Shor, et al. 2007). This is achieved by using the estimated microeconomic (firm-level) regression intercepts as ‘data’ to then be ‘explained’ by a separate set of macroeconomic, ‘group-level’, predictors. These intercepts are estimated as the country- and time-varying intercept coefficients after accounting for key firm-level explanatory variables and controls. Our two group predictors are aggregated versions of the FINCF variable, with the aggregation taking place over years, countries, or both, depending on which variation is trying to be explained:³⁰

³⁰Note that exploration of this hypothesis is only feasible if firms’ estimated intercept coefficients — which becomes the ‘data’ that we try to explain — are in fact declining notably over time and/or showing considerable variation between countries.

1. The decreasing **aggregate corporate external financing balance** ($= \Sigma \text{FINCF}$) is positively related to the decline in estimated investment rates (intercept coefficients) between countries and across time. When **FINCF** is aggregated, it tells us if the corporate sector as a whole is a net ‘borrower’ or a net ‘releaser’ of funds externally.
2. The increasing **proportion of firms that are net ‘releasers’ of financing externally** is negatively related to the decline in estimated investment rates (intercept coefficients).

For robustness we run two dozen other specifications with different macroeconomic predictors.

3.2 Bayesian Hierarchical Model: Overview and Motivation

Hierarchical models, also known as ‘mixed, fixed and random coefficient’ models, are increasingly discussed in economics, but are not yet common place (Greene 2003; Hsiao 2014; Meager 2019; Sims 2010).³¹ They allow for the effects of coefficients to vary across groups — in our case, ‘country’ and ‘year’ (and ‘country-year’) — but still treat countries (and years, etc.) as related entities, to be estimated together as part of a single larger population group. This allows for the inferences for each country, say, to ‘learn’ from one another (McElreath 2018). Following James and C. Stein (1961), it can be shown that the estimator that estimates these parameters jointly produces a lower *total* mean squared error for all parameters combined than the maximum likelihood estimator, which estimates each parameter separately (Kreft and De Leeuw 1998; Lehmann and Casella 1998).³² For a discussion on the relationship between the Bayesian hierarchical estimator to the fixed effect and random effect estimators see Greene (2003, Chapter 16.7).

When relevant differences in coefficients exist among clusters, pooled estimators can create seriously misleading findings (Barcikowski 1981; Hsiao 2014; Pepper 2002; Pesaran and Smith 1995).³³

Using Bayes rule, we present a very general form of the posterior density of our unknown parameters conditional on the data. Given the student-t likelihood and the Multivariate Normal (MVN) prior, we have the following joint posterior distribution, with N number of observations, K number of predictors

³¹They are, however, a natural extension of ‘analysis of variance’ (ANOVA) models (Gelman 2006; Malinvaud 1980).

³²The extent to which each country’s inference learns from another country, is based on how similar their observations are to one another, for any given variable. The more similar they are, the tighter — and more ‘informative’ — the adaptive prior becomes, such that each observation ‘regularizes’ the other more dramatically. As such, the degree of ‘partial pooling’ between observations (‘clusters’) within each group is informed by the data itself, and reflects a compromise between the no-pooling estimate for that cluster’s parameter, and the parameter’s grand mean.

³³Ignoring any level of variation in the model can also result in variation being misattributed to the wrong level of the model and, as a result, to an incorrect predictor (Moerbeek 2004; Schmidt-Catran and Fairbrother 2015; Tranmer and Steel 2001; Van Landeghem et al. 2005).

and, J number of groups:

$$\begin{aligned}
p(\theta|y) &\propto p(y|\theta) p(\theta|\phi) p(\phi) \\
&\propto \underbrace{\prod_{j=1}^J \text{student-t}(y_{.j}|\beta_j, \nu, \sigma_y)}_{\text{Likelihood}} \underbrace{\prod_{j=1}^J \text{MVN}(\beta_j|\mathbf{M}_\beta, \mathbf{\Sigma}^\beta)}_{\text{Prior}} \underbrace{p(\mathbf{M}_\beta, \mathbf{\Sigma}^\beta)}_{\text{Hyper prior}} \\
&\propto \prod_{j=1}^J \prod_{i=1}^N \left[\frac{\Gamma((\nu+1)/2)}{\Gamma(\nu/2)} \frac{1}{\sqrt{\nu\pi}\sigma_y} \left(1 + \frac{1}{\nu} \left(\frac{y_{ij} - \sum_{k=1}^K \beta_{kj} x_{ij}}{\sigma_y} \right)^2 \right)^{-(\nu+1)/2} \right] \\
&\quad \times \frac{1}{(2\pi)^{K/2}} \frac{1}{\sqrt{|\mathbf{\Sigma}|}} \exp \left(-\frac{1}{2} (\beta - \boldsymbol{\mu}_\beta)^\top \mathbf{\Sigma}_\beta^{-1} (\beta - \boldsymbol{\mu}_\beta) \right) p(\boldsymbol{\mu}_\beta) p(\mathbf{\Sigma}_\beta) p(\nu) p(\sigma_y), \quad (4)
\end{aligned}$$

where β is $K \times 1$ vector of β_k , $\boldsymbol{\mu}_\beta$ is the $K \times 1$ mean vector of the MVN, and $\mathbf{\Sigma}$ is the $K \times K$ positive-definite variance-covariance matrix of the MVN.

The multivariate normal distribution is used as the prior sampling distribution from which our unknown group-level parameters (‘random effect’ β_j) are drawn. In our case, we have three *groups* over which each of the designated ‘random’ coefficients vary: These are ‘year’ ($t = 1 \dots 24$ clusters), ‘country’ ($c = 1 \dots 24$ clusters), and ‘country-year’ ($j = c \times t = 576$ clusters). We interpret the ‘year-country’ group as country-specific year effects, or year-specific country effects. Each of these three groups reflect a different ‘macro-context’, within which a common group of firms operate, which might impact their investment behaviour differently. Our model has four levels though, since our first level is the pooled ‘population’ or ‘firm’ level ($i = 1 \dots 283,702$), where coefficients are ‘fixed’, in the sense that they do not vary by group. All levels of the model are estimated concurrently, conditional on the data, leading to 625 regressions being estimated jointly — one for each cluster within each group.³⁴

Our likelihood function, used to model the fixed, pooled level, of our model is the symmetric student-t distribution.³⁵

³⁴This 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.

³⁵The likelihood becomes ‘normal’ shaped, as $\nu_y \rightarrow \infty$, but has a longer tail than the normal distribution. We use it to accommodate occasional unusual observations in the data distribution, as well as to focus inferences on the posterior mode of the distribution — approximately the mean and median of the student-t distribution — rather than on the less-representative mean under a normal likelihood. A ‘t-likelihood’ also effectively adjusts for a particular model of heteroskedastic normal errors (Arnold 2019).

3.3 Model Specification

Our model is specified as a log-level model, where y_i is the investment rate of the firm i :³⁶

$$\log(y_i) \sim t_\nu(\boldsymbol{\mu}, \sigma_y^2, \nu_y), \quad (5)$$

$$\boldsymbol{\mu}_{[i]} = X_i^0 \boldsymbol{\beta}^0 + X_i \boldsymbol{\beta}_{t,c,j[i]} + \boldsymbol{\rho} \epsilon_{i,t-1} + \gamma_{it}, \quad \text{for } i \in 1 : n \quad (6)$$

$$\boldsymbol{\beta}_{t,c,j} \sim \text{MVN}(M_\beta, \Sigma_{t,c,j}^\beta), \quad \text{for } j, c, t \in 1 : T, C, J, \quad (7)$$

where $\gamma_{it} \sim N(0, \sigma_\gamma^2)$. $\boldsymbol{\mu}$, σ_y^2 , and ν_y are the location, scale, and the degree of freedom of the non-central student-t distribution, and $\epsilon_{i,t-1}$ is the error term at time $t - 1$. The time and country level grouped regressions each contain 24 clusters $T = C = 24$, and the country-year level $J = 24 \times 24 = 576$. $\boldsymbol{\rho}$ represents the estimated AR(1) error process.³⁷

X_i^0 are the fixed effect (local) predictors, with parameter estimates $\boldsymbol{\beta}^0$ from the pooled, population level regression. X_i are the random, group-level predictors with parameter estimates $\boldsymbol{\beta}_{t,c,j[i]}$ varying across groups. For each group (t, c, j) , $\boldsymbol{\beta}_{t,c,j}$ is a vector of length 3 random effects corresponding to the t^{th} c^{th} or j^{th} row of $\boldsymbol{\beta}$.

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, a capacity utilization dummy (or capital-output ratio), a net external financing (EF) dummy — i.e. is the firm a net external ‘borrower’ or ‘releaser’ of funds, and we also interact the net EF dummy with cash flow to test for differing financing constraints.

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 pa-

³⁶A log specification dramatically improves our sampling efficiency by making the dependant variable roughly normal. It also helps reduce heteroskedasticity considerably. This can be seen by running simple quantile investment regressions of $\log(Q)$ on investment, and plotting the fits across quantiles (Deaton 1997; Koenker and Hallock 2001). We log our Q predictor, which we proxy by the firm’s market-to-book ratio — MTB ratio (Alexander and J. Eberly 2018).

³⁷For computational reasons, we do not apply the error structure to the covariance matrix. This is also why we do not use a higher order process, since model improvement is minimal — judged by Bayesian R^2 — 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.

rameters, and so is not discussed further.³⁸

$M_\beta = \{\mu_\alpha, \mu_q, \mu_{cf}\}$, the grand (population) mean effect for each random effect parameter: μ_α for the intercept, and μ_q and μ_{cf} for the coefficients of *Q* and *cash flow*, respectively. This means that each group’s random parameters can be seen as draws from a normal distribution with a common population mean specific to each parameter, rather than each group. Later we use group predictors — the net external corporate financing balance and the proportion of firms that are net ‘releasers’ of funds — to model $\mu_\alpha = \gamma_0^\alpha + \gamma_1^\alpha \mu$, where μ will vary for each group $\{t, c, j\}$. As a result, the X_i matrix is able to contain group-level predictors too.

The deviation of clusters (within a group) from the parameter’s estimated grand population mean value M_β results in an error, with error distribution Σ_β for each group $\{t, c, j\}$ ’s parameters. As a result, the error for each group t, c, j , is the estimated random effect for that group, indicating its deviation from the population mean parameter value. Put differently, every random effect parameter, within each group t, c, j , is given its own variance parameter to be estimated from the data, leading to three variance parameters per group $(\sigma_\alpha, \sigma_q, \sigma_{cf})$.³⁹

3.3.1 Hierarchical Priors and Variance-Covariance Structure

Our model is a full Bayesian Hierarchical model, such that our hyper-parameters $(M_\beta, \Sigma_{t,c,j}^\beta)$ are given priors — ‘hyper-priors’ — which are estimated from the data, where $\Sigma^\beta = D(\sigma) \Omega D(\sigma)$; $D(\cdot)$ is a diagonal matrix; and Ω is a correlation matrix for all random effect parameters estimated within the same group. The hyper-priors are:

$$M_\beta \sim N(0, 0.5), \quad (8)$$

$$\sigma_y, \sigma_{\alpha,q,cf \in t}, \sigma_{\alpha,q,cf \in c}, \sigma_{\alpha,q,cf \in j} \sim \text{Cauchy}(0, 2), \quad (9)$$

$$\Omega_{t,c,j} \sim \text{LKJcorr}(5). \quad (10)$$

The prior for the parameters’ population means follows the normal distribution centered at zero

³⁸Under 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).

³⁹Since we put the same prior on all random effect variances for each group, we condense the notation as above. All σ parameters are given half cauchy priors centered at 0 with a scale parameter of 2. This restricts the scale parameter to be positive, but keeps it moderately informative to aid in convergence and estimation. In the limit of $\sigma_\beta \rightarrow \infty$, there is no pooling for a cluster’s parameter. This means that the random effect for a specific country/year/country-year, is estimated in complete isolation from the other countries’/years/country-years, within that group. As $\sigma_\beta \rightarrow 0$, the specific cluster’s estimate is pulled all the way to zero, yielding a complete-pooling estimate for that cluster, thereby setting it equal to the coefficient’s overall grand mean level, μ_β .

with the standard deviation of 0.5. By using the normal prior, we allow for an equal probability of negative and positive parameter values. We can write our variance-co-variance structure more explicitly, beginning with the random effects being drawn from a wider population distribution, governed by the hyper-parameters:

$$\begin{pmatrix} \alpha_{t,c,j} \\ \beta_{t,c,j}^q \\ \beta_{t,c,j}^{cf} \end{pmatrix} \sim \text{MVNormal} \left[\begin{pmatrix} \mu_\alpha \\ \mu_q \\ \mu_{cf} \end{pmatrix}, \Sigma_{t,c,j}^\beta \right], \quad (11)$$

where $\Sigma_{t,c,j}^\beta$ is estimated for each group t, c, j , leading to:

$$\Sigma_{t,c,j}^\beta = \begin{pmatrix} \sigma_\alpha^2 & 0 & 0 \\ 0 & \sigma_q^2 & 0 \\ 0 & 0 & \sigma_{cf}^2 \end{pmatrix} \Omega \begin{pmatrix} \sigma_\alpha^2 & 0 & 0 \\ 0 & \sigma_q^2 & 0 \\ 0 & 0 & \sigma_{cf}^2 \end{pmatrix}. \quad (12)$$

Ω is the correlation matrix for the random coefficients within each group t, c, j :

$$\Omega_{t,c,j} = \begin{pmatrix} 1 & \rho_{\alpha,\beta^q} & \rho_{\alpha,\beta^{cf}} \\ \rho_{\alpha,\beta^q} & 1 & \rho_{\beta^q,\beta^{cf}} \\ \rho_{\alpha,\beta^{cf}} & \rho_{\beta^q,\beta^{cf}} & 1 \end{pmatrix}. \quad (13)$$

We provide the covariance matrix of the multivariate *normal* distribution with an LKJ prior (see Appendix for further discussion). The full list of priors can be found in Appendix F. Our model is not sensitive to the priors chosen for several reasons: The first is that our priors overlap sufficiently with the inference from our likelihood — i.e. our data. Secondly, given how much data we have (283,702), our priors are unlikely to overwhelm our likelihood. Even though the number of parameters we estimate is large at 1,917 — or 1,920 plus group predictors — the same data points are used for more than one regression if the firm belongs to more than one group.⁴⁰ Thirdly, our priors are not strongly informative,

⁴⁰576 × 3 random country-year effects, 24 × 3 random country effects, 2 × 3 random year effects, 3 × 3 variance parameters per group, 3 × 3 correlation parameters per group, 2 t-distribution parameters, 24 population level predictors, and 1 AR process coefficient.

but still informative enough to help aid in the convergence properties of the model.

4 Estimation and Results

The model is estimated using R Stan, interfaced into using the **brms** package (Burkner 2017, 2018; Stan Development Team 2019a).⁴¹ To help reduce correlation among co-variants, which can induce strong posterior correlations, we use a QR decomposition.⁴² In addition, our design matrix is mean-centred, and, as such, our intercept can be interpreted when other co-variants are at their mean value.

4.1 Random Intercept and Random Slope

Table 2 presents the summary output from our hierarchical regression model without any group-level predictors. The Bayesian R^2 , indicating the model ‘fit’, is moderate and between [0.369, 0.43] for the 95% credible interval.⁴³ The results are robust to alternative priors, likelihoods, and regression specifications.⁴⁴

Five findings stand out (with the estimated error in brackets()):⁴⁵ (i) Firms that are net external ‘releasers’ of funds have a much lower predicted modal investment rate, as indicated by the estimated FINCF dummy variable, ‘External Borrower’ = 0.22. This implies that net external ‘borrowers’ have investment rates almost 25% higher than net external ‘releasers’, with all else being held at their mean-centred values; (ii) Advanced economy firms of both types tested here (net external ‘borrowers’ and ‘releasers’) are not financially constrained. This can be shown by adding together the relevant fixed effect and random effects cash flow coefficients for advanced economy firms. (The country-year cash flow coefficient we do not include since it has a high uncertainty interval. Instead, we use it to hold

⁴¹Stan uses two Markov chain Monte Carlo (MCMC) algorithms: The Hamiltonian Monte Carlo (HMC) algorithm and its adaptive variant, the no-U-turn sampler (NUTS), (Stan Development Team 2019a).

⁴²The decomposition is based on the notion that any design matrix, x , can be decomposed using the QR decomposition into an orthogonal matrix, Q , and an upper-triangular matrix, R , such that $x = QR$. Although in practice, we use $x = Q^*R^*$ where $Q^* = Q * \sqrt{n-1}$ and $R^* = \frac{1}{\sqrt{n-1}}R$. The thin decomposition we use is shown by (Betancourt 2019). The QR decomposition improves our effective sample size, increases the precision of posterior estimates, and reduces computational time.

⁴³We are unable to calculate the Bayesian R^2 over our entire sample at once due to computational limitations. So, instead, we calculate it across three sub-time periods. The fit improves over time with a large portion of the predictive power coming from the auto-regressive error structure. Posterior predictions by year and country (not shown) show good fits for most countries, but less good fits for years, indicating that the model is not able to explain variation in investment rates across years, as well as across countries, on the basis of the current predictors.

⁴⁴Using a normal likelihood Certain aspects of the data are predicted better. Fixed effect coefficients are almost identical and some non-critical variation in the random effect coefficients occurs. In general, the Bayesian R^2 is higher for the student-t likelihood model than for the normal model by around 5%-10%, with a 95 percentile interval range between [0.34, 0.39] for the normal likelihood, compared to [0.369, 0.43] for the student-t likelihood, across the three sub-periods looked at.

⁴⁵These results are robust to use of alternative priors on all parameters, using a normal likelihood, and to measurement error — see Appendix.

Table 2. Summary of Regression Coefficients: Benchmark Hierarchical Model

	Variable	Estimate	Est.Error	l-95% CI	u-95% CI	\hat{R}
Fixed Effect	Intercept	-2.94	0.07	-3.09	-2.80	1.00
	FINCF Dummy (External Borrower)	0.22	0.00	0.21	0.22	1.00
	Cash Flow Rate	0.20	0.03	0.13	0.26	1.00
	Log(Q)	0.21	0.01	0.18	0.23	1.00
	FINCF _{EB} : Cash Flow Rate	-0.08	0.01	-0.10	-0.06	1.00
Country Random Effect	SD(Intercept _c)	0.20	0.03	0.15	0.28	1.00
	SD(logQ _c)	0.06	0.01	0.04	0.09	1.00
	SD(Cash Flow Rate _c)	0.13	0.02	0.09	0.18	1.00
Year Random Effect	SD(Intercept _t)	0.23	0.04	0.17	0.31	1.00
	SD(logQ _t)	0.02	0.00	0.01	0.03	1.00
	SD(Cash Flow Rate _t)	0.07	0.02	0.04	0.11	1.00
Country-Year Random Effect	SD(Intercept _j)	0.12	0.01	0.11	0.13	1.00
	SD(logQ _j)	0.03	0.00	0.02	0.04	1.00
	SD(Cash Flow Rate _j)	0.14	0.01	0.12	0.16	1.00
student-t Parameters	σ	0.56	0.00	0.56	0.57	1.00
	ν	4.85	0.05	4.75	4.96	1.00

Note: Results are for Regression Model 5. 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 are reported. The latter two percentile ranges represent the 90% credible/uncertainty interval. \hat{R} is the convergence metric and close to one when the MCMC chains are well-mixed and converged.

constant those effects.) This is summarized in Figure 4 that shows the country — and time — random effects for the cash flow coefficient, after taking into account the fixed effect cash flow coefficient estimate for all firms.⁴⁶ The time-varying random effect cash flow coefficients show a strong cyclical tendency, reflecting easing and tightening monetary conditions and relative investment demand over the business cycle.

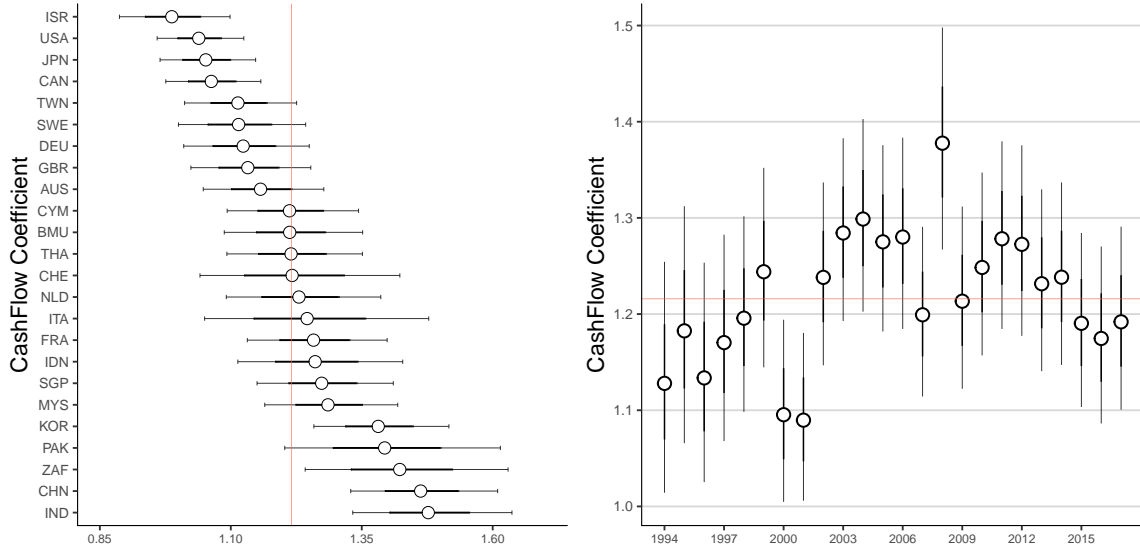
The FINCF dummy (net ‘borrower’) interaction effect with cash flow has a negative coefficient at $\beta_{cf}^{NB} = -0.08(.01)$. This means that net ‘borrowers’ are less ‘financially constrained’ (cash flow coefficient = 0.12) than net external ‘releasers’ of funds (cash flow coefficient = 0.20).⁴⁷ This is the opposite of what we expected based on our interpretation of the FINCF variable previously. However, the 95% credible interval for the fixed effect cash flow predictor is wide — [0.13, 0.26] — and overlaps with the 95% credible interval of the fixed effect, cash flow coefficient interaction term with ‘net releasers’. Moreover, as noted above, once our country random effects are added to the fixed effect, cash flow does

⁴⁶Note that since we interact the FINCF dummy with cash flow in the fixed effect, part of the regression, the default fixed effect cash flow coefficient, is for net external borrowers.

⁴⁷Such that a 100% increase in cash flow — i.e a one unit increase — results in a $\exp(0.2) = 1.22 = 22\%$ increase in investment rate.

not matter for both net external ‘borrowers’ and ‘net releasers’ in advanced economies. This highlights the importance of accounting for country-differences in coefficient values. Lastly, the cash flow coefficient changes surprisingly little when we correct for measurement error (Appendix H).

Figure 4. Cash Flow Coefficients (Net External ‘Releaser’) by Country and Time



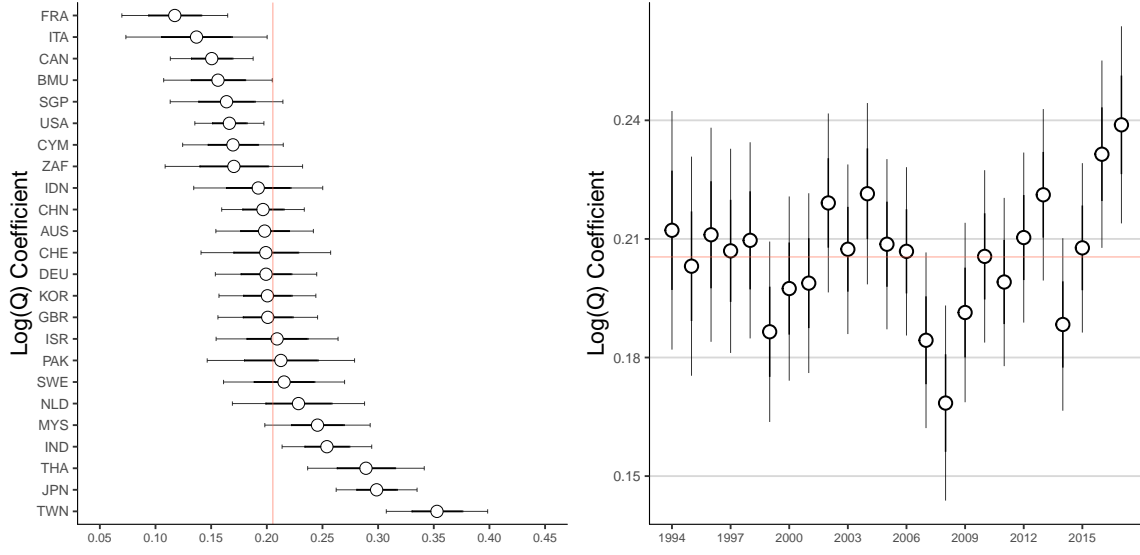
Note: Fixed effect is the red line. In general, the effect of cash flow is weak, especially for developed economy firms, which all effectively have negative cash flow coefficients — i.e. less than one, since plotting the exponentiated coefficient. The coefficient shows a strong cyclical tendency over time. The horizontal red line is the exponentiated fixed effect coefficient. A coefficient of above one for an exponentiated coefficient implies a percentage increase in the geometric mean of y , relative to its baseline level for a one unit difference in cash flow rate — i.e. a doubling — while a coefficient of below one implies a percentage decrease. The 95% credible interval is shown in dark black and the 68% confidence interval in grey. We do not show year-country effects here as the credible interval is too large

(iii) Figure 5, presents country and time random effect Q coefficients. The lack of a trend in the time-varying Q plot demonstrates that firms are not becoming less, or more, responsive to investment opportunities, despite the increase in net external dispersing of funds. As a result, we find little evidence for theories of the investment slowdown that rely, at least in part, on Q coefficients decreasing secularly (Gutiérrez and Philippon 2017a; Lazonick et al. 2014), or increasing secularly (Gutiérrez and Philippon 2018).⁴⁸ Remember that this Q time effect is estimated holding constant country affects and year-country group affects.⁴⁹

⁴⁸Though the upward time trend in Q following the 2008 crisis might reflect the reigning in of over-investment by managers.

⁴⁹The country-specific time effects (‘year-country’ group) have too large a credible interval to explore properly.

Figure 5. ‘Random’ Q Coefficients by Country and Time



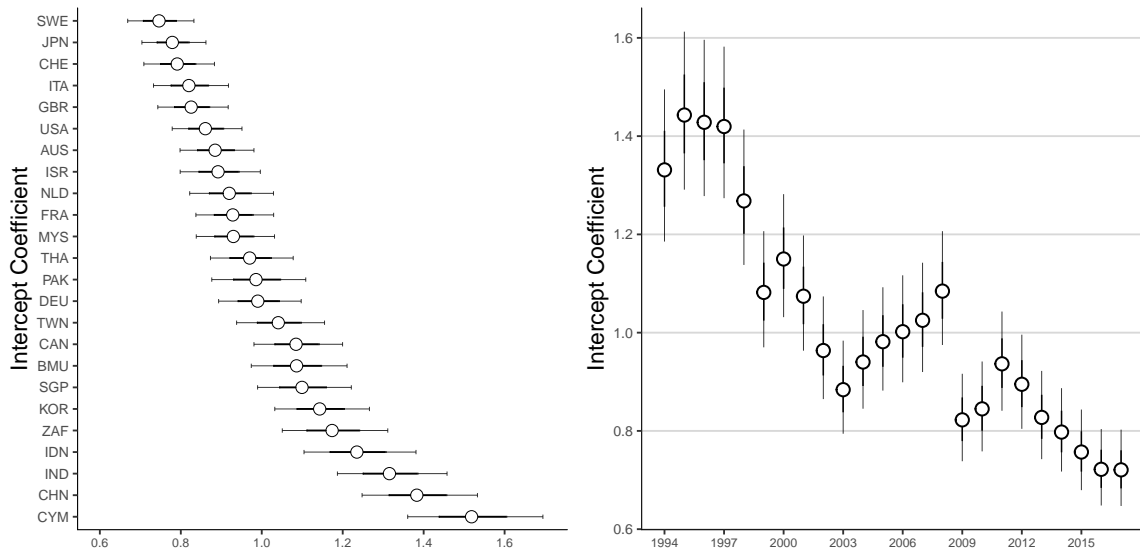
Note: Q coefficient shows a strong cyclical tendency but no secular tendency — though with a considerable degree of posterior uncertainty. Post-2007 financial crisis, the Q coefficient has continuously increased, indicating that firms are not less responsive to investment opportunities, despite lower investment rates. The Q coefficient, interpreted as an elasticity, shows a fairly large impact on investment rates, such that a 1% increase in Q value leads to around a 20% increase in the investment rate. The 68% credible interval is shown in dark black, and the 95% confidence interval in grey.

(iv) The ‘fixed-effect’ value of $\log(Q) = 0.21$ is fairly large relative to previous estimates given in the literature (Andrei et al. 2019; Erickson and Whited 2000, 2012; Peters and Taylor 2017) — even if the variable adds little to the predictive power (R^2) of our model. A 1% increase in the value of Q increases the firm’s investment rate by 21% — i.e. from an investment rate of 5% to 6.05%, for example. This finding may reflect the fact that previous studies tend to focus on the U.S. which, as shown in Figure 5, has a lower Q coefficient than most other countries estimated here. Variation between countries and time periods means that the Q coefficient can vary by 0.11 in either direction. In addition, our log-log specification — possible only because of our use of MTB as a proxy for raw Q values — greatly helps reduce heteroskedasticity and improve the MCMC sampling. Lastly, after correcting for measurement error the Q coefficient value increases further (Appendix H).

(v) Estimated investment rates (intercept coefficients) are declining over time and are weaker for advanced economies than developed economies (with one or two exceptions). This is depicted in Figure 6. (Although not shown, the Bayesian credible interval for the country-year intercepts were estimated fairly precisely.) The pattern has some resemblance to the dummy time-effects in U.S. firm-level regressions

in Gutiérrez and Philippon (2017b).⁵⁰

Figure 6. Intercept Coefficients by Country and Time



Note: This shows the exponentiated random intercept coefficient — i.e the predicted mean/median investment rate. In general, developed economy firms (notably Sweden and Japan) invest less, while developing economy firms (notably China and India) invest more. Above (below) 1 the exponentiated intercept shows an increasing (decreasing) mean-centred investment rate. The time trend of the intercept is stark, with cyclical tendencies dominated by a secular downward trend, save for a peak in 1995. The fixed-effect intercept is not included. Bayesian 95% credible intervals display a high degree of certainty, especially for later years and for developed economies.

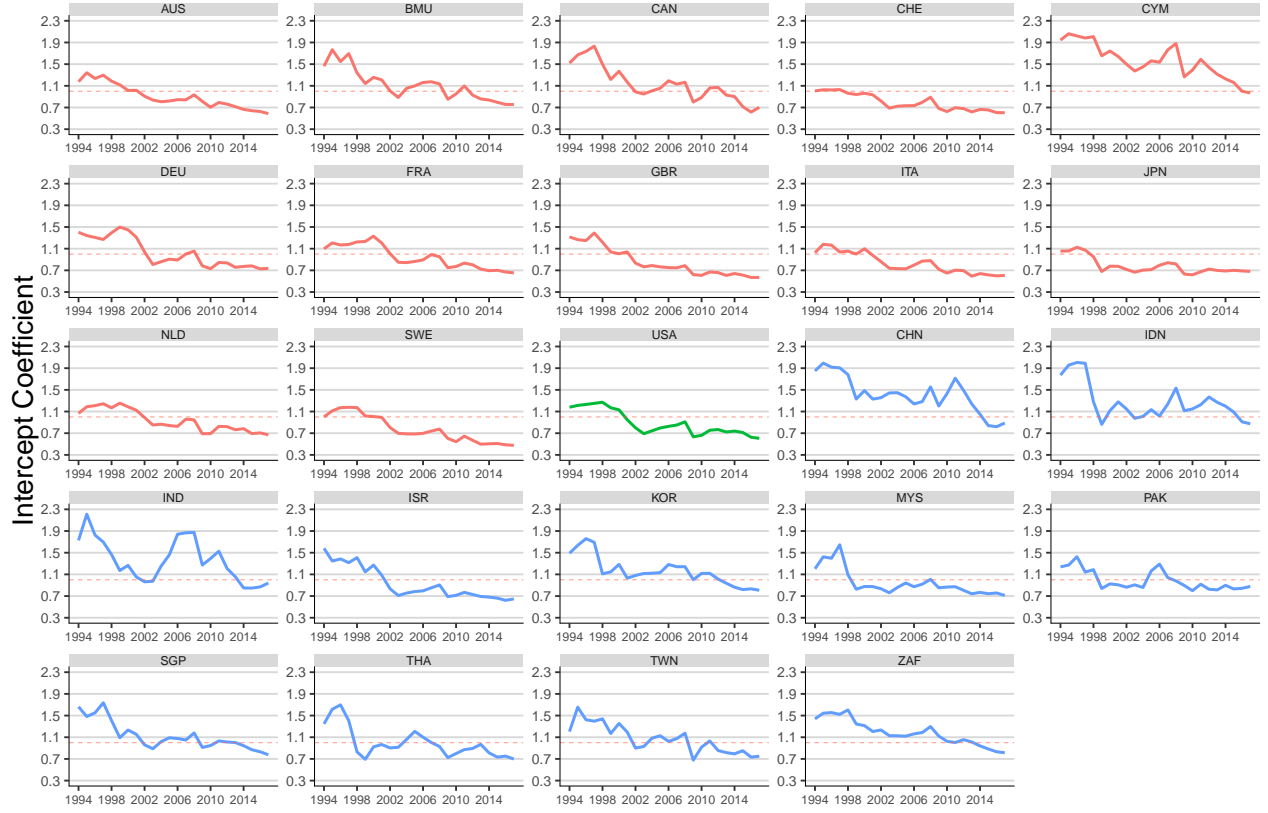
Figure 7 shows the time-evolution of the intercept coefficient for each country by combining all three random effect levels for the intercept. This also confirms the secular decline in overall investment rates in the advanced economies.⁵¹

Next, we try to ‘explain’ the unexplained differences in firms’ estimated investment rates — i.e. intercept coefficients — *between* countries and across time, using our macroeconomic secular stagnation predictors. Subsection 4.2 contains our main finding: The shifting corporate external financing balance ‘explains’ around 50% of the variation in firms’ estimated investment rates between different countries, while the proportion of net ‘releasers’ of funds externally ‘explains’ nearly two-thirds of the annual variation in firms’ estimated investment rates across years. We put the word *explains* in inverted commas, since the relationship between FINCF and predicted investment rates (intercept coefficients) is to a large extent endogenous.

⁵⁰We do not include the fixed effect intercept in Figure 6 as the fixed effect intercept is largely arbitrary, being sensitive to both changes in the dependent variables’ units of measurement (as it is a log-level regression) (Wooldridge 2016, p. 37), as well as to the dummy baselines. As such, we do not care about the exact value of the fixed effect intercept, but instead its variation across clusters and groups.

⁵¹We do not provide a credible interval for this. Though we are able to combine all three random effects, it is difficult to estimate ‘country-year’ random effects, as they have a fairly narrow credible interval for the intercept coefficient.

Figure 7. Intercept Coefficients of All Random Effects Combined



Note: Here we see all three random effect levels combined, without the fixed effect, for the intercept coefficient. Investment rates decline for advanced economies as a secular tendency. For developing economies, this occurs following the 2007 financial crisis. The considerable impact of the 1997 Asian financial crisis can be seen for Thailand, South Korea and Indonesia, who were hit hardest. China's intercept dips below one (dotted pink line) around 2014. For the U.S., this occurs around 2000, indicating declining investment rates. Tax haven countries have higher predicted investment rates indicating the importance of pooling and partial pooling of firm-level investment data.

4.2 Modelling Differences in Firm's Estimated Investment Rates Between Countries and Years

We test our corporate secular stagnation hypothesis by seeing if it can predict *macroeconomic variation* in firms' predicted investment rates: defined as variation in firms' 'true' investment rates *between* countries and years. Secular stagnation reflects, theoretically, a set of common (unexplained) exogenous shocks, as a result it should impact all advanced economy firms. We do not provide a causal interpretation to this relationship though, since a large degree of endogeneity (arising from simultaneity) exists. This can be seen theoretically in Figure 2, whereby the net external financing balance is described as an *outcome* of weak investment demand and strong internal financing.

To try and 'explain' the unexplained variation in firms' predicted intercept coefficients ('true' investment rates), we add two new group-level predictors, constructed out of the FINCF variable, to each of the

three levels of the model, each with its own type of variation. This results in the addition of six additional predictors to the model when both group-predictors are used concurrently. The predictors are: (1) The proportion of total firms in a given year or economy that are net ‘releasers’ of funds externally ($\beta_{T,C,J}^{\alpha_1}$); and (2) The external financing balance for the corporate sector as a whole ($\beta_{T,C,J}^{\alpha_2} = \sum \text{FINCF}_{i=1}^{j,c,t}$). To construct β^{α_1} and β^{α_2} as a predictor to predict variation across years, say, aggregation must occur over the other two groups, namely the ‘country’ group and the ‘year-country’ group. A broad graphical description of the two predictors were plotted in Figure 3, previously.⁵²

Formally, our hierarchical model remains the same, except now we are modelling the mean of the intercept distribution M_{β}^{α} , from which the random effect intercept coefficients are drawn for each group t, c, j :⁵³

$$\beta_{t,c,j} \sim \text{MVN}(M_{\beta}^{\alpha}, \Sigma_{\beta_{t,c,j}}), \quad (14)$$

$$M_{\beta}^{\alpha} \sim \text{N}(\gamma_0 + \gamma_1 \mu, \sigma_{\alpha}), \quad (15)$$

where μ will vary for each group $\{t, c, j\}$ which runs from 1 to 24, 24, and 576, respectively. This is the number of estimated cluster intercepts within each group that now also serve as the data observations to be predicted in the above macroeconomic regressions. Is this too few observations to attain robust results? Not according to our output. For one, the uncertainty is accounted for by the posterior distribution and, in turn, our reported confidence intervals.⁵⁴ In addition, our findings are robust when using different specifications of the FINCF variable, such as the median instead of the mean – which provides even more striking results in fact.

Group-level predictors (GPs) are primarily of interest to us because they can help reduce unexplained variation between clusters within a group — i.e. the standard deviation of coefficient estimates within a given group. This is primarily how we assess their effectiveness in this paper, rather than their addition

⁵²The macroeconomic predictions, under financial market imperfections, from a shock to profitability – which FINCF to some extent captures in Section 2.2.4 – is that investment and in turn output, should increase as retained earnings or net worth increase (Bernanke and Gertler 1989; Bernanke, Gertler, and Gilchrist 1999). This may also operate through asset prices (Kiyotaki and Moore 1997). This assumes that firms are financially constrained, though, due to external imperfections in financial markets and strong investment demand. In reality, following corporate secular stagnation, the mechanism instead seems to operate through firms’ (now excess) financial resources being recycled to consumers to increase household consumption spending. This in turn can boost output. Consumer spending — not investment spending — is what drove the boom in output in the U.S. and Europe during 2002-2007 when profitability was high, for example (Emmons 2012; McCarthy and Steindel 2007; Palumbo and Parker 2009).

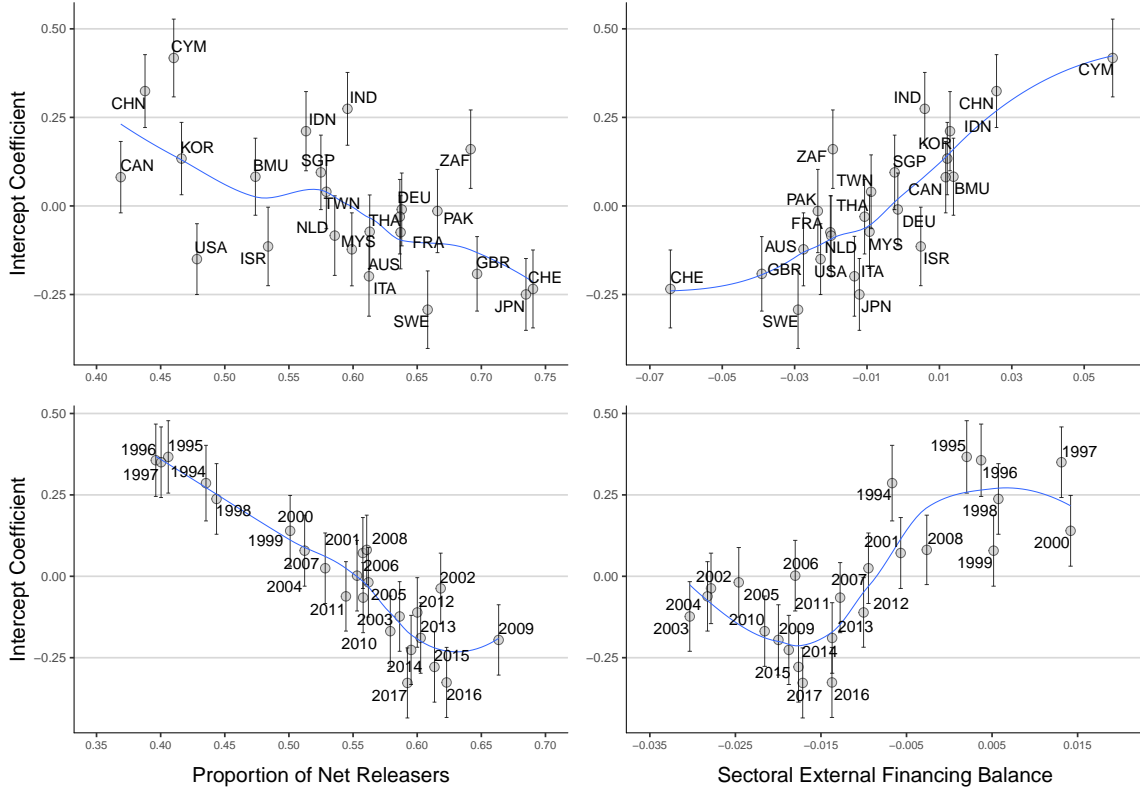
⁵³In a classical regression, the 576 group-level coefficient indicators and the group-level predictor would be collinear, and instead must be run as two separate regressions (as in Hsiao and Tahmiscioglu (1997)). This problem is avoided in a multilevel model because of the partial pooling of the random group-level coefficients toward the group-level linear model. 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, p. 497). While group-level predictors are often interpreted as ‘contextual effect’ in the social sciences.

⁵⁴We run the same regression, but with only the j (year-country) model level. This uses 576 observations. Now all variation is (mis)attributed to this level, however the amount of variation ‘explained’ is still very high (over 50%). This indicates that it is explaining real variation in the data.

to the overall predictive power of the model. Reducing variation in coefficient estimates within a group in turn increases the amount of partial pooling done by the Bayesian hierarchical estimators, giving more precise estimates of the random coefficients for each cluster (Gelman and Hill 2006). This results in $\beta_{t,c,j}^\alpha$ being shrunk further towards the estimate mean $\alpha_0 + \alpha_1\mu$, for each group t, c, j .

The predictive fit of our GPs is intuitively illustrated in Figure 8.

Figure 8. Estimated Mean Group Investment Rate Plotted Against Secular Stagnation GPs



Note: This shows a fitted ‘LOESS’ (Local Polynomial Regression) line through the intercept coefficients (the data before additional partial pooling) against the two group predictors used to ‘explain’ country — and time — variation between firms. Non-linear fit is evident for the external financing balance of the corporate sector in the bottom RH corner, indicating that too much borrowing is unhelpful.

This shows a fitted blue ‘LOESS’ (Local Polynomial Regression) line between the estimated intercept coefficients (the data for the macroeconomic regressions) and the corporate secular stagnation, group-level, explanatory variables. Most countries and years follow the predicted line very well. The U.S. stands out as having a low intercept coefficient, considering the relatively low proportion of ‘net releasers’ it contains. While India appears to have a higher intercept coefficient than expected by both our predictors. Finally, the years 2016 and 2017 are not predicted well by the GPs: they have lower intercepts than both our predictors would forecast.

Table 3 summarizes more concretely the regression output of the hierarchical model with the above

Table 3. Hierarchical Model Coefficient Estimates With and Without Group Predictors

		No GP		GP: Sectoral Bal.		GP: Prop. NR		GP: SB & PNR	
Variable		Est.	Est.Err	Est.	Est.Err	Est.	Est.Err	Est.	Est.Err
Random Effects	SD(Intercept _c)	0.203	0.034	0.110	0.018	0.154	0.025	0.113	0.019
	SD(Intercept _t)	0.229	0.036	0.156	0.027	0.080	0.014	0.082	0.015
	SD(Intercept _j)	0.121	0.005	0.113	0.005	0.099	0.004	0.099	0.005
Group-Level Predictors	SB _c			5.218	0.909			-1.842	0.337
	SB _t			10.356	2.884			-0.775	0.072
	SB _j			1.030	0.131			0.513	0.355
	NR _c					-1.892	0.238	5.260	1.327
	NR _t					-0.819	0.059	0.470	2.135
	NR _j					-0.513	0.334	0.156	0.143

Note: This table compares the posterior distributions of relevant coefficients for the baseline hierarchical model in Equation 5 against the hierarchical model with group-level predictors from Equation 14. For the latter, three different estimations are run: With the sectoral balance (SB) GP, with the net releasing (NR) proportion GP, and with both at the same time. For each coefficient, the mean (Est.) and the standard deviation (Est.Err) are reported.

two group predictors. Our focus is on whether the GPs reduce the unexplained variation between country or year clusters within each group, as summarized by the top three rows, which show each group’s $SD(Intercept_{c,t,j})$.

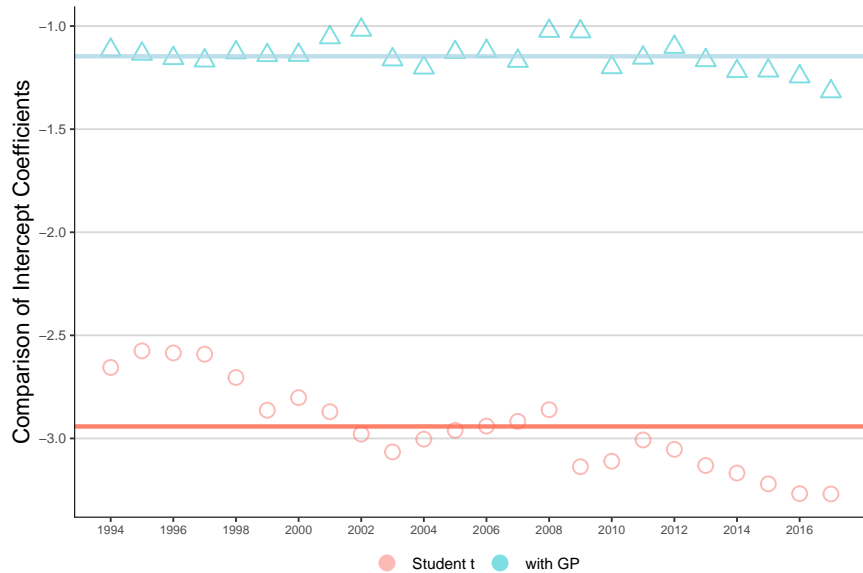
The ‘**sectoral balance**’ GP, or the ‘aggregate external corporate financing balance’, explains almost 50% of the (unexplained) variation in estimated firms’ investment rates *between countries*, with the standard deviation of the coefficients declining considerably from 0.2 to 0.11. Uncertainty of the estimated intercept coefficients within the year group is also reduced by around one-third too. GP explains nearly two-thirds of the (unexplained) variation in investment rates *between years* — i.e. over time — such that the standard deviation of the coefficients declines from 0.23 to 0.08. In addition, uncertainty in the estimates is reduced by around three-quarters. When both predictors are included, the benefits of both are combined and made more apparent. The sectoral financing balance coefficient becomes insignificant in explaining year variation and country-specific year variation, while its coefficient interval for explaining country variation remains largely the same, though with some modest increase in uncertainty. While the proportion of net ‘releasers’ remains as effective in explaining variation between years, though with some modest increase in uncertainty, it remains ineffective in explaining between-country variation, as the coefficient interval still includes zero, but with a sign switch.

Looking at the coefficient value of the group-predictors more closely (bottom half of Table 3), the sectoral financing balance group-predictor coefficients are all positive as expected (top-right plane), such that an increase in the external borrowing balance for the sector, as a whole, leads to an increase

in the predicted investment rate. In particular, for the country-level group predictor, which has the most amount of explanatory power judged by its ability to explain variation between predictors, the coefficient's impact is $\exp(5.22/100) = 1.054$. This shows that a 1% increase in the external financing sectoral balance, relative to sales, leads to an 5.4% increase in the investment rate, relative to its geometric baseline. The coefficients for the 'proportion of firms as net releasers' group-predictor are all negative, as expected, such that an increase in the proportion of firms that are net 'releaser' of funds, externally leads to a decrease in the predicted group-level investment rate. In particular, for the year-level group predictor, which has the most amount of explanatory power, we have $\exp(-1.89/100) = 0.98$, such that a 1% increase in the proportion of firms that are net 'releasers' leads to an 2% decrease in the group investment rate relative to its geometric baseline.

Figure 9 shows how the estimated investment slope intercepts within the year group are pulled toward the improved mean regression line now estimated by the 'proportion of net releasers' group-predictor. Most of the secular variation in intercepts before the crisis is 'explained' by inclusion of this macroeconomic predictor, with only a cyclic tendency largely remaining. The trend in the post-crisis period remains though.

Figure 9. Predicted Investment Intercept With and Without Group Predictor



Note: Using the proportion of the net 'releasers' as a group predictor sees the predicted investment rate across years shift up, as they are drawn from a distribution with a new higher mean, or fixed effect value, represented by the horizontal thick line. This group predictor helps explain, and so reduce, a lot of the secular trend in the intercept across time, except for the post-crisis period, which this group-predictor is unable to account for fully. The y-axis shows the raw unexponentiated coefficient value to aid in comparability.

For **robustness**, we run the above specifications with two dozen other group-level predictors. The

first set of robustness checks involve using as our group predictors various forms of aggregated and median cash flow rates (for the corporate sector as a whole), as well as economy-wide Q values of various forms. These variables are unable to explain much of the variation between clusters within each group — even if some of them have reasonable coefficient values. For our second set of robustness checks we use aggregated versions of **CHECH** and **IVNCF - CAPX** as our GPs to see if the two other main cash flow statement items, representing cash accumulation and net (external) financial asset accumulation, respectively, can explain the variation between estimated investment rates equally well. If they do then **FINCF**’s predictive power may stem purely from the cash flow identity. The sectoral net external financial asset accumulation GP (**IVNCF - CAPX**) explains, surprisingly, none of the differences in estimated investment rates between clusters within each group. The GPs coefficient credible intervals are incredibly large too. This may partly be due the variable including acquisitions of other companies as well as goodwill. Both of which we were unable to remove. In contrast **CHECH**, representing the sectoral tendency to retain cashflow (relative to sales), has considerable explanatory power as a group predictor — especially in explaining variation between countries — but still only roughly half of that of the sectoral external financing balance overall ($\sum \text{FINCF}$). The **CHECH** GPs reduce the $SD()$ of the intercept for countries to 0.14 (from 0.2) and for years to 0.20. (from 0.229). In comparison, the improved $SD()$ for the **FINCF** sectoral balance GPs are 0.11 and 0.15, respectively. Estimated errors are the same as those for the **FINCF** sectoral balance GPs. Moreover, the **CHECH** GPs regression coefficients have very high uncertainty intervals, with the smallest being the country-level group predictor coefficient $= [9.2, 23.5]$. This is unsurprising since in theory, firms retain cash not just as a ‘reflux’ from high cashflow rates and low investment opportunities, but also to avoid financing constraints and to fund high rates of growth (Almeida et al. 2004; Denis and McKeon 2018). While the variable itself lacks sufficient variation and is in general smaller in magnitude than **FINCF**.

5 Conclusions

Beginning in 2000, raw investment rates shift in secularly for firms in the U.S. and other advanced economies. For developing economy firms, this is largely a cyclical post-2008 financial crisis tendency. These trends are unlikely due to measurement error since our sample covers 24 countries with differing accounting standards. This is confirmed by movements in firms’ ‘true’ investment rates, estimated from our hierarchical model as the sum of the fixed effect and random effects intercepts, and which account

for key firm-level explanatory variables and controls.

Among the most common explanations for this decline in advanced economy investment rates is that a relevant portions of firms are finance constrained in their investment behaviour (Fazzari, Hubbard, Petersen, et al. 1988). If only they had more cash flow, or more predictable cash flow, then their investment rates might increase and their precautionary savings decline, or so the argument goes. Our evidence strongly rejects this finding for advanced economy firms, since cash flow coefficients are economically insignificant and centered around zero, absolute cash flow rates have increased, and most firms' and corporate sectors are choosing to release their funds in net externally in a materially significant manner.⁵⁵ The proper conduct of monetary policy in such an environment is an important question, since non-financial corporate money demand becomes more deeply tied to factors other than their fixed capital investment demand.

We find little evidence for explanations, such as declining effective competition or increasing 'financialization' of firms' behaviour, that rely on firms becoming less (or more) responsive to investment opportunities (Lazonick et al. 2014; Philippon 2019), since the estimated *slope* of firms' investment demand schedule (as proxied by the time-varying Q coefficients) shows no secular trend. Firms' remain profit maximizers. Instead, the estimated *intercept* coefficients of the investment demand curve shift inwards, especially for advanced economy firms', indicating a weakening in the underlying impetus to invest.

In this paper, we advanced a (descriptive) 'corporate secular stagnation' explanation for the decline in the impetus to invest, as reflected by declining advanced economy intercept coefficients. This acts at the microeconomic (firm) level, but also strongly at the macroeconomic level, to depress estimated investment rates across all firms within a given country or year. We showed that corporate secular stagnation reflects an increase in cash flow rates even as investment opportunities have stagnated or declined and that this has manifested in firms, and the corporate sector as a whole, borrowing less funds externally (in net) and releasing more. So much so that the non-financial corporate sector in advanced economies are no longer reliant on the external sector for net financing inflows, and instead use it to drain the 'swamp' of cash flow that is constantly at risk of overflowing. The implications are that the corporate sector's negative net external money demand is likely a major contribution to depressed real interest rates in advanced economies and highlights a growing mismatch between investment and savings

⁵⁵For developing economy firms we find the opposite: cash flow coefficients remain meaningful, despite increasing cash flow rates over time.

at the firm and sectoral level.

This behaviour we argued is consistent with a simple cash flow-Q model, whereby (Figure 2): (1) Internal financing increasingly exceeds investment demand as firms' investment demand curve shifts inward while cash flow rates increase; and (2) Firms face some cost to retaining unneeded surplus, such that it is largely released externally through dividends, net share repurchases/issuance, and net debt repayments and issuances. However, the underlying causes of these shifts in investment demand and financing supply, as reflected in movements in FINCF (our proxy for corporate secular stagnation) are assumed to be exogenous here and similar to those listed in Summers (2015).

A growing body of models and empirical research links fiscal policy in mature economies (with a focus on 'fiscal consolidation') to secular stagnation (DeLong et al. 2012; Fatás and Summers 2018; Ollivaud et al. 2016; Rachel and Summers 2019; Skott 2019). Our paper makes no real attempt to explore this linkage via changing pre- and post-tax rates of return on fixed capital and financial capital, for example. But future research might profit from doing so.

Lastly, an increasing amount of evidence posits that increasing inequality may constrain demand growth (Auclert and Rognlie 2018; Dabla-Norris et al. 2015), if not simply through higher savings rates at the top of the income distribution, with no effective interest rate mechanism to recycle these funds to firms (Cynamon and Fazzari 2015; Saez and Zucman 2016).⁵⁶ However, further research is required to statistically link this type data to changing firm-level investment rate patterns (Alvaredo et al. 2018; Summers 2015). Bayesian hierarchical models offer one potentially productive way to achieve this.

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⁵⁶The top 1% save about 20-25% of their income, according to 'synthetic' savings rates constructed by Saez and Zucman (2016).

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Appendices

For Online Publication.

A Cash flow-Q Investment Model

Following J. Lewellen and K. Lewellen (2016), the value of the firm, V_t is maximized 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 . Adjustment costs are also related to an exogenous parameter stochastic parameter λ_t . The recursive Hamiltonian is:

$$V_t = \Pi(K_t, s_t) - I_t - C(I_t, K_t, \lambda_t) + \beta E_t[V_{t+1}]. \quad (16)$$

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

$$1 + C_I(I_t, K_t, \lambda_t) = \beta E_t[V_k(K_{t+1}, s_{t+1}, \lambda_{t+1})] \quad (17)$$

$$= q_t. \quad (18)$$

This states that the firm invests until the marginal cost of capital: with the purchase price of capital fixed at 1 (left hand side), equals the marginal value of capital (right hand side). q_t is the present discounted value of future marginal revenue products of an additional unit of capital. As such, q is the market value of a unit of capital. With a purchase price of capital fixed at 1, q is the ratio of the market value of a unit of capital to its replacement cost. q is proxied by the book to market value of the firm. We use assets as the denominator instead of capital stock.⁵⁷

Quadratic investment adjustment costs for $C(\cdot)$ are assumed. Substitution of this into the first order condition (f.o.c) leads to the following - with subscript I referring to the partial derivative with respect to investment:

$$C_t = 0.5\alpha \left(\frac{I_t}{K_t} - \lambda_t \right)^2 K_t, \quad (19)$$

$$C_I = \alpha \left(\frac{I_t}{K_t} - \lambda_t \right), \quad (20)$$

$$\frac{I_t}{K_t} = -\frac{1}{\alpha} + \frac{1}{\alpha} q_t + \lambda_t, \quad (21)$$

⁵⁷This keeps the variable strictly positive despite some loss of interpretation.

where λ becomes the error term in the investment regression, α is a time-invariant adjustment cost parameter, and q_t is a sufficient statistic to explain the firm's investment rate.

To get cash flow into the regression assume internal and external finance are not perfect substitutes, such that external finance is more costly. This creates a 'Pecking Order' of preferred sources of financing based on the idea that there are financial market imperfections (Myers 1984; Myers and Majluf 1984). Assume the external financing need of the firm is roughly proportionate to $I_t/K_t > \Pi_t/K_t$, with quadratic external financing cost, EF:

$$EF_t = 0.5b \left(\frac{I_t}{K_t} - \frac{\Pi_t}{K_t} \right)^2 K_t, \quad (22)$$

$$EF_I = b \left(\frac{I_t}{K_t} - \frac{\Pi_t}{K_t} \right). \quad (23)$$

The cost of external financing is assumed to be $b \geq 0$. Plugging the above into the Equation 16 leads to the following final regression specification:

$$\frac{I_t}{K_t} = -\xi + \xi * q_t + \beta * \xi \left(\frac{\Pi_t}{K_t} \right) + \xi * \alpha(\lambda_t). \quad (24)$$

The q coefficient declines in proportion to $\xi = 1/(\alpha + \beta)$ - i.e as adjustments costs or external financing costs increase, and cash flow, Π_t/K_t , enters directly into the regression equation.

We interact the 'cash flow' variable with our FINCF variable to try and distinguish firms that are more (potentially) financially constrained from those who are less (or not at all) financially constrained. A firm could be financially unconstrained for two reasons. One, if it faces near perfect (i.e. costless) external financial markets. And two, if its demand for financing falls short of its investment opportunities, i.e. if $I_t/K_t < \Pi_t/K_t$. In practise it is hard to distinguish between the two and has been a source of underlying tension in the literature (Almeida et al. 2004; Fazzari, Hubbard, and Petersen 1996; Kaplan and Zingales 1997).

The above model captures the dynamics for what we consider to be a growing minority of potentially finance *constrained* firms. In practise, an increasing number of firms are financially *unconstrained* and instead subject to corporate secular stagnation. Their demand for (net) external financing is zero or negative due to their investment opportunities falling short of available internal financing, such that $I_t/K_t < \Pi_t/K_t$. These firms are identified by a weakening of their net external demand for financing, so much so that they increasingly are net releasers of funds externally.

B Explaining Net Releasing: Agency Theory

Pecking Order Theory expects firms to have an ingrained retention bias, since most financial slack should be retained to avoid accessing costly external financing now or in the future (H. DeAngelo, L. DeAngelo, and Stulz 2006; Myers and Majluf 1984). Exacerbating this retention bias is the fact that dividends may be taxed more heavily than capital gains and managers may have an incentive to retain unneeded free cash flow for their own self-interest.

By contrast, in a Miller-Modigliani world (Miller and Modigliani 1961), 100% of free cash flow is distributed and payout policy itself is, by definition, irrelevant with investment policy being held fixed (H. DeAngelo and L. DeAngelo 2008; H. DeAngelo, L. DeAngelo, and Stulz 2006). Date t distribution to stockholders also cannot exceed the sum of contemporaneous free cash flow and stock sale proceeds. The fact that firms that are large net external ‘releasers’ of finance have lower rates of investment than net external ‘borrowers’ is consistent with Miller and Modigliani (1961) (Brealey et al. 2011), which sees distributions as a residual after investment decisions have been made. But, in Miller and Modigliani (1961), distributing all free cash flow is true by definition and so, trivial. Moreover, market imperfections do not exist. While any increase in retained earnings would, by definition, lead to an increase in investment spend, to the extent that temporary increases in cash piles could only explain increasing, not decreasing, investment rates.

At the microeconomic level, Agency Theory (Easterbrook 1984; Jensen and Meckling 1976), and its models (Hart and Moore 1994; Stulz 1990; Tirole 2010), are much better suited to explaining when firms would disgorge unneeded cash under market imperfections.⁵⁸ Its predictions underlie our use of FINCF as a proxy for secular stagnation. In Agency Theory there are agency costs to the retention of funds internally in excess of investment need (Jensen 1986). This follows from the assumption that there is: (1) A degree of manager–stockholder agency conflict and, (2) The existence of firms with internal funds in excess of investment opportunities. As such, this theory is particularly relevant to ‘cash cow’ firms (Brealey et al. 2011). The solution to this moral hazard problem is through optimal contract design, such that all relevant surplus is forcibly released externally (Tirole 2010).

At the macroeconomic level, Agency Theory is more consistent with a world of corporate secular stagnation too than Pecking Order theory. While Pecking Order models predict under-investment by the *individual* firm, they are more relevant to a world with strong overall investment demand, since

⁵⁸See J. C. Stein (2003) for an overview of its models.

otherwise financial constraints — at least in advanced economies — are unlikely to bind (Fazzari, Hubbard, Petersen, et al. 1988; Myers and Majluf 1984), Where financial markets are more liquid and efficient. By contrast, in Agency Theory models, while the *individual* firm might engage in over — or under-investment — depending on the existence or absence of constraints on wasteful managers, it is still a world in which ‘free’ cash flow is the primary problem facing firms. As a result, the overall context is one of a shortage of investment opportunities relative to available cash flow and cash. The literature assumes that the Agency Theory problem is more applicable to certain industries (Jensen 1989), or mature firms in their corporate life cycle (Brealey et al. 2011). Below, we show that this has now become *the* problem facing most advanced economy firms who are experiencing corporate secular stagnation and at risk of a cash flow swamp forming on their balance sheet. In response, advanced economy firms are releasing externally, in net, their cash flow in increasing quantities.

In practise, agency contracts (both formal and informal) are widespread, especially in advanced economies, to ensure surplus cash is returned to shareholders. This is occurring through several channels today, including:⁵⁹ Increasing levels of debt issuance and debt refinancing undertaken by cash-rich firms (Federal Reserve Board 2019; Stulz 1990), activist investors pushing cash-rich firms to distribute excess cash holdings (Denes et al. 2017; Gillan and Starks 2007), and public pronouncements of cash-rich firms targeting ‘cash neutral’ as a goal. Apple, for example, is ‘fighting’ to become ‘net cash zero’ by 2023, returning around \$100 billion annually to shareholders as it battles against its bottomless cash tsunami (Kim 2018).⁶⁰ The underlying mechanisms pushing firms to disgorge unneeded surplus may be weaker or stronger in countries with different levels of financial development, different corporate ownership structures, and different reporting and accounting standards for public firms (Demirgüç-Kunt and Maksimovic 1998; La Porta et al. 2000; Rajan and Zingales 1998; Wurgler 2000).

C Data and Variable Description

Perhaps the most important starting point for working with firm data is a good understanding of accounting terms and standards. When using cross-country data this requires reading the most up-to-date GAAP and IFRS accounting manuals as well as documentation which compares differences between the two (for example PWC (2018)). We do not attempt to cover all of this material here when

⁵⁹Agency Theory is also consistent with the observed use of debt to repurchase equity, especially in the U.S.. And the fact that S&P firms that engage in share repurchases outperform those that do not (Zeng 2014).

⁶⁰By one widely-cited study, this almost unavoidable increase in Apple’s cash pile from its high cash flow would make it finance constrained (Almeida et al. 2004).

discussing how variables might reasonably differ across countries, and in particular between Compustat North America which follows GAAP standards and the rest of the world which follows IFRS to varying extents and in different forms.

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.

Around 19.5% of observations have negative cash-flow (OANCF). We find little evidence of a rising portion of loss making firms in our combined sample or for separate Compustat databases, and weak evidence that these firms are growing in importance or their nature is changing substantively.

C.1 Data Cleaning

Vietnam and Zimbabwe are removed due to erratic behaviour in key variables (such as the capital stock).

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, remove financial companies but keeping 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 observations. 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.⁶¹

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 measure or at least adjust for it now (Fernald et al. 2017; Peters and Taylor 2017). See also: Haskel and Westlake (2018). Intangible assets are measured net, however. 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 note that positive impact on Q coefficient values from the inclusion of intangible assets.

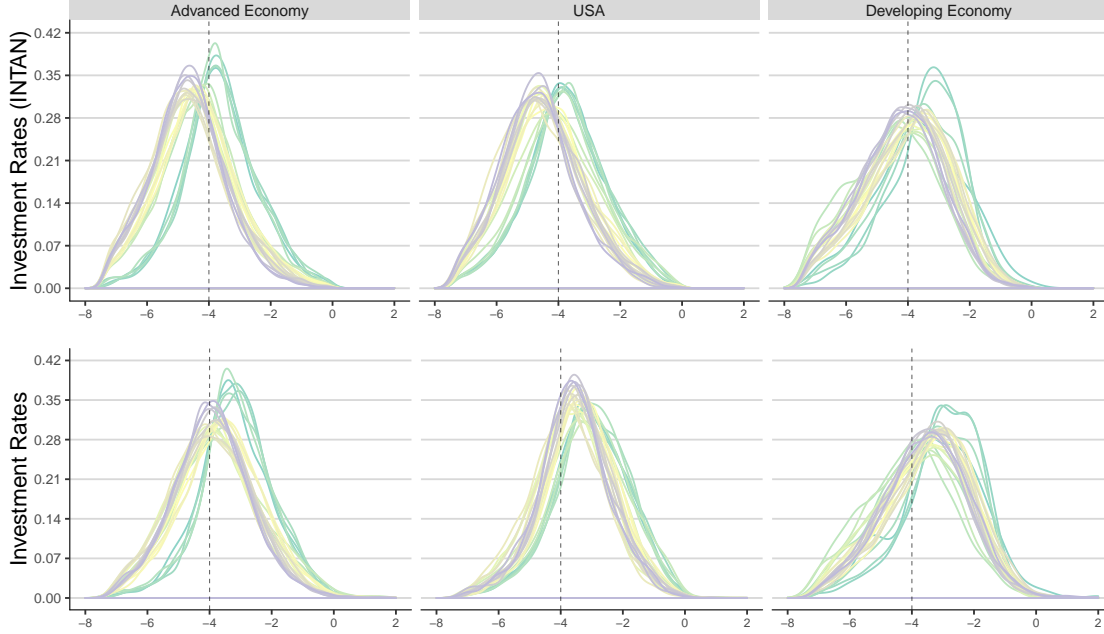
Gross investment rates are recommended, rather than ‘net’, for cross-country comparisons for national accounts and firm-level data (Lequiller and Blades 2014). GAAP and IFRS contain important differences in depreciation rules, implied by how development costs are capitalized differently, and also differences 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 definition of this differs somewhat for North America and Global firms in accordance with IFRS and GAAP differences. The variable is measured gross after taxes and interest payments adjusting for changes in working capital and other non-operating income. See Compustat Balancing Models excel documents for a moderately detailed

⁶¹If firms calculated value of CHECH is more than 200% bigger or smaller than the actual value of CHECH then they are removed.

Figure 10. Investment Rates by Capital Stock Definition



Note: Comparing Investment Rates with different capital stock definitions: Top row is our default investment measure and includes intangible capital (INTAN) and inventories (INVT) in the capital stock denominator, in addition to gross property, plant, and equipment PPEG. Kernel density approximation showing firm-level investment rates for 24 countries (13 advanced economy and 9 developing economy), shifting in sharply in 2001. On the $\text{Log}_2()$ scale. Dotted line at -4 is for a $\approx 6\%$ investment rate. Dark green is for 1994, becoming yellow-green from 2001, to light yellow by 2007, to dark grey by 2017. This plot informs the chosen periodization in this study.

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 deducing taxes and interest payments and income.

FINCF: We normalize by sales.

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.

The firm size dummy is a rough proxy and consists of 10 equal bin dummies based the firm's capital stock size. Industry Dummy consists of the SIC one industry code assigned to the firm, and capital utilization / productivity dummy is the capital-output ratio, defined as the firm's output over its capital stock.

Tobin's Q: We calculate as the firm's market-to-book ratio (MTB). Books values and 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 firm's 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* 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 $marketcap_T = \text{sum}(marketcap)$, 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. Like with Compustat North America our calculation excludes non-traded shares. The literature tends to define Q as : $\text{Market Value of Fixed Capital} / \text{Book Value of Capital}$. 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 are only equal under restrictive assumptions (Hayashi 1982). Use of MTB is motivated by several considerations: theoretically, the meaning of a negative Tobin's Q is unclear: 'what is a negative investment opportunity?'. And in Compustat Global (and North America to a lesser extent) many negative values exist. In particular Japan contains around 17% negative Q values. Almost 30% of the total negative Q values come from Japanese firms (or 30% of all observations on Japanese firms). Over 8% of negative values come in 2008 with the financial crisis. Moreover, its explanatory power is roughly the same as other Q measures (Erickson and Whited 2006, 2012).

Damodaran (2013) notes in particular that non-traded shares, management options, non-traded debt, off-balance sheet debt, trapped cash, and convertible securities all can lead to measurement error in enterprise value which ideally one should adjust for. In particular, cross-holdings in other companies may upwardly biasing the (consolidated market) value of the enterprise. A closer look at the top 4% of pooled Q values in our entire sample shows that holding companies feature very strongly. This also partly helps explain why firms in the Cayman Islands and Bermuda have such large Q values.

The above also implies that, for cross-country purposes, the MTB value may be preferred since countries such as the U.S. will have a larger portion of ‘trapped cash’ on their balance sheet than others due to tax considerations. Traditional Tobin’s Q proxies must deduct all or most of the firm’s cash to arrive at just the firm’s operating assets. This may also create a strong time bias in Tobin’s Q measures for the U.S. (Damodaran 2013). In addition, many firms in compustat do not separate their assets into current and non-current assets (such as Berkshire Hathaway) required for a proper computation of Tobin’s Q, making the MTB the least sensitive measure to differing accounting reporting requirements between and within countries. We compared several different measures of Q across countries in our sample. The distribution of Q as the MTB is most similar and with a lower variance between Compustat Global and Compustat North America.

Certain issues though will be present across all proxies for Tobin’s Q. We would expect Q values to vary greatly depending on the accounting rules used by the firm regarding revaluation of the market value of PPEGT. The ability to revalue assets (to fair value) under IFRS might create significant differences in the carrying value of assets as compared with US GAAP (Gordon et al. 2008; PWC 2018). While IFRS permits revaluation, US GAAP generally utilizes historical cost and prohibits revaluations of fixed capital. *As a result a downward bias will be expected in book values of U.S. GAAP firms.* Compounding this is that with US GAAP, reversal of impairment is prohibited, while under IFRS it is permitted. We would expect then that Q values would be much higher in the U.S. than in other advanced economies. This is exactly what we see in Table 4.

Table 4. Summary Statistics of Tobin’s Q Proxy by Country Group

	Min.	1st Qu.	Median	Mean	MAD.	3rd Qu.	Max.
Advanced Economy	0.08	0.55	0.79	1.20	0.45	1.26	33.13
U.S.	0.08	0.76	1.22	2.11	0.85	2.19	33.59
Developing Economy	0.08	0.68	0.99	1.47	0.59	1.69	33.60

Note: MAD stands for ‘median absolute deviation’. U.S. Q values are higher and with greatest spread. High Q values for U.S. firms is probably partly due to the downward bias over time in the book values of fixed capital under US GAAP methods, which do not allow for revaluation upward of fixed assets to fair value, or reversal of impairment charges. Developing economies values have greater spread than Developed Economies (less U.S.).

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.

We have 24 countries in total. To be included in the sample the country needed to have 2,000 or more observations in the Compustat file between 1990-2017. This amounts to around 83 observations per year, per country, as a minimum since most countries only begin to feature in the sample from 1994.

Country categorisation of developed vs. developing is based on average GDP per capita (nominal) US\$ between 1994-2017. A nominal series is used since this goes back further in time. We use \$25,000 per capita average as the cut-off point between the two groups. This gives us 15 developed economies = 12 + U.S. + 2 major tax havens (namely Bermuda and Cayman Islands) and 9 developing economies.

Advanced economy plus tax haven firms: come from Great Britain, Australia, France, Italy, Sweden, the Netherlands, Singapore, Israel, Germany, Japan, Canada, Bermuda, Cayman Islands, and Switzerland. *Developing Economy Firms* come from the following 9 countries: Thailand, India, Taiwan, Malaysia, South Africa, India, China, Pakistan, and the Republic of Korea (South Korea).

The top five countries in our sample are: U.S. (82,775), Japan (44,242), China (24,490), India (14,379), and Taiwan (15,455). Korea and Canada are close behind. Tax haven countries feature prominently too. For example, Cayman Islands (4,798) and Bermuda (3,959) combined have just more observations than Germany (6,314) plus Italy (1,997) in our sample.

Table 5. Data Sample Summary

	1994-2001	2002-2007	2008-2017
Advanced Economy	20,840	35,259	55,587
U.S.	36,103	20,687	25,985
Developing Economy	8,560	22,960	57,721

Note: Showing number of datapoints in our sample, by year and country grouping. Prior to 2000, and 1995 especially, our developing country sample is limited. After which it grows rapidly. Shows shrinking number of new lists in the U.S.. Tax haven country firms are included with advanced economies.

A more detailed breakdown of the same size by country follows:

Table 6. Detailed Data Sample Summary by Country and Year

Year	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
Advanced Economy	772	1045	1315	1593	1832	4076	4935	5272	5480	5579	5826	6000
U.S.	4218	4530	4908	4893	4677	4537	4373	3967	3686	3504	3521	3422
Developing Economy	121	399	728	1200	1215	1271	1268	2358	2946	3460	3771	4065
Year	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Advanced Economy	6221	6153	5880	5323	5387	5543	5650	5585	5668	5620	5488	5443
U.S.	3331	3223	3042	2816	2741	2683	2634	2581	2616	2505	2355	2012
Developing Economy	4342	4376	4709	4470	5450	5950	6121	5665	5947	6247	6374	6788

C.4 Movement of Key Variables by Time and Country Group

Table 7. Cash Flow Rate Percentiles by Country and Year Group

Country Group	Time Period	P10	P30	P50 / Median	P75	P95	MAD
U.S.	1990-1999	-0.3295	0.0047	0.071	0.14	0.43	0.123
U.S.	2000-2007	-0.4427	0.0090	0.076	0.15	0.43	0.130
U.S.	2008-2017	-0.2080	0.0431	0.089	0.16	0.41	0.098
Advanced Economies	1990-1999	-0.0482	0.0437	0.080	0.13	0.31	0.073
Advanced Economies	2000-2007	-0.0653	0.0389	0.075	0.14	0.40	0.080
Advanced Economies	2008-2017	-0.0055	0.0523	0.086	0.15	0.46	0.075
Developing Economies	1990-1999	-0.0812	0.0243	0.074	0.14	0.34	0.098
Developing Economies	2000-2007	-0.0578	0.0371	0.084	0.16	0.38	0.098
Developing Economies	2008-2017	-0.0542	0.0405	0.087	0.16	0.39	0.099

Note: Cash flow rates increase for most countries and percentiles, with the main exception being the 95th percentile of firms in the U.S., and the middle of the distribution for advanced economy firms. Variability declines strongly for the U.S. sample.

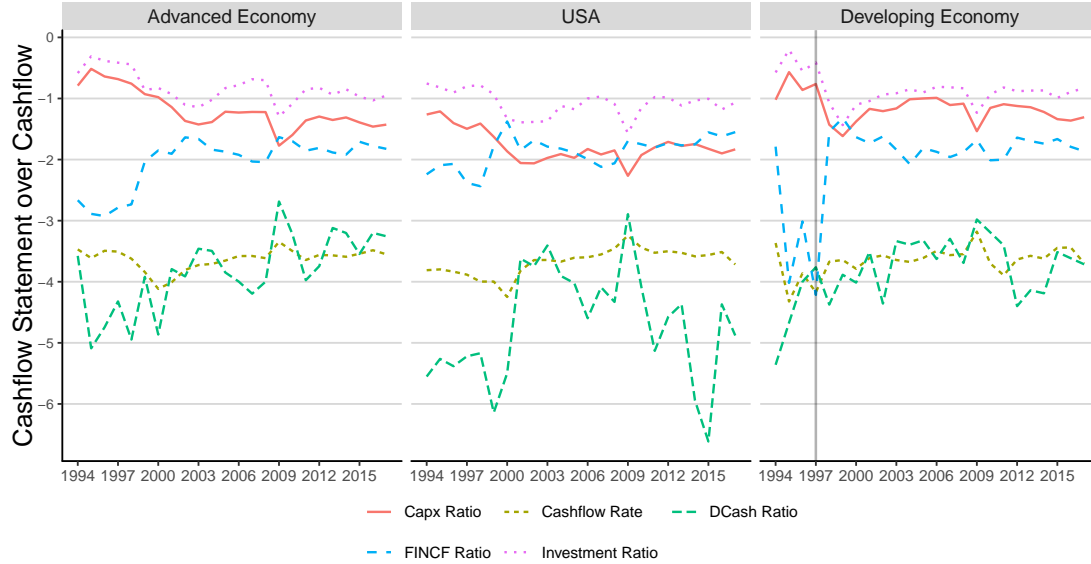
Table 8. Q (Book) Value Percentiles by Country and Year Group

Country Group	Time Period	P10	P30	P50 / Median	P75	P95	MAD
U.S.	1990-1999	0.48	0.84	1.25	2.5	8.9	0.95
U.S.	2000-2007	0.45	0.82	1.21	2.2	6.4	0.88
U.S.	2008-2017	0.51	0.85	1.19	2.0	5.3	0.75
Advanced Economies	1990-1999	0.42	0.67	0.91	1.6	5.7	0.57
Advanced Economies	2000-2007	0.40	0.62	0.82	1.3	3.4	0.47
Advanced Economies	2008-2017	0.39	0.59	0.79	1.3	3.1	0.45
Developing Economies	1990-1999	0.44	0.63	0.79	1.2	2.8	0.36
Developing Economies	2000-2007	0.47	0.70	0.93	1.5	3.3	0.52
Developing Economies	2008-2017	0.49	0.73	1.00	1.7	4.2	0.61

Note: Q values decline for advanced economy firms and increase for developing economy firms. The biggest fall in Q values for advanced economy firms have been at the 95th percentile. Lower percentiles increase in the U.S.. Variability declines in advanced economies and increases in developing economies.

D Alternative Explanations for FINCF and the Other Cash Flow Statement Items

Figure 11. Uses of cash flow by cash flow statement activity on Log2() scale



Note: Showing $\text{Log2}(\text{median})$ values of primary cash flow statement variable normalized by cash flow (Compustat *OANCF*), 1994-2017. Also showing cash flow rate which is over capital stock. Dcash is change in cash holdings. Apparent volatility in this variable for the U.S. is due to it being a very small number (< 0.09) such that log transformation ‘blows it up’ further. Investment Ratio is investment in both fixed and financial assets. Gap between Investment Ratio and Capx Ratio reflects net financial asset accumulation over cash flow. Grey line for 1997 Asian financial crisis. Insufficient data points prior to then in Developing Economy sample.

Firms’ increasing tendency to retain cash flow (CHECH) has accompanied the increase in the release of funds externally through FINCF (Figure 11). It appears that both are connected to the corporate secular stagnation tendencies described in this paper (see findings below). This is supported by previous findings, which link increases in corporate cash piles to cash flow (Opler et al. 1999, 2001). However, the tendency to retain relative to sales is weak for most U.S. firms in our sample, and for the U.S. economy as a whole. Moreover, the relationship between CHECH and investment rates is highly ambiguous. Both developed and developing economy firms show an increase in retentions out of cash flow, despite very different sets of investment rates (Figure 11). This may be because growth firms with high ‘burn rates’ also tend to have high cash stocks (Denis and McKeon 2018). While cash serves as important collateral for finance constrained firms (Almeida et al. 2004). As such the accumulation of cash stocks can be under the firms’ control or not.

The other potential outlet for surplus funds through the cash flow statement is the net acquisition of financial assets (IVNCF – CAPX). The increasing tendency to use cash flow for net financial asset accumulation (excluding cash) may primarily be a U.S. phenomenon, though (Appendix E, Figure 11).

We find it to be a very poor macroeconomic predictor in our regressions.

Is the positive observed relationship between FINCF and investment not simply a result of a ‘debt-overhang’ (Myers 1977)? Our sample shows signs of de-leveraging by firms in several countries consistent with a debt-overhang. This could provide a compelling narrative if it leads to firms paying off principal debt, resulting in a negative FINCF, and increasing savings (or retention out of cash flow) to fund debt repayment rather than reinvestment (Koo 2011).⁶² In addition, median leverage levels (defined as short-term plus long-term debt over equity) are much higher for net external ‘borrowers’ than net external ‘releasers’ of funds (roughly double).⁶³ This implies that leverage levels are probably declining over time for most firms. The fit of this to our data is weak though. Firstly, the level of median leverage at < 0.5 is not high. Secondly, the decline in leverage is evident across the distribution of firms in both advanced economies and developing economies, despite their very different investment rate trends. Moreover, no decline in leverage is evident for U.S. firms, except during 2002-2007 or so. The latter is consistent with the findings by Gutiérrez and Philippon (2017b) that U.S. firms have been positive issuers of net debt, including highly credit-worthy firms. Thirdly, the number of firms in our sample experiencing a balance sheet recession, proxied by ‘negative equity’, never goes above $\approx 4.5\%$, such that they are unlikely to have a notable impact. Fourthly, the relationship between leverage and investment in our sample is complex and weak: Leverage levels are highest among developing economy firms, but also declining most strongly for them. These firms also have higher rates of investment, even though the literature tends to find that firms with lower debt burdens should invest less (J. C. Stein 2003).

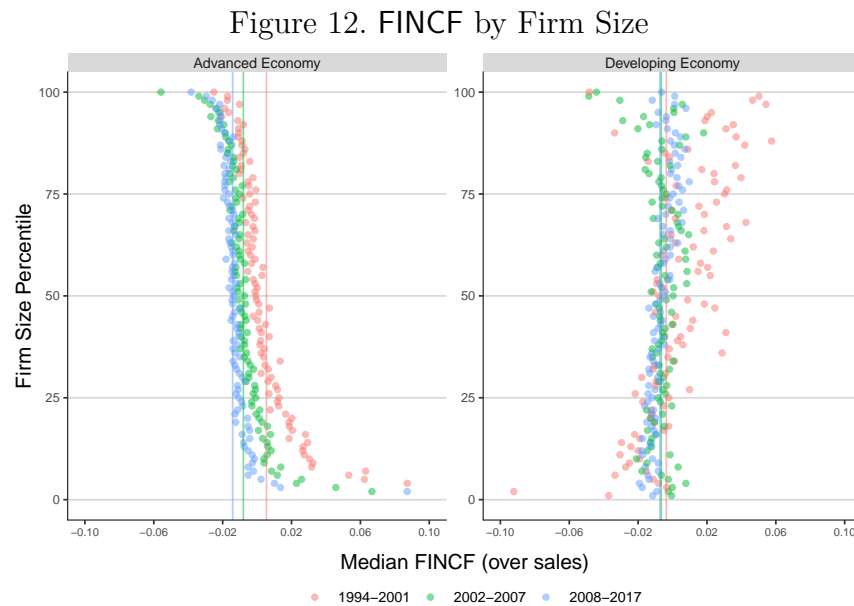
Lastly, studies increasingly focus on the corporate sector shifting from being ‘net borrowers’ to being ‘net lenders’ in the national accounts (NA). This is linked either to increased savings (Armenter and Hnatkovska 2017; Chen et al. 2017), or decreased investment (Gruber and Kamin 2015). The national account concept of net lending is defined as $\text{Savings (profits less dividends)} - \text{Investment}$. As such, these findings, while generally supportive of ours, are not directly comparable for several important reasons: Firstly, corporate net lending in the NA is highly sensitive to how activities in other sectors of the economy are classified (Ruggles 1993). Secondly, the NA concept only shows what firms are *able* to lend (or borrow) based on movements in the sectoral flows of retained profits relative to investment expenditure. It does not indicate what firms are *actually doing*. Thirdly, it also does not indicate what

⁶²Even though CAPX out of cash flow has not declined at the median in the U.S. since the 2000s, and in fact has even increased.

⁶³Firms that are very large net external ‘borrowers’ of funds, tend to have very low leverage levels, though, since they are young firms. This makes sense, since firms with low and negative levels of cash flow are almost always net ‘borrowers’ of external funds, while firms with high levels of cash flow are net ‘releasers’ of funds.

firms are *able to do*. This would require taking into account how a firm’s cash and other stocks impact its financial constraints. The NA effectively ignores share repurchases from its concept of ‘net lending’, since it is treated as a use of funds rather than a prior deduction from profits to arrive at savings, or retained earnings. The NA concept also excludes share and debt issuances, since this is again a use of funds rather than a change in the firm’s profits and retained earnings. As such, the concept gives us no real indication of firms’ overall — i.e. net — financing demand, financing constraint, or actual behaviour. It is merely an accounting identity.

D.1 Life Cycle of the Firm and FINCF



Note: Net external ‘releasing’ (negative x-axis values) and net external dispersing of funds (positive x-axis values) tends to follow the life cycle of the firm: smaller firms (0 → 50 on y-axis) in their infancy with plenty of investment opportunities but negative cash flow borrow more (relative to sales), while larger (50 → 100), mature, firms tend to release more as their investment opportunities tend to fall short of their by now large cash flow rates. The trend for developing economy firm is less clear, but seems to more closely reasonable that of advanced economy firms post-crisis. Some values cut off for top and bottom percentiles to reduce graph sale. Capital stock deflated using non-residential fixed capital stock deflator from U.S. NIPA tables.

Does the above observed pattern in FINCF not reflect simply the life cycle of the firm? As firms mature and relative investment opportunities dry up firms tend to distribute more surplus (Damodaran 2010; H. DeAngelo, L. DeAngelo, Skinner, et al. 2009; H. DeAngelo, L. DeAngelo, and Stulz 2006).⁶⁴ Figure 12 shows that firms’ net external financing flow position follows the firm’s life cycle (proxied by its size) quite closely: younger firms have larger investment opportunities relative to their low or negative cash flow, as a result they borrow substantially relative to sales (large and positive FINCF). While more mature firms with fewer investment opportunities relative to a large and positive cash flow land up

⁶⁴The shortening of firms’ life cycle may be speeding this up (Damodaran 2015).

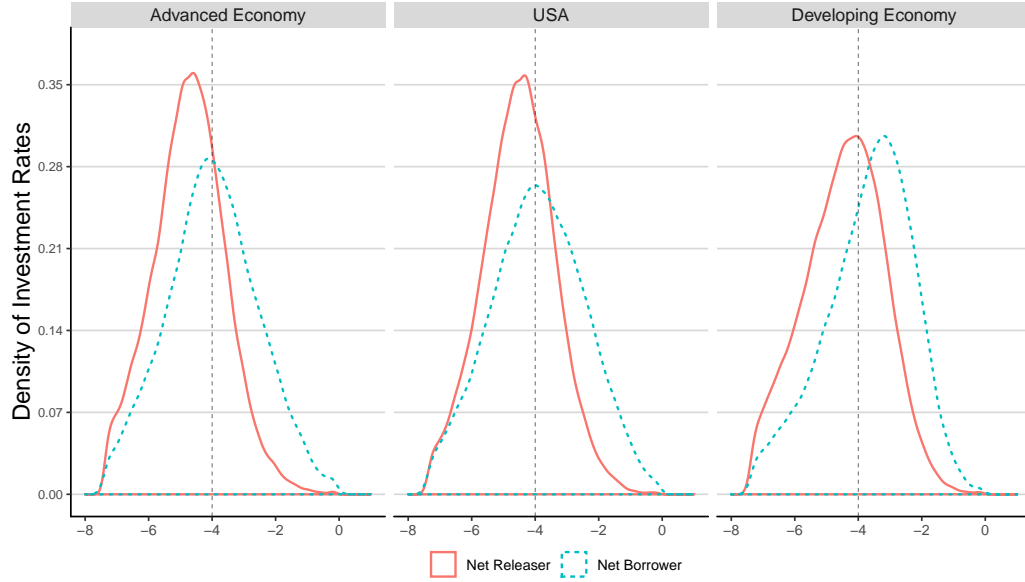
distributing in net their excess surplus, resulting in a large negative FINCF. We see a very similar shape and tendency if we instead used deflated firm capital stock percentiles as the y-axis variable.

This raises the question of whether the trends in investment rates and FINCF is simply a Compustat sample issue, i.e. average firm age increasing in Compustat. This is unlikely. Firstly, the growing trend towards firms’ engaging in less borrowing and more dispersing of funds externally is a feature across all firm sizes in advanced economies. This is unsurprising since the increase in cash flow rates and the decline in investment opportunities has been a feature across all firm sizes. This further emphasizes the importance of the broader macroeconomic context. Secondly, Table 5 shows that developing and developed economy firms in our sample do not display this same decline in public listing as in the U.S., except since the financial crisis. This decline begins in 1997 in the U.S. and 1996 in our specific sample. Evidence on international companies listings are such that outside of the U.S. listing have not been declining since the late 1990’s (Doidge et al. 2018; Piwowar 2019). Thirdly, it is possible that the firm’s life cycle has simply become compressed (Damodaran 2015). This would account for the shift across all firm sizes in FINCF. However, this seems to largely be a feature of ‘technology’ firms (loosely defined), which are only a small portion of our total sample of firms. Fourthly, we base the country of the firm on its FIC code - its country of incorporation which can be different from where the company’s shares are traded (and listed). Our sample includes advanced economies, and most notably Bermuda and Cayman Islands, which have a large increase in incorporations. This may be u.S. firms and would help offset any apparent bias from declining incorporation of firms in the U.S. rather than its country of listing.

E FINCF Visual Description

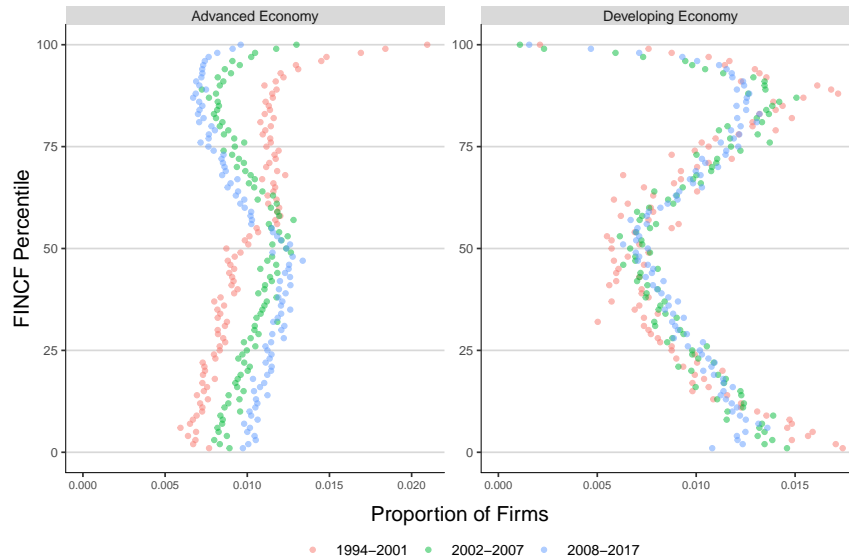
The DNA graphs show changes in our key quantities of interest over time by FINCF percentile and country grouping. Each DNA dot (‘atom’) shows the median value of the variable in question for a specific FINCF firm percentile (unless stated otherwise). While the different coloured strands reflect different time periods. Strands loosen or tighten over time. Vertical lines for each time period show the median pooled value.

Figure 13. Investment Rates by FINCF and Country Grouping



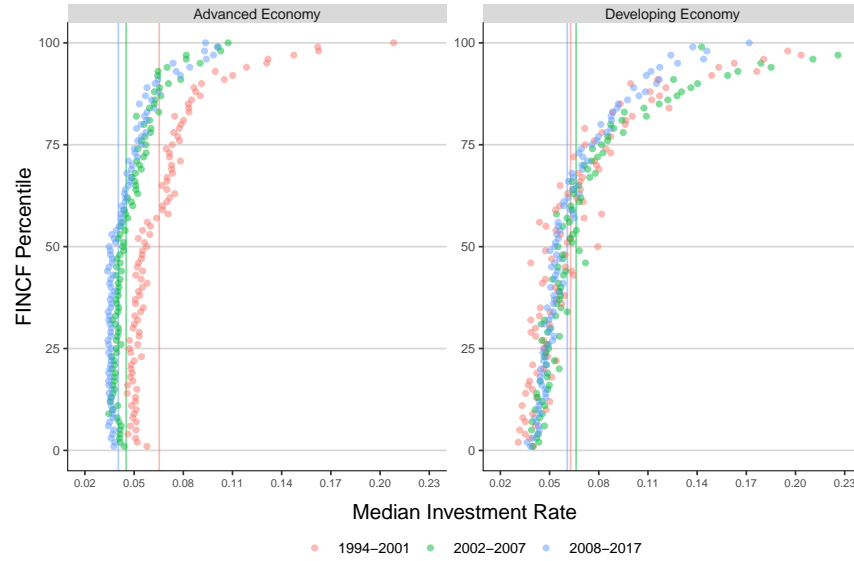
Note: Kernel density approximation of firm-level investment rates on $\log_2()$ scale. Firms' investment rates are closely tied to their net external financing positions. Firms that are net external 'releasers' of funds have a median investment rate of 4.2% (.032 MAD), compared to an investment rate of 7.1% (.065 MAD) for firms that are net external 'borrowers'. As more firms in the economy become net external 'releasers' of funds, economy-wide investment rates should slow.

Figure 14. Proportion of Firms in each FINCF Bin by Time Period



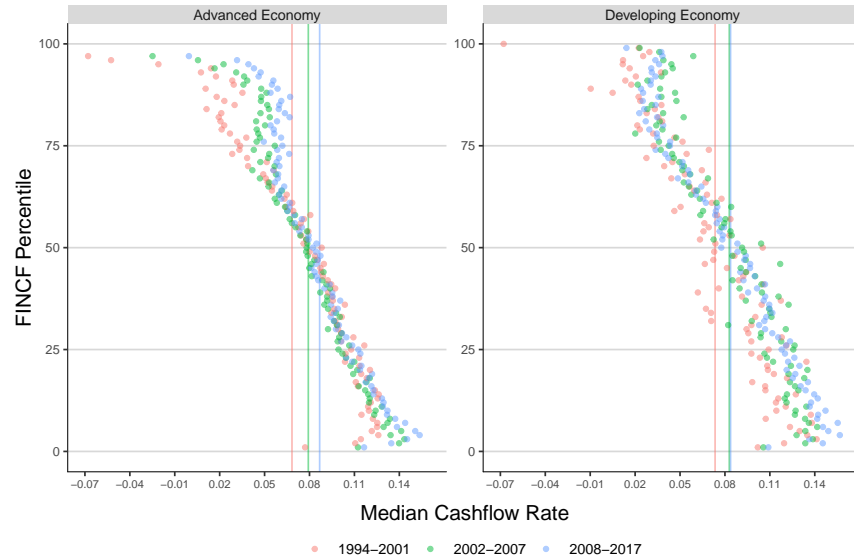
Note: In advanced economies: we see an increase over time in the proportion of total firms that are large net external releasers of funds (percentiles 50 \rightarrow 0) and a decline in the proportion of firms that are net external borrowers (percentiles 50 \rightarrow 100). For developing economy firms we see a narrowing of the borrowing distribution overall. This is reflected in a shifting out - an increase - in the proportion of mid-tier FINCF firms (percentiles 75 \rightarrow 10), but a shift in (decrease in the proportion of) the largest net releasers of funds (percentiles 10 \rightarrow 0) and the largest net borrowers of funds (percentiles 10 \rightarrow 0).

Figure 15. Investment Rates by FINCF Bin



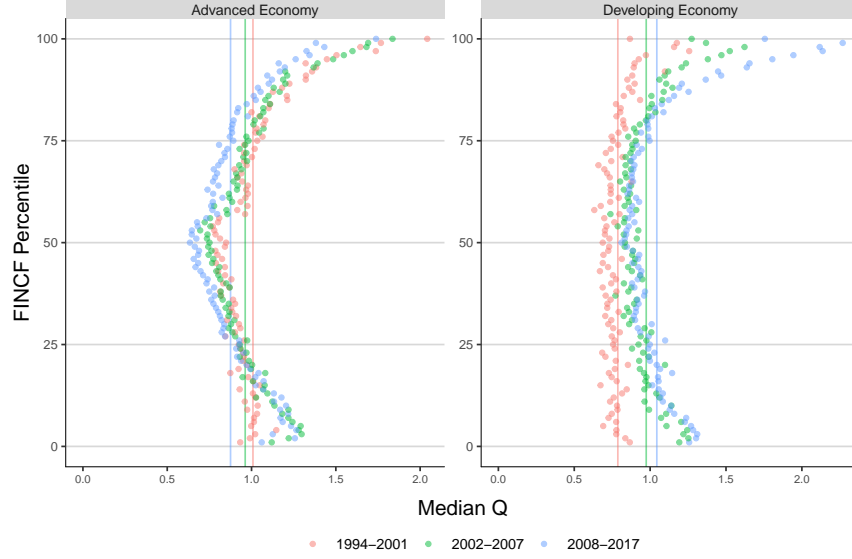
Note: Investment rates tend to be higher for firms that borrow more and release less (percentiles 50 \rightarrow 100). This is particularly pronounced for developing economy firms (who may be more financially constrained). These differences flatten for developed economy firms. Investment rates have shifted inwards for all percentiles across all 3 time periods for advanced economy firms, from 6.5% to 4.5% to 4%. They have declined the most for firms that are larger net borrowers (percentiles 100 \rightarrow 50)) of external funds. (This is unlikely to reflect a growing financial constraint since these firms have also had the largest increase in cash flow rates over time - see following graph.) The opposite investment trend has been the case for developing economy firms, where the median investment rate has declined only post-2007 crisis, first increasing from 6.2% to 6.6%, before declining to 6%. Some values cut off for top and bottom percentiles to reduce graph sale. Bin widths calculated on pooled, unstratified sample.

Figure 16. Cash flow rates by FINCF Bin



Note: Median cash flow rates are highest for firms that release the most (around 14%), declining constantly and lowest for firms that borrow the most (negative for around the top 5 percentiles - values not able to fit on graph's scale). Margins tend to be higher for larger more mature firms so this will be reflected in the above too. Median cash flow rates have shifted upward over time, especially for advanced economy firms that tend to borrow the most (percentiles 75 \rightarrow 100) and for firms that release the most (top 5 percentiles). They have increased from 6.8% to 7.9% to 8.6% post-crisis for advanced economy firms. While for developing economy firms it has increased from 7.3% to 8.29% to 8.38%. That this has gone hand-in-hand for advanced economy firms with lower Q values points to the role of higher profit margins in higher cash flow rates. Some values cut off for top and bottom percentiles to reduce graph sale.

Figure 17. Investment Opportunities by FINCF Bin



Note: *FINCF* seems to capture a stable relationship across countries and firms in firms' underlying investment opportunities. The relationship between *Q* and *FINCF* percentile is non-linear. Firms that borrow the most or release the most have more investment opportunities than firms in the middle. (The main difference between these two types of firms is their degree of cash flow: borrowers have negative or low cash flow rates while releasers have high positive cash flow rates.) Median *Q* values have in general shifted inwards for advanced economy firms over time (from above 1 to below 1). While the opposite is true for developing economy firms, who have seen the median *Q* value shift up over time, from below 1 to above 1. Interestingly *Q* values have increased for the top 15 or so *FINCF* releasing percentiles in advanced economies. Some values cut off for top and bottom percentiles to reduce graph sale.

F Hierarchical Model Priors

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

$$\alpha^0 \sim N(0, 1.5), \quad (26)$$

$$\beta^0 \sim N(0, 0.5), \quad (27)$$

$$\log(Q)^0 \sim N(0.3, 0.3), \quad (28)$$

$$\nu \sim \text{Gamma}(2, 0.1), \quad (29)$$

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

$$\mathbf{R} \sim \text{LKJcorr}(5). \quad (31)$$

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 of $\Sigma^{\beta} = \mathbf{L}\mathbf{L}^{\mathbf{T}}$, where \mathbf{L} is a lower-triangular matrix.

Inverting Σ^β is numerically unstable and inefficient. This is the preferred modern Bayesian prior (Stan Development Team 2019b). 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.

G Hierarchical Model ‘Fit’

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

Year	R2	Est.Error	Q2.5	Q97.5	Country	R2	Est.Error	Q2.5	Q97.5
1994	0.11	0.00	0.10	0.12	AUS	0.43	0.00	0.42	0.43
1995	0.12	0.00	0.11	0.13	BMU	0.37	0.00	0.36	0.37
1996	0.12	0.00	0.11	0.13	CAN	0.47	0.00	0.47	0.48
1997	0.11	0.00	0.11	0.12	CHE	0.46	0.00	0.45	0.47
1998	0.11	0.00	0.10	0.12	CHN	0.39	0.00	0.38	0.39
1999	0.20	0.00	0.19	0.21	CYM	0.35	0.00	0.35	0.36
2000	0.18	0.00	0.17	0.19	DEU	0.44	0.00	0.44	0.45
2001	0.15	0.00	0.15	0.16	FRA	0.45	0.00	0.44	0.46
2002	0.15	0.00	0.15	0.16	GBR	0.46	0.00	0.45	0.46
2003	0.17	0.00	0.16	0.18	IDN	0.41	0.00	0.41	0.42
2004	0.16	0.00	0.15	0.17	IND	0.41	0.00	0.41	0.41
2005	0.15	0.00	0.14	0.15	ISR	0.48	0.01	0.47	0.49
2006	0.15	0.00	0.15	0.16	ITA	0.42	0.00	0.41	0.42
2007	0.17	0.00	0.16	0.18	JPN	0.00	0.00	0.00	0.00
2008	0.16	0.00	0.15	0.17	KOR	0.35	0.00	0.35	0.36
2009	0.19	0.00	0.18	0.19	MYS	0.38	0.00	0.38	0.38
2010	0.23	0.00	0.22	0.24	NLD	0.49	0.00	0.49	0.50
2011	0.23	0.00	0.22	0.23	PAK	0.35	0.00	0.35	0.36
2012	0.19	0.00	0.18	0.20	SGP	0.38	0.00	0.37	0.38
2013	0.17	0.00	0.16	0.18	SWE	0.48	0.00	0.47	0.49
2014	0.14	0.00	0.13	0.15	THA	0.41	0.00	0.40	0.42
2015	0.13	0.00	0.12	0.13	TWN	0.39	0.00	0.38	0.39
2016	0.13	0.00	0.12	0.14	U.S.	0.00	0.00	0.00	0.00
2017	0.14	0.00	0.14	0.15	ZAF	0.46	0.00	0.46	0.47

Note: The mean (R^2), Standard deviation (Est.Error) and the 95% credible interval are reported for each Bayes R^2 . Note that R^2 for the year-level prediction is substantially lower than for the country-level

H 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 effect and the random effects of observed Q. To our knowledge this is the first time a Bayesian error correction model has been applied to a cash flow-Q regression. This has the impact of increasing the size of the Q coefficients - both the

fixed effects and the random effects - in non-linear proportion to the assumed degree of attenuation.⁶⁵ Interestingly, cash flow coefficients do not change in the measurement error model, even though one might expect this to be the case if cash flow and q are correlated as is generally assumed.

A Bayesian approach to measurement error is computationally demanding but has several advantages. Firstly, the Bayesian estimator provides a posterior distribution that takes into account uncertainty due to estimating other parameters. In contrast, the classical estimator corrected for attenuation would require bootstrapping or some type of asymptotic approximation to account for this uncertainty. Secondly, Bayesian inference averages over plausible values of mismeasured Q in light of the data, rather than imputing a single best-guess and then proceeding as if this guess is correct. Uncertainty in estimation of Q is then propagated forward. Thirdly, we can integrate the measurement error with a more complex model: largely keeping our random effects structure, an autoregressive error structure, a student-t likelihood, and other deviations from a simplistic panel regression model (Carroll et al. 2006).

A Bayesian approach to measurement error is formulated by treating the true quantities being measured as missing data (Clayton 1992; Gelman, Carlin, et al. 2013; Richardson and Gilks 1993). This requires a model of how the measurements are derived from the true values. In what follows Q is an imperfectly measured surrogate for the unobservable \tilde{Q} measured without error. We assume classical measurement error such that $Q = \tilde{Q} + \epsilon$. This implies greater variability in the observed surrogate, Q , than true \tilde{Q} . The error is assumed to be homoskedastic with zero mean and identity covariance matrix independent of true covariates, $\text{Var}(\epsilon|\tilde{Q}) = \tau_{me}\mathbf{I}$, where τ_{me} governs the variance of the measurement error ϵ . This implies that surrogate Q is an unbiased version of the true covariate \tilde{Q} , hence $E(Q) = E(\tilde{Q})$.

We assume a normal model for our error term as well as multiplicative measurement error such that $Q = \tilde{Q}\epsilon$ (Iturria et al. 1999), which with our log-log *investment-q* model turns into an additive error model $\log(Q) = \log(\tilde{Q}) + \epsilon$.

This leads to the following measurement error model on the fixed effect and random effect Q values:⁶⁶

$$Q_{ij} \sim \mathcal{N}(\tilde{Q}_{ij}, \tau_{me}), \quad (32)$$

$$Q_i \sim \mathcal{N}(\tilde{Q}_i, \tau_{me}). \quad (33)$$

For computational purposes we apply this measurement error correction model to a single random-

⁶⁵This is called a ‘sensitivity analysis’.

⁶⁶We treat τ as data rather than as a parameter. As a result no prior is put on τ . This increases computation speed and facilitates identifiability for the measurement error model, but comes at the cost of reducing the uncertainty in our parameter estimates. We do, however, put a prior on \tilde{Q} . The uncertainty of the measurement error model will partially be reflected in the estimate of the population parameters of perfectly measured \tilde{Q} , and in particular in σ_Q

effects level version of our hierarchical model, with only random effects being estimated for the 576 country-year groups.⁶⁷

Adding in a measurement error model for Q introduces the additional unknown \tilde{q} , with a joint posterior $h(y, q, \tilde{q}, z)$. Given our mixed effect multilevel model this integral cannot be solved directly as it is too complex. But Bayesian MCMC methods can be used to sample from the distribution.

We make the following assumption when factoring the above joint distribution: Y and Q^* are conditionally independent given true covariates $\{Z, X\}$. This is the *nondifferential measurement error* assumption: $h(y|q, \tilde{q}, z) = h(y|q, z)$. With this assumption we have:

$$h(y, q, \tilde{q}, z) = h(y|q, \tilde{q}, z) h(q, \tilde{q}, z) \quad (34)$$

$$= h(y|q, z) h(q, \tilde{q}, z) \quad (35)$$

$$= h(y|q, z) h(\tilde{q}|q, z) h(q, z). \quad (36)$$

We do not adopt a so-called ‘structural modelling’ common to likelihood based measurement error methods, which involves elaborating the joint density of the true covariates into an ‘exposure model’ of the type $h(q, z) = h(q|z)h(z)$. We have no specific interest in the distribution of the precisely measured covariates $h(z)$, and so dispense with a model for them. Instead we treat the joint distribution of the true covariates as fixed (so-called ‘functional method’) - thereby basing inferences conditioning on $\{Q, Z\}$. This has the benefit of being robust to distributional assumptions regarding $h(q)$ and computationally more efficient, but at the cost of not modelling any explicit dependence between q and z . As a result, we model the conditional distribution of the outcome variable given the observed covariate variables as (Grace 2016):

$$f(y|\tilde{q}, z; \theta) \propto \int f(y|q, z; \beta) f(q|\tilde{q}, z) d\eta(q). \quad (37)$$

This leads to the following model:

$$y_i \sim t_\nu \left(X_{i-Q}^0 \beta^0 + X_{i-Q} \beta_{j[i]} + \tilde{Q}_i^0 \beta^0 + \tilde{Q}_i \beta_{j[i]}, \sigma_y^2, \nu_y \right) \quad \text{for } i = 1, \dots, n, \quad (38)$$

$$Q_{ij} \sim \mathcal{N} \left(\tilde{Q}_{ij}, \tau_{me} \right), \quad (39)$$

$$Q_i \sim \mathcal{N} \left(\tilde{Q}_i, \tau_{me} \right), \quad (40)$$

$$\beta_j \sim \text{MVN} (M_\beta, \Sigma_\beta) \quad \text{for } j = 1, \dots, J. \quad (41)$$

We provide no additional (‘exposure’) model for true Q - which does not contribute very much

⁶⁷The findings do not change materially when applied to the full model.

to inferences generally except under certain circumstances (Fuller 1987; Gustafson 2003, pp. 85-92). Another way of thinking about the measurement error model for Q is as an additional random effects model, where measured Q is drawn from a population with a true population mean and variance estimated from the data. Additional priors are required for this model, including tightening existing ones to help with model convergence. This does not materially impact the posterior inference though.⁶⁸ Our priors are as follows:

$$\alpha \sim \text{Normal}(0, 1.5), \quad (42)$$

$$\beta_{\alpha}^0 \sim \text{Normal}(0, 0.5) \quad (43)$$

$$\beta_{\tilde{Q}}^0 \sim \text{Normal}(\tau, 0.3), \quad (44)$$

$$\mu_{\alpha}, \mu_{\beta^{CF}} \sim \text{Normal}(0, 1), \quad (45)$$

$$\mu_{\tilde{Q}} \sim \text{Normal}(0.5, 0.5), \quad (46)$$

$$\nu \sim \text{Gamma}(2, 0.1), \quad (47)$$

$$\sigma_{\alpha}, \sigma_{cf}, \sigma_y \sim \text{HalfCauchy}(0, 2), \quad (48)$$

$$\sigma_{\tilde{Q}} \sim \text{HalfCauchy}(0, 1), \quad (49)$$

$$\mathbf{R} \sim \text{LKJcorr}(5). \quad (50)$$

Our prior for \tilde{Q} is centred at τ . As the value of τ increases or decreases our prior increases in turn. This is done purely for computational purposes. The results are summarised in Table 10 below for $\tau = \{0.1, 0.3, 0.5\}$. This is called a sensitivity analysis.⁶⁹

As expected, the size of the Q coefficient increases as the value of τ increases, with strongly non-linear effects. The variability in the random effects of Q increase strongly too, from $[0.05, 0.06]$ to $[0.25, 0.29]$, indicating that the lack of variability in Q across time and country might be an artifact of measurement error. The explanatory power of our group predictors are largely unchanged under measurement error. Country and country-year variation is weakened mildly while year variation is improved.

⁶⁸Note again that τ_{me} is treated as data rather than a random variable and so does not have its own prior.

⁶⁹In the simplifying case with no additional perfectly measured variables z and assuming normality of x and the measurement error model, and unbiased, nondifferential, changes in τ translate directly to changes in bias in our estimated coefficient, where $\tau = SD(Q|\tilde{Q})/SD(Q)$ can be interpreted as the magnitude of the measurement error relative to the variability in X , and the relative bias is defined as $(Q - \tilde{Q})/\tilde{Q}$ or 1 minus the attenuation factor $Q/\tilde{Q} = 1/(1 + \tau^2)$. $\tau = 0.1$ can be viewed in this simplified setting as yielding 10% imprecision in the measurement of X . This, however, translates into a negligible attenuation factor - leading to a relative bias in the coefficient of only 1%. While τ of 0.5 corresponds to a roughly 20% bias in the coefficient (Gustafson, 2003). The bias, however, also depends on $\rho = COR(\tilde{Q}, z)$, worsening as ρ increases, such that bias with a single additional regressor we have: $Q/\tilde{Q} = 1 / \left(1 + \frac{\tau^2}{1 + \rho^2} \right)$. For the Z univariate case see Gustafson, equation 2.7 where $Q/\tilde{Q} = 1/(1 + \tau^2 K)$ where K is a complex expression including a correlation matrix for Z and a vector of correlation between X and Z .

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

	Variable	Non ME		ME .1		ME .3		ME .5	
		Est.	Est.Err.	Est.	Est.Err.	Est.	Est.Err.	Est.	Est.Err.
Fixed Effect	Intercept	-2.94	0.07	-2.95	0.04	-2.96	0.04	-2.98	0.04
	External-Borrower	0.22	0.00	0.22	0.00	0.22	0.00	0.21	0.00
	cash flow Rate	0.20	0.03	0.19	0.01	0.19	0.01	0.18	0.01
	Log(Q)	0.21	0.01	0.20	0.00	0.25	0.01	0.42	0.01
	External-Borrower:cash flow	-0.08	0.01	-0.09	0.01	-0.09	0.01	-0.09	0.01
Country-Year Random Effect	SD(Intercept _j)	0.29	0.01	0.29	0.01	0.28	0.01	0.28	0.01
	SD(cash flow _j)	0.20	0.01	0.20	0.01	0.20	0.01	0.20	0.01
	SD(logQ _j)	0.05	0.00	0.06	0.00	0.10	0.01	0.27	0.01
Student-t Parameters	σ	0.56	0.00	0.56	0.00	0.55	0.00	0.51	0.00
	ν	4.85	0.05	4.85	0.05	4.76	0.05	4.32	0.05

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 effect and random effect Q coefficients increase, but non-linearly.

Of interest is that the cash flow coefficients - both fixed and random - are largely unchanged. This may be due to no strong correlation between the two, 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 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 but not unambiguously. Using Bayesian R^2 we see an improvement for all 3 sub-time periods looked at in the model fit when a measurement error model is added. This improvement declines strongly across time though. Model fit is around 16% higher for the period 1994-2001, 10% higher for 2002-2007, and around 8% for the period 2008-2017. The 95 percentile range for the R^2 across the sub-periods is [0.43, 0.46] for the ME model and [0.37, 0.43] for the non-ME model. Though caution should be used when employing the Bayesian R^2 for the comparison of models if different x predictors are used (Gelman, Goodrich, et al. 2019).⁷⁰

⁷⁰However, this does not use in the calculation the correctly estimated measurement error variables in the posterior predictions - of which we have $N + 2$ - and so is likely to be unreliable.

We next estimate the WAIC (Vehtari et al. 2015) on a 30% sub-sample of 85,105 datapoints using the saved measurement error variables. We find that the differences between the measurement error model and the reduced baseline model cannot be clearly identified: the standard error of the difference in the ELPD (The expected log pointwise predictive density for a new dataset) is too large. This ambiguity is probably because - as noted above - Bayesian model fit is a predictive measure, and prediction is not necessarily greatly impacted by measurement error. Optimality of the predictor in classical - and Bayesian - regression does not require zero covariance between x_t and $(\epsilon_{y[t]}, \epsilon_{me[t]})$. If observed (x, y) is distributed as a bivariate normal random vector then using x_t in a regression for y_t will provide for an optimal predictor of y_{t+1} , even if x_t is measured with error (Fuller 1987). Under measurement error, the variance of the prediction error does not depend on the true but unknown value of x , but only on the variance of the measurement error $var(\epsilon_{me[t]})$ (and $var(\epsilon_{y[t]})$). This is because predictions are averaged for a fixed observed value of x , not a fixed true value, and are averaged over y , the observed data. The same is true for Bayesian prediction.