Corporate Secular Stagnation: Empirical Evidence on the Advanced Economy Investment Slowdown*

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Abstract

We find strong evidence of a secular slowdown in investment rates using a large panel of advanced economy firms between 1994-2017 across 18 jurisdictions. A decline in the underlying impetus to invest begins around 1997 and falls precipitously till the present, with only a mild recovery between 2003-2008. We test competing explanations for the investment slowdown using a Bayesian 'mixed effects' model, with time-varying and country-varying coefficients which allows us to highlight considerable variation in financing constraints and responsiveness to investment opportunities among firms in different countries. The slope of the investment demand curve (approximated by time-varying Q regressions coefficients) remains roughly constant, indicating that 'financialization' and growing monopoly power have not dulled how responsive firms are to investment opportunities. Contrary to precautionary savings arguments, advanced economy firms are not meaningfully financially constrained. Moreover, firms and the corporate sector as a whole are increasingly net external 'releasers' of funds to shareholders, creditors, and bondholders. The secular slowdown in investment closely tracks changes in this net external money demand.

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1 Introduction

Have the investment rates of non-financial publicly listed firms declined over time across advanced economies?[1] And if so, why? There is a consensus that investment rates have declined in the U.S. since around 2000 (IMF 2015; Gutiérrez and Philippon 2017b; Alexander and Eberly 2018).[2] For other advanced economies the evidence is more discordant (Caselli et al. 2003; Lewis et al. 2014; Döttling et al. 2017).[3] We, however, show the investment slowdown is clearly a feature across most advanced economies (Figure 2 and Tables A.4).

Our investigation into the causes of investment slowdown has three areas of focus. This helps clarify the nature of the slowdown as a cross-country and 'secular' occurrence, largely unrelated to financing constraints, or to firms responding less to good investment opportunities. Instead, the close association of slowing investment rates to firms' releasing funds externally to shareholders, creditors, and bondholders would imply causal factors at work which are creating an absence of good investment opportunities relative to abundant internal financing.

Our first area of focus is estimating firms' underlying impetus to invest, other things being held equal. Although there is no consensus as to the causes of the investment slowdown, given its long-standing nature causes are generally sought in variables showing secular trends. These would show up as a persistent decline in firms' baseline investment rates, we propose. Fernald et al. (2017) finds that falling total factor productivity growth and labour force participation have resulted in a slowing of capital formation in the U.S., with cyclical shortfalls in government spending after the 2008 global financial crisis (GFC) making it worse. Slowing productivity growth may go back to the 1960s, with a variety of possible precipitating factors (Aschauer et al. 1989; Summers 2015; R. J. Gordon 2017).

Our second area of focus is assessing how responsive firms are to good investment opportunities. Following the Q theory model of investment (Summers et al. 1981; Hayashi 1982), marginal Q summarises the firm's investment opportunities (which we approximate using the book-to-market value of the firm's assets). Two theories in particular imply that firms may be becoming less responsive to investment opportunities, thereby diminishing investment rates overall: 'financialization' and declining competition. These arguments often stem from the correct observation that investment has declined even as prof-

[1] We define the 'corporate sector' as non-financial publicly listed companies. See Appendix A for further details on our sample.

[2] Investment rate = capx/capital stock, where capital stock= intangible assets + inventories + gross property plant and equipment.

[3] Country categorisation is first based on average GDP per capita (nominal) US$ between 1994-2017 of $20,000 or more. The country then needs a minimum of 1,400 observations to be included.

itability has increased (Appendix A.4).[4] Jones and Philippon (2016) argue that declining competition in goods markets explains low investment despite both high profitability and high investment opportunities (Q values). Similarly, Gutiérrez and Philippon (2017b) find that industries with more concentration and more common ownership invest less. The impact of declining competition is often emphasised within the U.S. context (Gutiérrez and Philippon 2017a; McAdam et al. 2019; Philippon 2019) and said to be aided by the growing importance of intangible assets (Gutiérrez and Philippon 2017b; Alexander and Eberly 2018; Crouzet and Eberly 2019). One issue with these arguments is that the investment slowdown is a cross-country and cross-industry feature, even though declining competition may not be (Döttling et al. 2017; Freund and Sidhu 2017; Bajgar et al. 2019).[5] And although Q values have been high (especially in the U.S.), they have in fact been stagnating or declining for firms (Appendix A.4).

Another increasingly common argument is that 'financialization' of capital markets is making firms pursue short-term financial goals over long-term profitable investments (Davis 2018; Lazonick et al. 2014). One channel through which both 'financialization' and declining competition potentially work to depress investment rates is through making firms less responsive to 'investment opportunities' (Gutiérrez and Philippon 2018).[6]

Our third and final area of focus is assessing if firms are financially constrained (Schiantarelli et al. 1995; Rajan and Zingales 1998; J. Lewellen and K. Lewellen 2016; Gutiérrez and Philippon 2017b). Following Fazzari et al. (1988), if external and internal finance are not perfect substitutes (owing to external finance being more costly), then firms' demand for investment may not rely exclusively on marginal Q, but also on the availability of internal funds for investment financing. If the firm's investment is sensitive to changes in its internal funds – proxied by present cash flow – then that firm, and those like it, are said to be 'financially constrained' in their investment decision by the availability of internally generated profits. In response, such models allow for coefficients to vary according to if the firm is likely to face a financing constraint.[7] With the growing importance of intangible assets (not easily collateralizable), it is now argued that firms face mounting external financing constraints. In response, firms are said to be increasing their precautionary savings and cash stocks (Han and Qiu 2007; Falato

[4]This is the opposite of what might be 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 2011 [1930]). Higher permanent profitability should entail higher Q values, and in turn higher temporary investment (Romer 1996). This relationship is absent from the data.

[5]Davydoff et al. (2013) for a more granular analysis on EU listed companies ownership.

[6]This is by no means the only channel through which these theories can depress investment rates.

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

et al. 2013; Chen et al. 2017; Armenter and Hnatkovska 2017; Caggese and Perez-Orive 2017; Faulkender et al. 2019). We use a simple firm-level cash flow-Q investment model to test the above three categories of explanations for declining investment rates. This paper's contribution is threefold:

Firstly, we provide cross-country and time-varying evidence on the existence and nature of the secular slowdown in investment rates. This evidence is considerably more robust than previous studies we believe (Hsiao and Tahmiscioglu 1997; Rajan and Zingales 1998; Gruber and Kamin 2015; Gutiérrez and Philippon 2017b). We use a large panel of firms from 18 countries, which includes the U.S. and 17 other advanced economies between 1994-2017, based on a merging of Compustat Global and Compustat North America databases. This unbalanced panel contains 199,155 observations on 25,136 unique firms. The cross-country panel helps ensure that our results are not by chance or due to measurement error of intangibles (Farhi and Gourio 2018).[8] While uncertainty in coefficients is reflected in posterior Bayesian credible intervals (Gelman and Loken 2013; Wasserstein, Lazar, et al. 2016).

Secondly, our Bayesian mixed fixed and random effects estimation approach (also known as a 'hierarchical model') allows us to extend the key insight of finance constrained models, which is that fixing coefficients to be equal across firms who face fundamentally different external conditions can lead to seriously misleading and even nonsensical inferences (Barcikowski 1981; Pesaran and Smith 1995; Pepper 2002; Wooldridge 2003; Hsiao 2014). We advance this approach by allowing for firms' coefficients to vary by country and year in order to assess if the constraints which they face are changing over time and between countries (Gelman and Hill 2006; Gelman, Carlin, et al. 2013).[9] Existing investment slowdown studies do not account for the time-varying movement of coefficients in general, making the interpretation of their time-varying dummy variables unclear (Gutiérrez and Philippon 2017b). While some assume that coefficients are constant over time for their estimator's reliability (Erickson and Whited 2000).

Thirdly, our hierarchical model allows us to use macroeconomic predictors to explore why there has been a secular slowdown in the estimated underlying impetus to invest among advanced economy firms over time. We focus on two predictors. We use the corporate sector's cash piles as a proxy for factors such as firms' attempting to deleverage from a 'debt-overhang' or balance sheet recession post-2000 dot-com bubble and 2008 GFC (Myers 1977; Koo 2011); or increasing (binding) external financial market imperfections. We also use as a predictor the corporate sector's net releasing of funds externally, to

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

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

shareholders, creditors, and bondholders. The latter implies that financing constraints are unlikely to be pivotal, and instead a dearth of good investment opportunities may be the binding constraint.

The findings from our hierarchical model's cash flow-Q regressions are consistent with a 'secular stagnation' in advanced economy firms' investment rates:

i *Investment rates decline for most advanced economy firms since circa 2000/2001.* This has gone hand in hand with increasing profitability and stagnant investment opportunities (Q values). The generalized nature of the slowdown, as Autor et al. (2020) also note, run counter to country-specific explanations of the investment slowdown, including declining competition in the U.S. only.[10]

ii *A decline in the underlying impetus to invest begins several years earlier, however, around 1997 and falls precipitously till the present, with only a mild recovery between 2003-2008.* This shows that firms are investing less at their baseline, after accounting for changing responsiveness to investment opportunities and changing financial constraints.

iii *There is considerable variation in the degree of financing constraints and how responsive firms are to investment opportunities in different countries.* U.S. firms, for example, face no financing constraints as a whole, while French firms may face moderate ones. Similarly, firms in the Netherlands are roughly twice as responsive to investment opportunities as Italian firms.

iv *We find no evidence of firms becoming less responsive to investment opportunities, as certain versions of 'financialization' and market power theories might imply.* Firms are not investing less, therefore, because they are passing up profitable investment opportunities. They instead show a strong cylicality in their responsiveness to investment opportunities, increasing more recently perhaps as easing monetary conditions meets slowing aggregate demand growth. Even though advanced economy firms are as responsive to investment opportunities as they have ever been (if not more), this is considerably less responsive than developing economy firms (Strauss and Yang 2020).

v *In general, advanced economy firms are not financially constrained.* No meaningful constraint in accessing external finance is apparent, in line with the findings of Gutiérrez and Philippon (2017b). In addition, we show that global financing constraints have been declining since the 2008 GFC – even if they remain structurally higher than before. The absence of a meaningful financing constraint is consistent with the increasing profitability of advanced economy firms (Appendix

[10]See also Bajgar et al. (2019) and Freund and Sidhu (2017) for evidence on market concentration in Europe and globally, respectively.

A.4), and the corporate sector releasing funds in net externally, rather than borrowing funds in net.

vi *At the macroeconomic level, the secular investment slowdown over time is strongly related to the corporate sector's net releasing of funds externally to shareholders, creditors, and bondholders. Retention of funds internally is a much less relevant indicator.* This runs counter to the view that the investment slowdown is related largely to the retention of funds to repair over-leveraged balance sheets (Myers 1977; Koo 2011) or as a result of growing external financing constraints. The net releasing of unneeded funds externally is a far greater signifier of a secular stagnation in investment rates than the retention of funds (cf. Summers 2015).

Our 'macroeconomic' findings overlap with Gruber and Kamin (2015), who note that large gross distributions by firms to shareholders are inconsistent with a view of the investment slowdown as being driven by firms' strengthening their balance sheets. Our 'microeconomic' findings advance the work of Gutiérrez and Philippon (2017b), who also find a clear absence of financing constraints on investment. However, our work goes beyond theirs in terms of method and in questioning their emphasis on market concentration. Our econometric estimation is a relation to the Bayesian hierarchical model used by Meager (2019) for a meta-analysis. While Hsiao and Tahmiscioglu (1997) use a classical version of a mixed fixed and random coefficients model in estimating 'cashflow-Q' regressions.

The next section details our investment model. Section 3 discusses our data and plots empirical trends in investment rates. Section 4 describes our Bayesian hierarchical model — a 'mixed effects' model with 'shrinkage' estimation. Section 5 reports the model's key findings. Subsection 5.3 extends the model by including macroeconomic predictors to explore secular stagnation in the estimated impetus to invest over time. Section 6 concludes. Online Appendices contains our dataset and variables (Appendix A), FINCF variable (Appendix D), model priors and fit (Appendix B), and a measurement error model (Appendix C).

2 Cash Flow-Q Investment Model

Following the formulation in J. Lewellen and K. Lewellen (2016), the value of the firm, V_t, is maximized with respect to the control variable investment I_t, given the capital stock K_t in period t, and subject to the net present value of its profits, $\Pi(K_t, s_t)$, less adjustment costs related to investment, $C(I_t, K_t, \lambda_t)$, and less investment expenditure, I_t. Profits are a function of a state variable s_t, reflecting past investment

decisions and the firm's capital stock K_t. Quadratic investment adjustment costs are related to an exogenous parameter stochastic parameter λ_t. The recursive Hamiltonian is:

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

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

$$1 + C_I(I_t, K_t, \lambda_t) = bE_t[V_k(K_{t+1}, s_{t+1}, \lambda_{t+1})] \tag{2}$$

$$= q_t. \tag{3}$$

This states that the firm invests until 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. This makes q 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. We proxy this by the book to market value of the firm.[11]

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

$$\mathrm{C}_t = \frac{1}{2}a\left(\frac{I_t}{K_t} - \lambda_t\right)^2 K_t, \tag{4}$$

$$\mathrm{C}_I = a\left(\frac{I_t}{K_t} - \lambda_t\right), \tag{5}$$

$$\frac{I_t}{K_t} = -\frac{1}{a} + \frac{1}{a}q_t + \lambda_t, \tag{6}$$

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

To get present cash flow in the regression, assume that external finance is more costly than internal finance for the firm. 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

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

(EF) cost:

$$\mathrm{EF}_t = \frac{1}{2} b \left(\frac{I_t}{K_t} - \frac{\Pi_t}{K_t} \right)^2 K_t, \tag{7}$$

$$\mathrm{EF}_I = b \left(\frac{I_t}{K_t} - \frac{\Pi_t}{K_t} \right). \tag{8}$$

The cost of external financing is assumed to be $b \geq 0$. Plugging the above into the Equation 1 leads to the following final regression specification which we estimate:

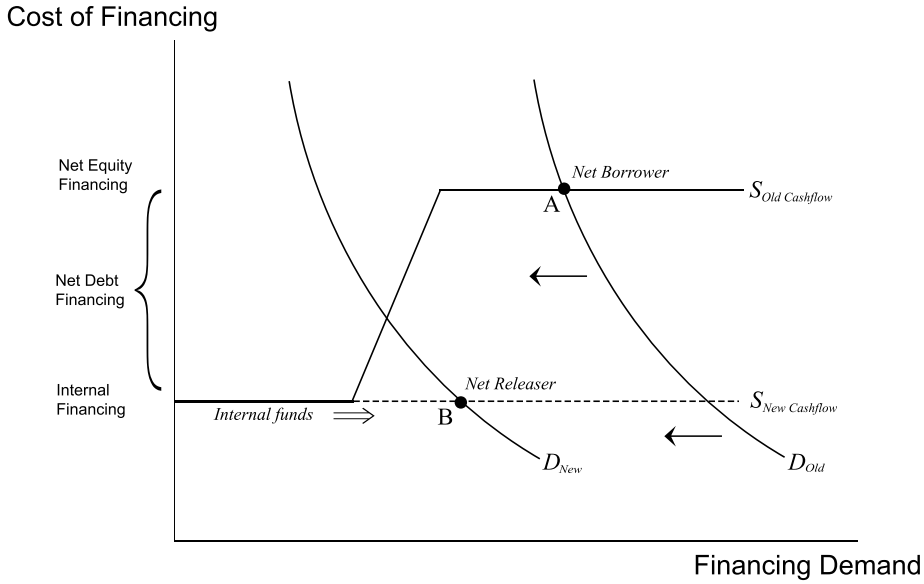
$$\frac{I_t}{K_t} = -\frac{1}{a+b} + \frac{1}{a+b} q_t + \frac{b}{a+b} \left(\frac{\Pi_t}{K_t} \right) + \frac{a}{a+b} \lambda_t. \tag{9}$$

Equation 9 is firms' investment demand schedule, with a slope of q in investment-Q space. The q coefficient declines in proportion to $1/(a+b)$, such that an increase in a, the time-invariant adjustment cost parameter, and/or in b, the cost of external financing, should reduce the coefficient size of q. Cash flow, Π_t/K_t, enters directly into the regression equation; but we can see it will be of little significance if the cost of external finance is $b \to 0$, or if the firm has no need to access external finance — i.e. $I_t/K_t < \Pi_t/K_t$.

The cash flow-Q model is often used to show that firms are finance *constrained*, reflected in a positive cash flow coefficient, arising from costly external finance *when* the firm's internal funds are insufficient to cover all appropriate investment needs. But as we show an increasing proportion of firms in our data appear, *a priori*, to be financially *unconstrained* such that $I_t/K_t < \Pi_t/K_t$. The net demand for external financing among these firms is zero or negative due to their relatively weak investment opportunities (declining marginal Q values) falling short of increasingly abundant internal financing.

This is depicted in Figure 1, where the intercept of the investment demand curve declines (shifting to the left) due to exogenous secular stagnation factors (from D_{Old} to D_{New}), while firms' horizontal supply of internal financing extends outwards to the right as cash flow rates increase ($S_{New\,Cashflow}$), eliminating the need for the firm to take on net external debt or equity financing at all. As a result, most firms move from equilibrium point A (financially constrained) to equilibrium point B (financially unconstrained). Position B, on the new (weaker) investment demand schedule, is identified by a negligible cash flow rate coefficient from equation 9. But even some firms on the old (stronger) investment demand schedule may still have a negligible cash flow rate coefficient since they too now have access to sufficient internal financing (where $S_{New\,Cashflow}$ meets D_{Old}). As such we might expect negligible cash flow coefficients for all advanced economies firms, no matter how we split our sample *a priori*, if they are all facing this same new abundant supply of internal financing ($S_{New\,Cashflow}$). The main distinguishing

Figure 1. Corporate Secular Stagnation Makes Firms Financially Unconstrained



Note: *Based on Fazzari et al. (1988). The supply of firms' internal funds increases (double lined arrow) as cash flow rates increase, extending the horizontal dotted line out, intersecting with a weaker investment demand schedule, at Point B. 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.*

feature today for cash rich advanced economies firms is, therefore, which investment demand curve they are on. The new investment demand curve is marked by a much weaker impetus to investment at its baseline, even as firms' responsiveness to marginal investment opportunities remains the same – as reflected by the slope of the investment demand function in investment-Q space, or q in equation 9, remaining constant. Empirically, we identify these different demand curves using firms' net external financing position, Compustat's FINCF variable, which highlights the shift from firms' being positive net external borrowers of funds to negative net external releasers of funds. FINCF, therefore, shifts up or down the intercept of the investment demand function in investment-Q space, with net external releasers of financing having a much lower intercept. This emphasis stands in contrast to what is expected in Fazzari et al. (1988), whereby the degree of external financial market imperfections (coefficient b in equation 9) potentially impacts what demand curve the firm lies on, since firms lack sufficient funds internally to cover all available investment opportunities (though we do not rule out this possibility in our estimation).

3 Data

Below we describe the main features of our data. Further details are contained in our Appendix.

3.1 Data Construction

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. Our final sample consists of 199,155 observations on 25,136 unique firms across 18 countries for the 24 years between 1994-2017. This includes all the major advanced economies plus the Cayman Islands and Bermuda, where an increasing number of advanced economy firms are legally incorporated. Only countries with at least 1,400 observations are included in the sample in order to ensure a sufficient credible interval for our results. U.S. incorporated firms comprise 41% of our sample and Japanese firms 22%. We use an unbalanced panel since a balanced design, with no gaps in observations for a firm between any two years, would exclude most of the largest firms in existence today and create considerable survivor bias.

Variable definitions differ somewhat by country, based on differing accounting standards. The U.S. follows GAAP accounting standards, while the rest of the world largely follows IFRS.[12] Values are in nominal US$, converted into a common currency using the Compustat Global currency file. Our variables are reported gross, before amortization and depreciation, but after tax, unless stated otherwise.[13]

Capital stock is our denominator for cash flow rate, investment rate, and capital-output ratio. Capital stock is defined gross as PPEGT + INTAN + INVT, which is the sum of gross property, plant, and equipment, intangible assets, and inventories. Our findings are not dependant on the inclusion of intangibles (or inventory) in our capital stock measure.[14] Cash flow is defined as Compustat's OANCF from the cash flow statement.[15]

We use the firm's market-to-book ratio (MTB), calculated as the market value of the firm's *total assets* (equity plus debt) over the book value of these assets, as our proxy for Tobin's Q. MTB likely captures average rather than margin Q, with the two only equal under restrictive assumptions (Hayashi 1982). Use of MTB based on total assets, as opposed to MTB based only on the firm's *capital stock*, is motivated by the desire to ensure Q remains strictly positive, since removing negative values would

[12]Firms listed in Japan are not required to report using IFRS standards. GAAP and IFRS contain important differences in depreciation rules, implied by how development costs are capitalized, and also differences in how impairment losses and component depreciation are treated.

[13]Gross investment rates are recommended, rather than 'net', for cross-country comparisons (Lequiller and Blades 2014).

[14]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). Various methods to adjust intangible assets (which is measured net) to a gross measure can be undertaken but have not materially impacted other studies results it seems (Peters and Taylor 2017). Peters and Taylor (ibid.) notes the positive impact on Q regression coefficient values from the inclusion of intangible assets in its calculation of capital stock.

[15]The variable is measured gross, after taxes and interest payments, and after making adjustments for changes in working capital and other non-operating income.

likely bias our dataset.[16] The explanatory power of MTB is also roughly the same as other Q measures (Erickson and Whited 2006, 2012). Lastly, 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.[17] This is exactly what we see (Appendix, Table 3).

3.2 Initial Data Description

Figure 2 shows the distribution of firm-level investment rates by country group, shifting to the left over time. The dotted black line is for 2001 around which time the shift is often most visible (see also Figure 10). Median investment rates decline for the U.S. from 6.9% between 1999-2001, to 4.5% between 2002-2007, and to 4.1% between 2008-2017. Japan shows less of a clear secular decline since their major investment slowdown predates our sample. Their equivalent shifts in median investment rates are: 3.6%, 3.7%, and 3.3%; and for the other 16 advanced economies (including two tax havens) it is 7.2%, 5.2%, and 4.5% (see Appendix A.4).

The timing of the shift in investment rates is in line with existing research on U.S. investment rates (IMF 2015; Gutiérrez and Philippon 2017b; Alexander and Eberly 2018), and helps to clarify the fact that Europe is undergoing a similar secular and long-running decline in investment rates (Caselli et al. 2003; Lewis et al. 2014; Döttling et al. 2017). The general tendency of declining investment rates among advanced economies has been accompanied by profitability (cash flow rates) increasing markedly across most of our sample,[18] and investment opportunities (Q values) stagnating or declining, particularly at the top of the distribution (Appendix A.4).

These generalised trends casts doubt on country-specific explanations for the investment slowdown.[19]

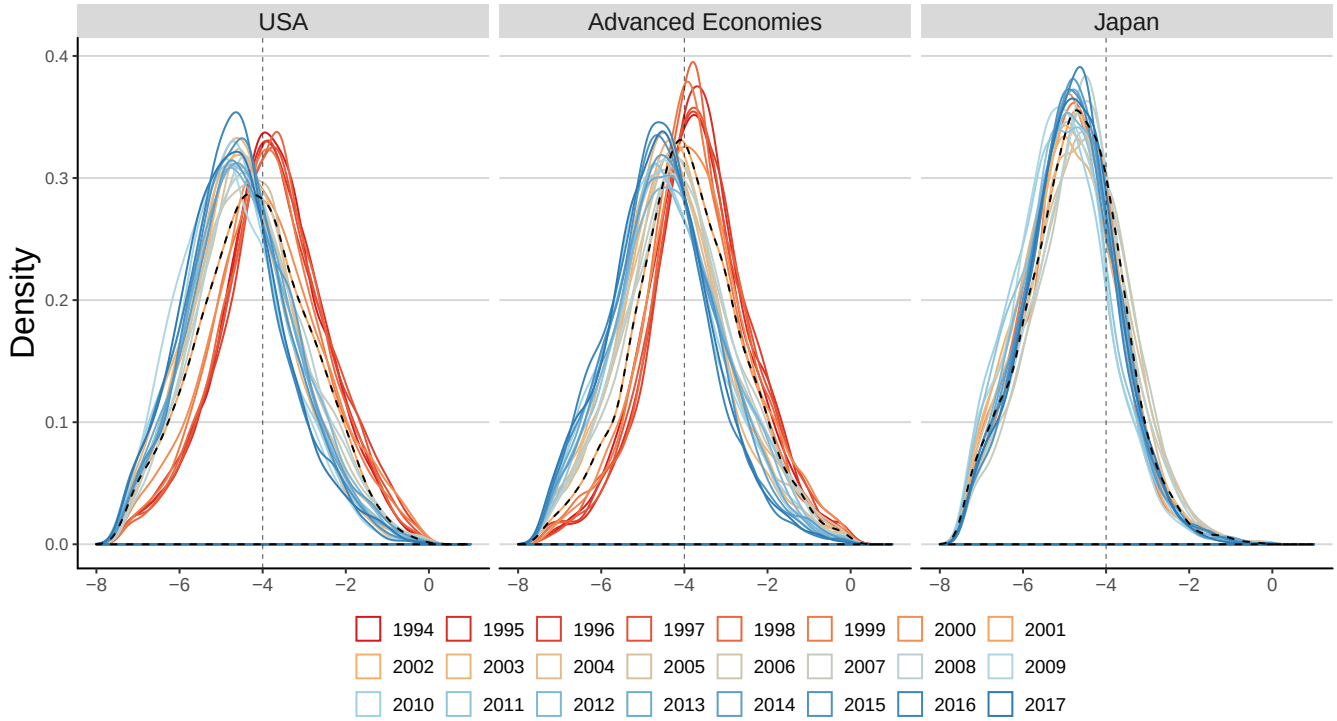
[16] In theory, certain countries and types of firms are more likely to have negative MTB capital stock values (Damodaran 2013). In our particular sample, Japan contains around 17% negative Q values (as a book to market value of the firm's capital stock). A large portion of negative values also arise in 2008 with the financial crisis.

[17] The ability to revalue assets to fair value under IFRS might create significant differences in the carrying value of assets as compared with U.S. GAAP (E. Gordon et al. 2008; PWC 2018). IFRS permits revaluation, while U.S. GAAP generally utilizes historical cost and prohibits revaluations of fixed capital. As a result a downward bias will be expected in book values (the denominator for our Q proxy values) of U.S. GAAP firms. Compounding this is the fact that under U.S. 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, only due to accounting reasons.

[18] Though less so for firms at the top of the distribution within the U.S.

[19] Such explanations include the outsourcing of labour-intensive production, low labour force participation rates, inflexible labour markets, and reduced government spending (Baldwin and Teulings 2014; Fernald et al. 2017; Alexander and Eberly 2018). While 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 the UK, and requires further investigation (OECD 2019a,b). See also: Ollivaud et al. (2016).

Figure 2. Distribution of Firm-Level Investment Rates by Advanced Economy, 1994-2017



Note: *Kernel density approximation of log2() firm gross investment rates for the U.S., Japan, and 16 other advanced economies, shifting in notably around 2000/1. Black-orange dashed line is for the year 2001. Sample shown for Japan here begins in 1999 due to insufficient sample size prior to this. The trend is less clear for Japan, though some decline is evident after the 2008 GFC. Dotted lined at log2(-4) is an investment rate of 6.2%. Removing intangibles from our definition of capital stock does not materially change these conclusions (Appendix, Figure 9.*

3.3 FINCF Variable: Demand Proxy

We use the FINCF variable as a dummy variable to estimate which investment demand curve the firm is on, following Figure 1. Later we transform FINCF in to a macroeconomic predictor to see how well it tracks the slowdown in the estimated impetus to invest among firms. FINCF, defined as 'net external financing activities', is one of the three primary cash flow statement balances. It records almost all cash inflows and outflows between the firm and its external creditors, bondholders, and shareholders,[20] and includes:[21]

- *Long-term debt issuance and principal repayments*[22]
- *Current debt issuance and principal repayments*
- *Cash dividends paid*
- *Purchase of common and preferred stock*

[20] It excludes dividend received. Dividend received is instead located in cash flow for North America firms.

[21] The definition below is for firms following U.S. GAAP accounting standards. Compustast Global firms instead tend to use IFRS accounting standards and so, define FINCF somewhat differently. IFRS permits interest and dividends received and paid, as well as bank overdrafts, to be classified as 'operating activities', 'investing activities', or under FINCF as 'financing activities'.

[22] FINCF 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.

- *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. As a 'net' variable it has the benefit of being largely invariant to transactions which only ultimately impact the firm's capital structure and which might mistakenly be taken as a sign of financial distress, or financial slack.[23] We propose that FINCF increasingly reflects the fact that firms have a surplus of available financing relative to diminishing investment opportunities (Appendix D.1). That such a relative surplus would manifest itself through firms releasing more funds, in net, is not true by definition since, following the cash flow statement identity, a surplus of funds relative to capital expenditure can instead be met through the firm increasing its net purchase of financial assets, or through a net increase in the retention of funds.[24]

4 Bayesian Hierarchical Model

In this section we detail the Bayesian hierarchical model which we use to estimate our cash flow-Q investment regressions.

4.1 Mixed Effects Investment Regressions

Following the investment function from eq. 9, the firm's investment rate is determined by Q and *cash flow* rates ('cash flow' for short). Our hierarchical regression model focuses on the intercept of the investment demand function, the slope of Q, and the slope of *cash flow*, by allowing for these (firm-level) coefficients to vary in their impact by year and country – in addition to be 'fixed'. This makes them our 3 'random effects'. Denoting $y_{c,t[i]}$ as the investment rate of firm i in country c and time t, our baseline regression which we estimate is:

$$y_{c,t[i]} = (\alpha + \alpha_{c,t}) + \left(\beta^q + \beta^q_{c,t}\right)\mathrm{Q}_{c,t[i]} + \left(\beta^{cf} + \beta^{cf}_{c,t}\right)\mathrm{CF}_{c,t[i]} + \gamma'^{eb}\mathrm{EB} + \mathrm{Controls} + \epsilon. \tag{10}$$

$\mathrm{Q}_{c,t[i]}$ and $\mathrm{CF}_{c,t[i]}$ are the Q and *cash flow* variables for firm i in country c and time t used to

[23] For example, if a firm repurchases \$20 million dollars of its shares while at the same time issuing corporate debt worth \$20 million, then we propose that all that has happened is that the firm's capital structure has become more leveraged.

[24] Or even a net *increase* in external financing.

estimate the 'fixed effects' population coefficients α, β^q, and β^{cf}. These 'fixed' coefficients represent the global 'average' intercept coefficient and global slope coefficients for Q and *cash flow* for our total pooled sample. Their 'random' effect counterparts are the coefficients $\alpha_{c,t}$, $\beta^q_{c,t}$, and $\beta^{cf}_{c,t}$ and have subscripts showing that they vary by country and year. They represent the intercept coefficient, and the slope coefficients of Q and *cash flow* for each of the 18 countries c and 24 years t. We also have a country:year group j (with $18 * 24 = 432$ clusters), which serves largely as a control group and so is not included in the above equation. The random effects coefficients estimate how each variable's impact, for a country or year, deviates from the coefficient's population average; such that $\beta^q_{c,t}$ shows how the impact of Q on firms' investment rates in country c, or year t, deviates from the average impact taken across all countries and years. γ'^{eb}EB is a categorical variable telling us if the firm is a net external lender or a net external borrower of funds. This helps us identify which demand curve the firm is on, following Figure 1. Controls consist of $\gamma'^{cor}\text{CoR} + \gamma'^{k}\text{K} + \gamma'^{sic}\text{SIC}$, where CoR, K, and SIC are the categorical control variables that represent the capital-output ratio, capital stock size (10 bins), and 1-digit NAICS industry code. ϵ is an error term which we specify in the Appendix (Section B.1), and which includes a more technical specification of our model as a whole. We include an AR(1) error process to account for the panel nature of our data.[25]

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

5 Results from Hierarchical Estimation of Cash Flow-Q Model

Using this model we test the following three hypotheses on the causes and nature of the investment slowdown:

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

5.1 Hypotheses

1. **Firms are investing less over time, other things being equal** (secularly declining *intercept* coefficients – $\alpha_{c,t} \downarrow$): The intercept of the investment demand curve is declining over time, reflecting a decline in the underlying impetus to invest, all else being held equal.

2. **Absence of external financing constraints** (negligible *cash flow rate* coefficients for advanced economy firms – $\beta_c^{cf} \to 0$): Firms are not financially constrained, due either to external financing becoming less costly and/or relative demand for external financing decreasing (Gutiérrez and Philippon 2017b; Döttling et al. 2017). This is consistent with a decline in the demand for fixed capital investment. We expect external financing constraints to display a somewhat cyclical pattern over time in line with the liquidity cycle.

3. **Consistent responsiveness to investment opportunities** (constant or cyclical Q coefficients – $\beta_t^q \rightsquigarrow$): Firms are not becoming less responsive to investment opportunities over time (Gutiérrez and Philippon 2018) due to the 'financialization' of capital markets making firms pursue other objectives (Lazonick et al. 2014), or increasing monopoly power of firms (Gutiérrez and Philippon 2017a). We expect advanced economy firms to be less responsive to Q values compared to developing economy firms (Strauss and Yang 2020), as they are more mature firms.

5.2 Findings

Table 1 presents the summary output from our hierarchical regression model, with estimated posterior credible interval in brackets( ).[26] Predictors are mean-centred. Bayesian R^2 indicates the model 'fit' is moderate and lies between $[0.480, 0.483]$ for the 95% credible interval. [28] The results are stable to using different priors and likelihoods.[29] We do not report the estimated correlations between coefficients within each group-level regression, which our LKJ prior estimates, as their estimated error is large. Interpreting the results properly requires some care, since they differ by country and year, making

[26] We use the Hamiltonian Monte Carlo (HMC) simulation with a No U-Turn sampler (NUTS) to estimate our Bayesian hierarchical models. The HMC with NUTS is extremely effective for a high-dimensional problem such as ours where we estimate around 2,000 parameters simultaneously. For this purpose, we use R Stan, interfaced into using the **brms** package (Stan Development Team 2019a; Burkner 2017, 2018). It is worthwhile to note that we use a QR decomposition to reduce posterior correlations.[27] The QR decomposition improves our effective sample size, increases the precision of posterior estimates, and reduces computational time.

[28] The fit is marginally worse after the 2008 GFC, with a large portion of the predictive power coming from the auto-regressive error structure. Posterior predictions by year and country (see Appendix B) show good fits for most countries, but far less so for years, indicating that the model is not able to explain variation in investment rates across years, as well as across countries.

[29] Using 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%.

visualization of the results important. In general, we plot the 'total' estimated coefficient for a given country or year, which is the sum of the population fixed effect and the random effect particular to that country or year. The credible interval shown in the plots is the random effects credible interval only.

Table 1. Summary of Hierarchical Model Regression Results

	Variable	**Estimate**	**Est.Error**	**l-95% CI**	**u-95% CI**	$\hat{\mathbf{R}}$
Fixed Effects	α	-2.84	0.09	-3.01	-2.67	1.00
	β^q	0.18	0.01	0.15	0.21	1.00
	β^{cf}	0.06	0.04	-0.01	0.13	1.00
	γ^{eb}	0.15	0.00	0.15	0.16	1.00
Country Random Effects	σ_{α_c}	0.20	0.04	0.14	0.30	1.00
	$\sigma_{\beta_c^q}$	0.05	0.01	0.03	0.07	1.00
	$\sigma_{\beta_c^{cf}}$	0.10	0.03	0.06	0.16	1.00
Year Random Effects	σ_{α_t}	0.26	0.04	0.20	0.36	1.00
	$\sigma_{\beta_t^q}$	0.02	0.00	0.01	0.03	1.00
	$\sigma_{\beta_t^{cf}}$	0.10	0.02	0.07	0.14	1.00
Country:Year Random Effects	σ_{α_j}	0.07	0.00	0.07	0.08	1.00
	$\sigma_{\beta_j^q}$	0.02	0.00	0.02	0.03	1.00
	$\sigma_{\beta_j^{cf}}$	0.13	0.01	0.11	0.16	1.00
Student-t Parameters	σ	0.51	0.00	0.51	0.51	1.00
	ν	3.98	0.04	3.90	4.06	1.00

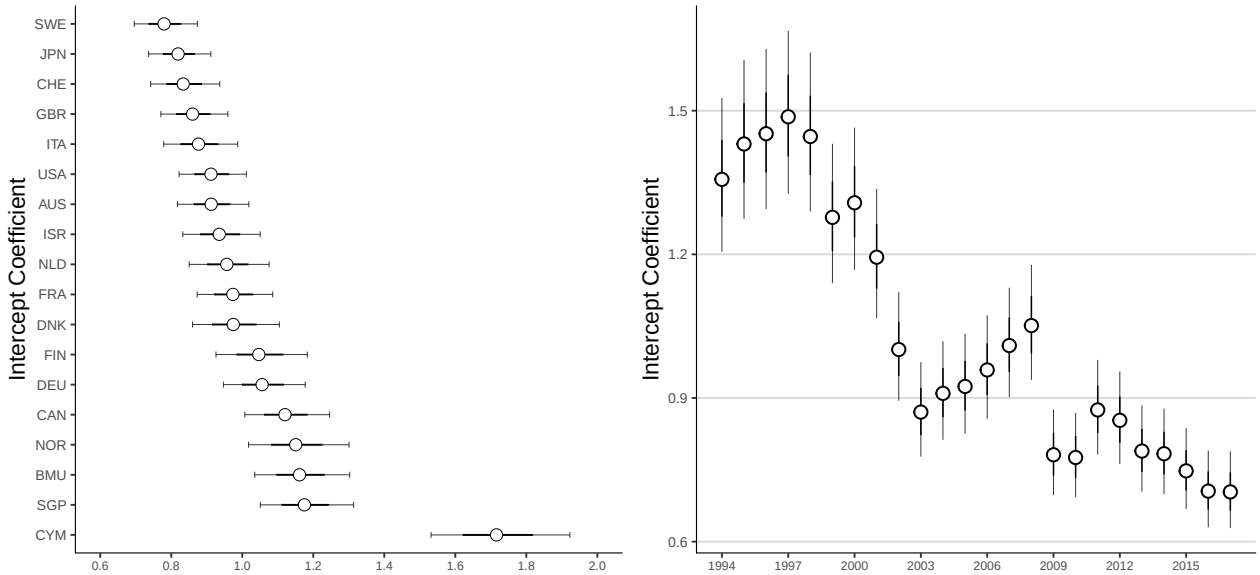
Note: *Results are for Regression Model 10. For each coefficient, the mean (estimate), standard deviation (Est.Err), 5% and 95% percentiles (l-95% CI and U-95% CI) of the posterior distribution is reported. The latter two percentile ranges represent the 90% credible/uncertainty interval.* $\hat{\mathbf{R}}$ *is the convergence metric and close to one when the MCMC chains are well-mixed and converged.*

Several findings stand out. Firstly, Figure 3 shows the estimated random effect intercept coefficients by country and year, reflecting the estimated underlying impetus to invest, all else being held equal. We see a clear secular decline in the intercept of the investment demand curve over time beginning around 1998. We do not include the fixed effect intercept in these particular figures since it 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 default category chosen for the FINCF dummy variable. The year-level intercept random effects show some resemblance to the dummy time effects in the U.S. firm-level regressions in Gutiérrez and Philippon (2017b).[30]

Firms from Canada ('CAN'), Norway ('NOR'), Bermuda ('BMU'), and Singapore ('SGP') have the highest estimated baseline investment rates (intercept coefficients), in ascending order. Cayman

[30]Figure 11 in the Appendix shows the time-evolution of the intercept coefficient for each country by combining all three random effect levels. We are able to do so because the estimated country:year random effect intercept coefficient has a small confidence interval.

Figure 3. Intercept Coefficients by Country and Year, 1994-2017



Note: *This shows the exponentiated random intercept coefficient, i.e the predicted mean/median investment rate. An exponentiated intercept coefficient of above (below) 1 shows an increasing (decreasing) mean-centred investment rate from the global average. The time trend of the intercept (right hand side graph) shows a clear secular downward trend marked by some cyclical fluctuations. The fixed effect intercept is not included. Bayesian 95% credible intervals display a high degree of certainty, especially for later years and for countries with larger sample sizes.*

Islands (a notable outlier) is number 1 though.[31] Compared to developing economy firms, these intercept coefficients tend to be lower (Strauss and Yang 2020).

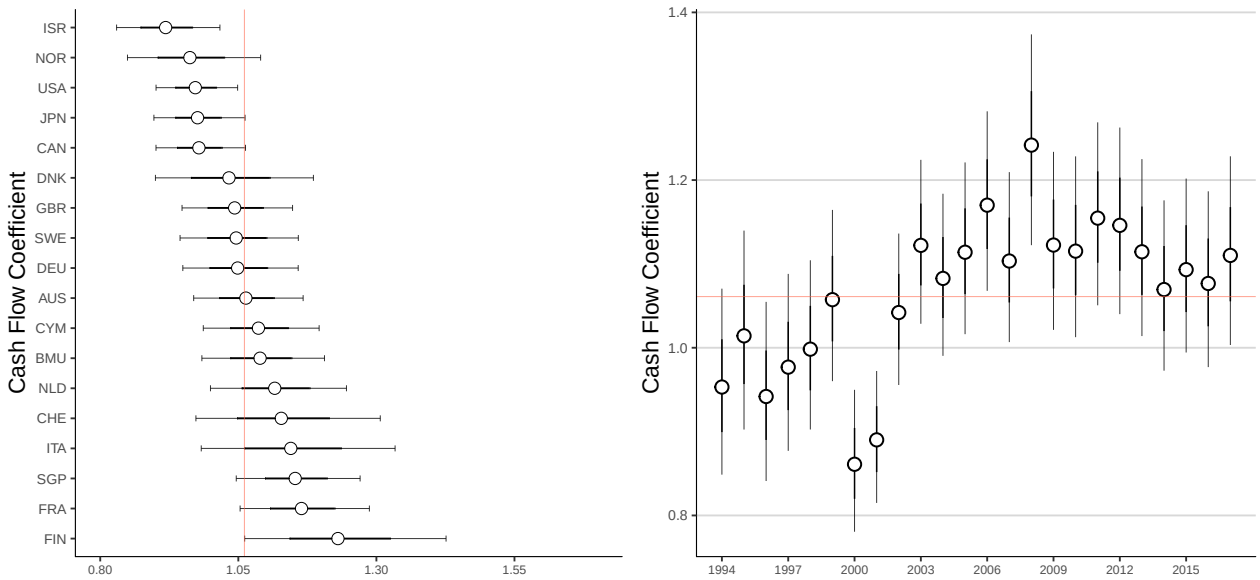
Following Table 1, our FINCF variable γ^{eb}, further helps us identify which demand curve the firm is on, shifting up or down the intercept of the demand curve. Firms that are net external 'releasers' of funds have a considerably lower predicted baseline investment rate, as indicated by the value of the fixed effects FINCF dummy variable 'External Borrower', which at $= 0.15$ notes (with very high posterior certainty) that net external 'borrowers' invest at a rate almost 15% higher than net external 'releasers' (all other variables being held at their mean-centred values). This is of concern since a growing majority of advanced economy firms are becoming net external releasers of funds.

Secondly, the results show that, as a whole, advanced economy firms are not financially constrained. This stands in contrast to developing economy firms who have somewhat higher cash flow coefficients (ibid.). Cash flow coefficients are negligible for advanced economy firms in most countries, and interestingly this does not change much when adjusting for measurement error in Q (Appendix C). Note that the total cash flow effect for any particular country or year is equal to the sum of the cash flow

[31] This also highlights the usefulness of our method which estimates the coefficients together and allows the intercept coefficients of countries with smaller sample sizes to learn from larger ones. This makes sense since many advanced economy firms are incorporated in BMU and CYM rather than the country where the majority of their production or sales occurs.

fixed effect β^{cf}, and the country- or year-specific random effects (β_c^{cf} or β_t^{cf}). We plot this total effect relative to the fixed effect (red line) in Figure 4. Since this regression relationship is log-level, we take the exponential of the cash flow coefficient to interpret it. An exponentiated coefficient of above 1 implies a percentage increase in the geometric mean of y for a one unit (i.e. 100%) increase in cash flow rates, while a coefficient of below one implies a percentage decrease. U.S. firms have an economically insignificant total cash flow coefficient of 0.91 (.037) (left hand side graph of Figure 4), implying that, when cash flow rates are increased by 100%, the geometric mean of the investment rate, which is 5.2% in our sample, in fact decreases marginally. Israel, Norway, Japan, and Canada have similarly negligible cash flow coefficients. Other advanced economy firms, including tax haven firms, have small cash flow coefficients ranging from $1 - 1.25$; implying that when their cash flow rates increase by 100%, their investment rates increase from 5.2% to between $5.2\% - 6.5\%$ (or an increase of 1.3 percentage points). The time-varying total cash flow coefficients, which effectively hold constant country- and country:year effects, shows a strong cyclical tendency (Figure 4, right hand side graph), increasing up until the 2008 global financial crisis and then decreasing subsequently, while remaining structurally higher. This increase prior to the GFC requires further investigation but still only leads to a cash flow coefficient of a bit above 1.2 at its peak.

Figure 4. Cash Flow Rate Coefficients by Country and Year, 1994-2017

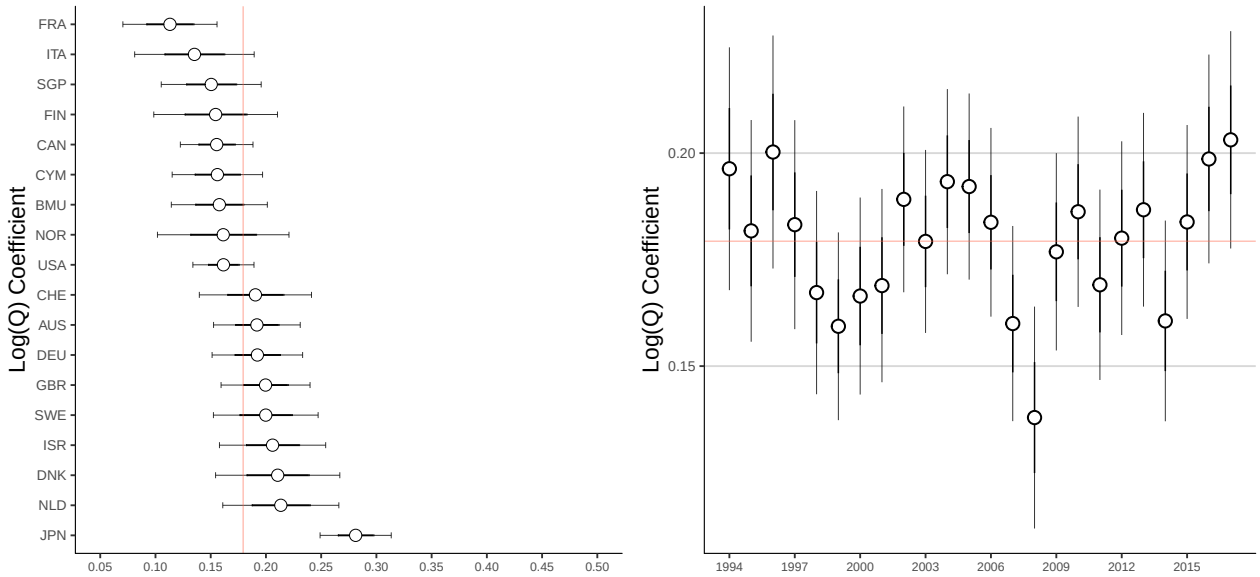


Note: *The 68% confidence interval is shown in grey and the 95% credible interval is shown in dark black. Exponentiated fixed effect coefficients are the red lines at* 1.06*. Total effect shown for country or year here is equal to the sum of fixed effect and random effect. These random effects are for net external releasers of finance (the least constrained group of firms).*

Thirdly, Figure 5 (right hand side graph) shows that firms are not becoming less responsive to

investment opportunities, due to growing market power or financialization of the investment decision (Lazonick et al. 2014; Gutiérrez and Philippon 2017a, 2018). We can see this since the time-varying Q coefficients – which reflect the slope of our investment demand curve – are not decreasing secularly, and instead show a cyclical movement with some uptick in 2016 and 2017. Note that this slope is estimating while effectively holding 'constant' country- and country:year effects.

Figure 5. Q Coefficients by Country and Year, 1994-2017



Note: *Q coefficient shows strong cyclical movements with no clear tendency to increase or decrease over time, except as the market value of their assets have recovered post-2008 crisis. The relatively high Q coefficients in 2016 and 2017 indicates that firms are not less responsive to investment opportunities, despite lower investment rates. The Q coefficient is interpreted as an elasticity. The 68% credible interval is shown in dark black, and the 95% confidence interval in grey.*

The lack of any visible trend in the time-varying Q coefficients demonstrates that firms are not becoming less responsive to investment opportunities, despite the increase in net external releasing of funds. Also of interest is that Q coefficients show much more variation by country than year (Table 1). Our Q coefficient estimates are not directly comparable to previous studies since we use log(Q), but they are larger (Erickson and Whited 2000, 2012; Peters and Taylor 2017; Andrei et al. 2019).[32] The 'fixed effect' value of log(Q) is = 0.18(0.01) (Table 1), such that a 100% increase in Q increases firms' investment rate by 18%, from an investment rate of say 5% to 5.9% (a 0.95 percentage point increase). These findings change somewhat when implementing measurement error correction in Q (Appendix C). Our Q coefficient estimate for U.S. firms, which previous studies focus on, at 0.16, is lower than for most other countries which we estimate (Figure 5, left hand side graph). The Scandinavian countries of

[32]The variable adds little to the predictive power (R^2) of our model.

Denmark and Sweden, along with Israel, the Netherlands, and Japan appear to the the most responsive to investment opportunities.

5.3 Secular Stagnation: Precautionary Savings or Declining Relative Investment Opportunities?

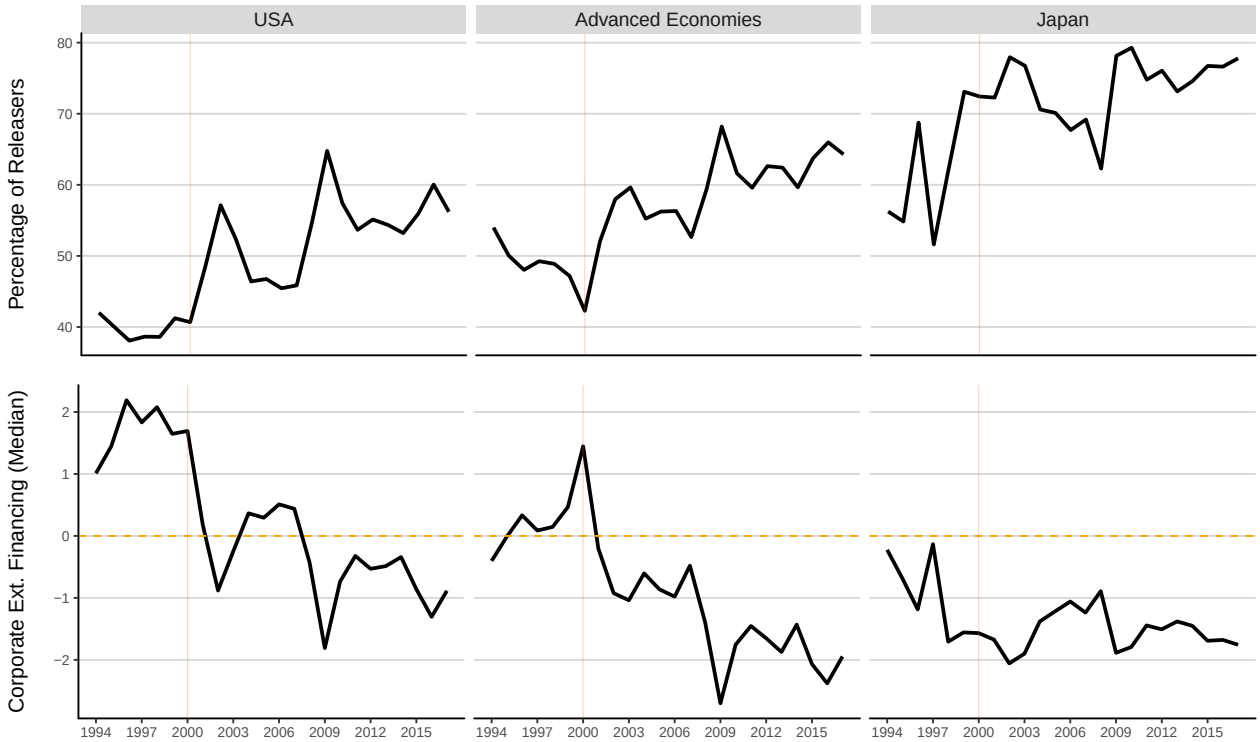
This subsection shows that the investment slowdown, at the macroeconomic level, does not appear to be driven by an increase in precautionary savings by the corporate sector as a whole; either as a response to the 2000 dot-com bubble or 2008 GFC (Gruber and Kamin 2015), or to guard against growing financial market imperfections more generally, including those arising from not easily collateralizable intangible assets (Han and Qiu 2007; Falato et al. 2013; Chen et al. 2017; Armenter and Hnatkovska 2017; Caggese and Perez-Orive 2017; Faulkender et al. 2019). Instead of the corporate sector intentionally accumulating net cash, the more prevalent tendency has been for it to release funds in considerable quantities through dividends, share repurchases, and entering into debt contracts (to commit to their future release). Note that there can be no presumption that this net releasing of funds is a poor use of capital, given that we have shown that firms are not financially constrained in general and remain responsive to investment opportunities. Instead, if saddled with too much 'free cash flow', committing to its release can be optimal to avoid managers taking up poor investment opportunities (Jensen 1986; Tirole 2010).

Plotting FINCF in Figure 6, we see a clear tendency for firms to become net external releasers of financing (top graph), and for the corporate sector as a whole to have a negative net external money financing demand (bottom graph). This reflects a shortage of investment opportunities relative to cash flow for the corporate sector as a whole. These findings are not driven by a decline in new listings on the U.S. public exchanges (Appendix D.3). In addition, although older firms do tend to release more net financing externally as cash flow rates become positive and stable and investment opportunities dry up relatively (Brealey et al. 2011), this increased tendency to release occurs across firms of all sizes and industries (cf. with Jensen 1989). The corporate tendency to release funds externally, in net, seems largely inconsistent with views of the investment slowdown as a response to a 'debt-overhang', balance sheet recession (Myers 1977; Koo 2011) or increasingly binding external financial market constraints.[33]

We use the two aggregate 'macro' predictors in Figure 6 to try and account for the secular slowdown

[33] It is often remarked that a gross measure of corporate distributions ignores share issuances and borrowing by firms (Fried and Wang 2018), and so does not provide the true extent to which firms are in fact engaging in precautionary savings or borrowing, or their true net external demand for financing. Our FINCF measure gets around this problem by combining the above inflows and outflows between the firm and its external creditors, shareholders, and debtors into one *net* measure of external money demand (defined in Subsection 3.3).

Figure 6. Corporate Secular Stagnation as Firms Become Net External 'Releasers' of Funds, 1994-2017



Note: *Japan, the classic example of secular stagnation, has since our series begins a negative net external corporate financing balance (bottom graphs) and the highest proportion of firms who are net external releasers of funds to shareholders, creditors, and bondholders (top graph). Advanced economies and the U.S. turn to a negative external financing balance around 2001. Red vertical line is for the year 2000. Net External corporate financing balance based on the median firm-level value for* FINCF *normalized by* sales*. 'Percentage of releasers' is proportion of total firms who have a negative* FINCF *value. Mean value shows a similar trend, but is less robust.*

in the impetus of firms to invest. This is achieved by using the previously estimated random effect intercept coefficients as our investment rate 'data' to now be predicted by our new macroeconomic group-level predictors from Figure 6. Formally, our hierarchical model now is simply extended to also predict the mean of the intercept coefficient distribution M_β^α for the year group t:[34]

$$\beta_t \sim \mathrm{MVN}(M_\beta^\alpha, \Sigma_{\beta_t}) \tag{11}$$

$$M_\beta^\alpha \sim \mathrm{N}(\gamma_0 + \gamma_1 \mu, \sigma_\alpha). \tag{12}$$

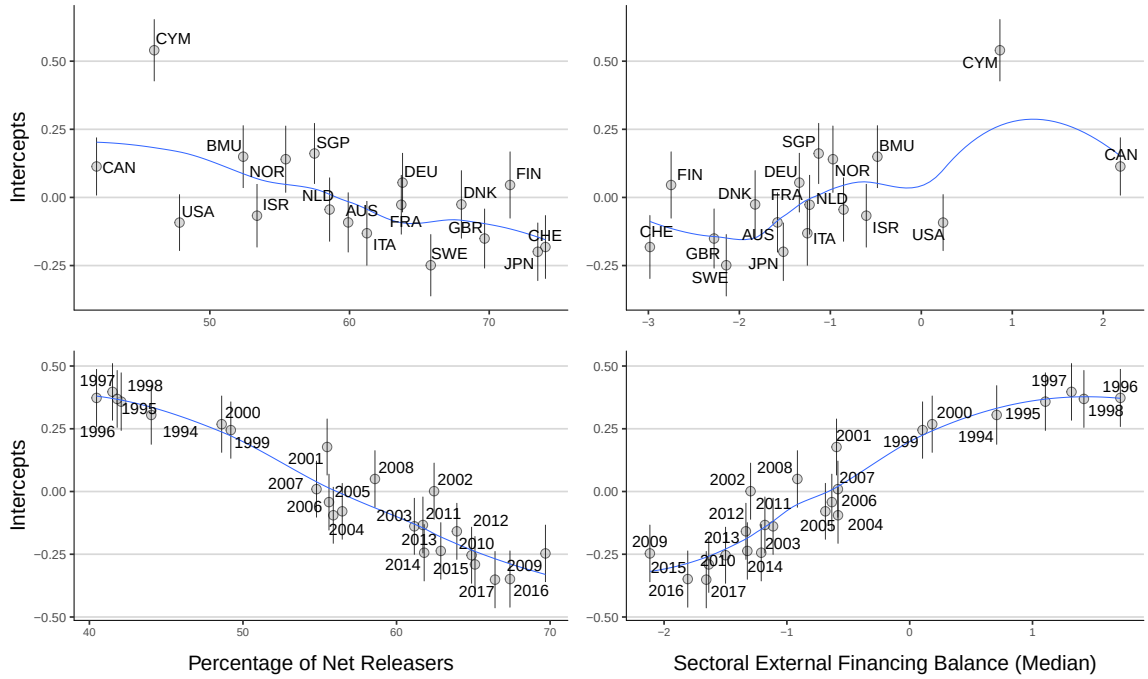
μ is estimated just for the year group t, using data points running from 1 to 24 – the number of

[34]In a classical regression the group-level coefficients (as data) and the group-level predictors would be collinear, and instead must be run as two separate regressions, as in Hsiao and Tahmiscioglu (1997). This problem is avoided in a Bayesian model because of the partial pooling of the random group-level coefficients toward the group-level linear model. 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). Group-level predictors are often interpreted as 'contextual effect' in the social sciences.

estimated intercept coefficients within the group.[35]

The fit of our model, using a simple local polynomial regression (LOESS), is intuitively illustrated in Figure 7. This shows the fitted regression (LOESS) line between the estimated intercept coefficients (the data) and the macroeconomic ('group-level') predictors. Although the regression we run only focuses on accounting for variation in the intercept across time, we can see that it would also be effective in accounting for variation between countries. Most countries and years follow the predicted line very well. The U.S. stands out as having a lower intercept coefficient given its relatively low proportion of 'net releasers' and positive median sectoral balance (telling us that the median firm is a net external borrower of funds).

Figure 7. Estimated Mean Group Investment Rate Plotted Against Macroeconomic Predictors



Note: *Fitted LOESS line between the intercept coefficients (the data) and the two group variable used to account for differences in investment rates over time - i.e. secular stagnation of our pooled advanced economy sample. Non-linear fit is evident for the external financing balance of the corporate sector in the bottom right hand graph, indicating that too much borrowing might be counterproductive. We exclude CYM from top right graph as it is an outlier.*

Table 2 summarizes the regression output of the hierarchical model with the above two macroeconomic predictors trying to explain the secular slowdown in the underlying impetus to invest. Our focus is on whether the macroeconomic predictors reduce the unexplained variation in the time-varying intercept coefficient, $\text{SD}(\text{Intercept}_t) = \sigma_{\alpha_t}$. In particular, the proportion of firms who become net external

[35] Is this too few observations to attain robust results? Not according to our output. The uncertainty is accounted for by the posterior distribution and, in turn, our reported confidence intervals. We run the same regression, but with only the j (country:year) model level. 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. In addition, our findings are robust when using different specifications of the FINCF variable.

releasers of funds in our pooled sample, in a given year, accounts for more than two-thirds (69%) of the variation in the time-varying intercept, reflected in the standard deviation of the coefficient declining from 0.23 to 0.08, while uncertainty in the estimates is reduced by around three quarters (Table 2). The median sectoral balance within a given – a more robust measure of the aggregate corporate sector's balance as a whole than the mean – accounts for a similar degree of variation in the secularly stagnating intercept coefficient. The coefficients values of the group predictors are as expected.

Table 2. Group Predictors Account for Variation in Time-Varying Intercepts

	No GP		**GP: Median SB**		**GP: Prop. NR**	
Variable	Est.	Est.Err	Est.	Est.Err	Est.	Est.Err
σ_{α_t}	0.26	0.04	0.09	0.02	0.08	0.01
SB_t			20.44	1.80		
NR_t					-0.25	0.2

Note: *FINCF is highly effective in reducing unexplained variation in the time-varying intercepts (top lines), such that it can account for the secular decline in the intercept of the investment function over time. Mean (Est.) and the standard deviation (Est.Err) of group predictor coefficients are reported in both lines.*

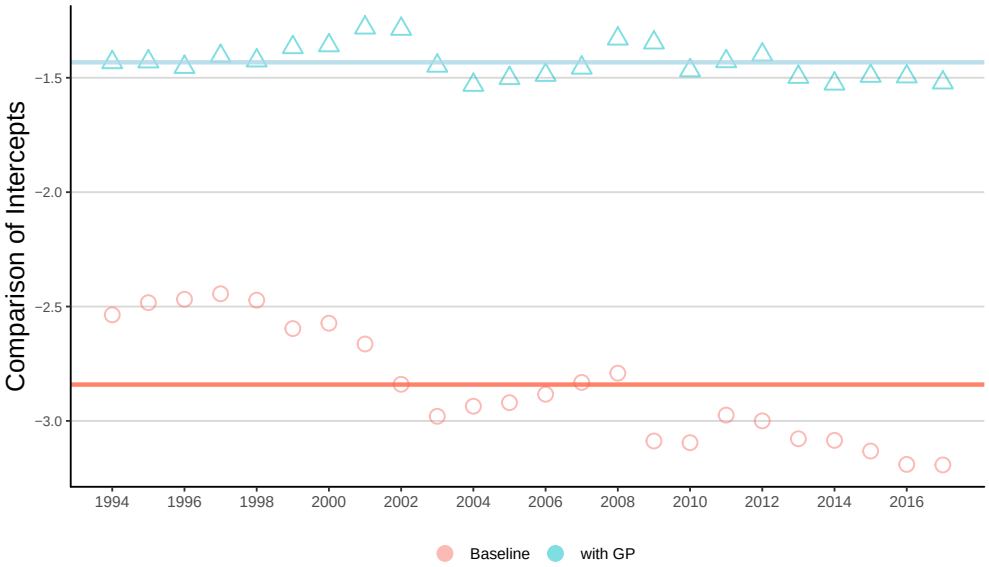
Finally, Figure 8 shows that with the inclusion of the 'proportion of net releasers' group predictor, the estimated time-varying investment intercepts are pulled toward the new and improved mean regression line estimate. Most of the secular variation in intercepts is now accounted for, with a cyclical tendency remaining.

The above result is not true by definition. For one, using the proportion of net lenders does not come from any identity. Moreover, following the cash flow statement identity there are two alternative outlets for an increase in cash flow relative to stagnant investment opportunities: either an increase in accumulation of cash balances (CHECH), or an increase in net accumulation of financial assets (IVNCF - CAPX).[36] Using the mean of these two cash flow statement group predictors offers much less explanatory power for the variation in the time-varying intercept coefficient. The median CHECH group predictor reduces the unexplained variation by 23% to SD(0.20) and the median adjusted IVNCF group predictor reduces the unexplained variation by 15% to SD(0.22). Neither improve the precision of the coefficients by much.[37] This is perhaps unsurprising since in theory, firms retain cash not just as a 'reflux' from high cashflow rates relative to low investment opportunities, but also to avoid financing constraints and

[36]For robustness we try two dozen other group-level predictors, including 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.

[37]Using the mean of these predictors leads to no variation being explained.

Figure 8. Predicted Investment Intercept With and Without Group Predictor



Note: *Plotting time-varying random effects plus fixed effects intercepts. 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, represented by the horizontal thick blue line. This group predictor helps account for much of the secular trend in the (non-exponentiated) intercept across time. A slight downward drift remains.*

to fund high rates of future growth (Almeida et al. 2004; Denis and McKeon 2018).[38]

[38]Statistically, the CHECH variable itself also lacks sufficient variation and is in general smaller in magnitude than FINCF.

6 Conclusion and Discussion

Using a Bayesian hierarchical model with time-varying and country-varying coefficients, and a large unbalanced panel of firms across 18 countries between 1994-2017, we provide robust evidence on the global investment slowdown. This helps clarify the nature of the slowdown as a cross-country and 'secular' occurrence, beginning around 1997 based on the estimated decline in the underlying impetus to invest among firms (approximated by the time-varying intercept of firms' investment demand function). We find that the slowdown in investment rates is largely unrelated to financing constraints, or to firms responding less to good investment opportunities. Financing constraints are weak or absent since cash flow coefficients are negligible for most advanced economies. Financing constraints decline since the 2008 GFC, even if remaining somewhat higher than during the pre-2002 period. Firms remain responsive to investment opportunities since time-varying Q coefficients – the slope of the investment demand curve – show only a cyclical tendency, and in fact increase more recently. The latter increase probably highlights a scurrying for good investment opportunities amidst slowing global growth yet easy financing conditions. The constant shape of the investment demand curve over time means that declining effective competition or increasing 'financialization' of firms' behaviour have not had any noticeable impact on how responsive firms have been to investment opportunities (Lazonick et al. 2014; Philippon 2019). The above findings are consistent with the fact that: (i) absolute profitability of firms has increased across most of the distribution over time; (ii) Q values have stagnated or declined; and (iii) advanced economy corporate sectors are choosing to release their net financing externally in a materially significant manner.

At the macroeconomic level we show that there is a close association between the secular slowdown in estimated baseline investment rates (time-varying intercept coefficients) and firms' releasing funds externally to shareholders, creditors, and bondholders. This would imply causal factors at work which are creating an absence of good investment opportunities relative to abundant internal financing. This runs counter to the view that the investment slowdown is related largely to the retention of funds internally post-dot-com bubble or post-2008 GFC, to deleverage and repair balance sheets (Koo 2011)

The proper conduct of monetary policy in such an environment is an important question, since non-financial corporate money demand becomes more intimately tied to factors other than their fixed capital investment demand. Asset allocation models which estimate the different returns to firms' various outlets for its funds may be helpful in exploring this more fully (Foley and Sidrauski 1970). 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; Ollivaud et al. 2016; Fatás and Summers 2018; Rachel and Summers 2019; Skott 2019). Our paper makes no attempt to explore this linkage, perhaps via changing pre- and post-tax rates of return on fixed capital and financial capital over time, for example. But future research might profit from doing so. Lastly, a growing body of evidence shows that increasing inequality may constrain demand growth (Cynamon and Fazzari 2015; Dabla-Norris et al. 2015; Saez and Zucman 2016; Auclert and Rognlie 2018).[39] However, further research is required to link this type of data to changing firm-level investment rate patterns (Summers 2015; Alvaredo et al. 2018).

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Appendices

For Online Publication.

A Data and Variable Description

Compustat North America follows GAAP accounting standards while the rest of the world largely follows IFRS to varying extents and in different forms. Familiarity with these accounting models can help one understand differences and similarities in variables (for example PWC 2018). Our variables are reported gross, i.e. before amortization and depreciation, but after tax, unless stated otherwise. All dates and plots are for the fiscal year rather than the calendar year.

We first look at and clean the combined sample of Compustat North America and Compustat Global before selecting our advanced economy sub-sample.

A.1 Data Cleaning

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

The first round of data processing limits the dataset to firms with positive values for all three of the following: gross capital stock, capital expenditure, and revenue. We exclude firms working in gardens, zoos, museums, non profit organisations, and utilities, but keep gas production and distribution. We remove financial companies but keep real estate and certain other related companies. This amounts to removing SIC codes 491, 84, 86, 493-499, 60-64, and 66-69. *The second round of data processing:* We trim (i.e. remove) the bottom 0.5% of observations by capital stock. This sets a minimum capital stock value of 0.299 and is done because capital stock serves as the denominator for the key quantities of interest. We trim the bottom 0.5% of observations by capital expenditure. Next we keep only observations with values greater than or equal to zero for key variables RECT, CHE, XINT, and DLC and strictly greater than zero for LCT. We then trim the top 0.1% of the quick ratio variable (defined as ACT/LCT), and we trim the top and bottom 0.5% of cash flow rate observations. *The third round of data processing:* revolves around FINCF. We remove the top and bottom 0.1% of FINCF/cash flow ratios, and the top and bottom 0.5% of FINCF/sales ratios. We test to see if firm's derived cash flow identity of CHECH

= IVNCF + OANCF + FINCF + EXRE is within an arbitrary range of accuracy of the given change in its cash flow (CHECH). We remove 1,093 observations.[40] *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.

A.2 Variable Definitions and Discussion

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

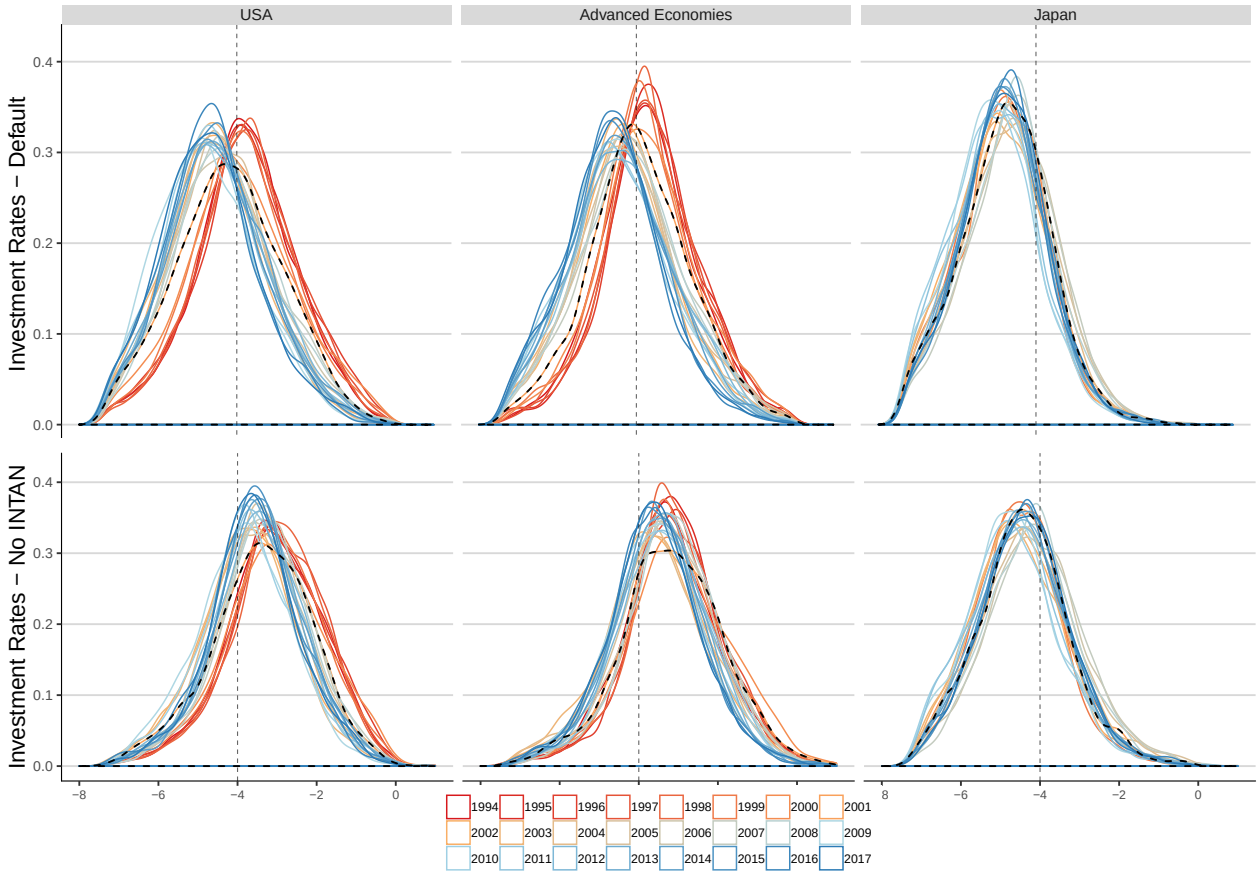
Capital Stock: Is defined gross (i.e. before depreciation and amortisation) as PPEGT + INTAN + INVT which is the sum of gross property, plant and equipment, intangible assets, and inventories. Our preferred capital stock measure includes intangibles and inventories, though our findings are not dependant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

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

Cash Flow: is defined as OANCF off the cash flow statement. The 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, after making adjustments for changes in working capital and other non-operating income. See Compustat Balancing Models excel documents for a

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

Figure 9. Investment Rates by Capital Stock Definition



Note: *Comparing Investment Rates with different capital stock definitions: top row is our default investment measure, which includes intangible capital (INTAN) and inventories (INVT) in the capital stock denominator, in addition to gross property, plant and equipment PPEG. Kernel density approximation shows firm-level investment rates for 18 countries, shifting in around 2000/2001 (dotted orange-black line is for 2001). Key shift in investment rates occurs during orange years. On the Log2() scale. Dotted line at -4 is for a ≈ 6% investment rate.*

moderately detailed definition. Cash flow rates on fixed capital will be exaggerated in Compustat since OANCF includes dividends received by the firm, for example, but does not deduct dividends made.

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

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 on 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 the firm's market-to-book ratio (MTB). Books values, the denominator, is calculated in the same manner across all countries in our sample. Market value calculations differ, however, between Compustat Global and Compustat North America. *For Compustat North America* this calculation is relatively easy, and is equal to the market capitalization of the firm's equity plus the book value of the firms debt: (CSHO * PRCC_F * AJEX) + (DLC + DLTT), while the book value of assets is AT. We adjust (i.e. multiply) CSHO by AJEX, which accounts for stock splits and stock dividends. *For Compustat Global* the process of calculating the 'equity market capitalization' component is somewhat more involved and requires making additional assumptions. Data is downloaded for the last available month of the year ('end of month' filter) and when 'earnings participation flag' is equal to 'yes'. The company may have market values on several exchanges globally. Market capitalization is calculated across each exchange before being aggregated across, whereby we have QCSHOC = ((CSHOC*QUNIT)/1,000,000), marketcap = PRCCD*QCSHOC and marketcap_T =sum(marketcap), across all exchanges, where shares outstanding are CSHOC, and PQUNIT represents the size of the block in which the shares are quoted on the exchange. In particular see Compustat (2009) for further details. As with Compustat North America our calculation excludes non-traded shares.

The literature tends to define Q as Market Value of Fixed Capital / Book Value of Capital. Erickson and Whited (2006) finds this performs better than other measures, such as market-to-book value of the firm, but not by much. We use the firm's market-to-book ratio (MTB) as our proxy for Tobin's Q. MTB likely captures average rather than margin Q though, which is only equal under restrictive assumptions (Hayashi 1982). 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 can all lead to measurement error in enterprise value which ideally one should adjust for. In particular, cross-holdings in other companies may upwardly bias the (consolidated market) value of the enterprise. A closer look at the top 4% of pooled Q values in our entire sample shows that holding companies feature very strongly. This also helps explain in part 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. This makes 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, across the Compustat Global and Compustat North America databases. 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 (PWC 2018; E. Gordon et al. 2008). 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 the fact 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 3.

Table 3. Summary Statistics of Tobin's Q Proxy by Country Group

Country	Min.	P25	P50	Mean	P75	Max.	MAD
Advanced Economies	0.08	0.69	0.94	1.46	1.54	33.56	0.57
USA	0.08	0.84	1.22	2.11	2.19	33.59	0.85
Japan	0.08	0.51	0.65	0.84	0.90	29.06	0.29

Note: *MAD stands for 'median absolute deviation'. U.S. Q values are higher and with greatest spread. High Q values for U.S. firms are probably partly due to the downward bias over time in the book values of fixed capital under US GAAP methods. These do not allow for revaluation upward of fixed assets to fair value, or reversal of impairment charges.*

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.

A.3 Country and Sample Selection and Categorisation

Country location of firm is based on foreign incorporation code (FIC) rather than country of headquarter or country of listing. We have 18 countries in total. Country selection is first based on average GDP per capita (nominal) US$ between 1994-2017 of $20,000 or more. To be included in the final sample the country needed to have 1,400 or more observations in the Compustat file between 1994-2017. This gives us 18 developed economies in our sample consisting of 15 countries, the U.S, and 2 major tax havens (Bermuda and Cayman Islands).

Advanced Economy (excluding U.S. and Japan): Includes Great Britain ("GBR" - 6,950 observations), Canada ("CAN" - 13,462), Australia ("AUS" - 6,719), Cayman Islands ("CYM" - 4,798), France ("FRA" - 6,362), Germany ("DEU" - 6,314), Singapore ("SG" - 5,881), Bermuda ("BM" - 3,959), Sweden ("SWE" - 3,332), Israel ("ISR" - 2,503), Switzerland ("CHE" - 2,799), Italy ("ITA" - 1,997), The Netherlands ("NLD" - 2,368), Norway ("NOR" - 1,510), Denmark ("DNK" - 1,416), and Finland ("FIN" - 1,768). While USA consists of 82,775 observations and Japan ("JPN") 44,242.

Table 4. Data Sample Summary

Country	1990-1999	2000-2007	2008-2017
Advanced Economies	9,694	28,253	34,191
USA	27,763	29,027	25,985
Japan	1,890	19,168	23,184

Note: *Showing number of data points in our sample, by year and country grouping. Shows shrinking number of new lists in the U.S.. Tax haven country firms are included with advanced economies.*

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

Table 5. Detailed Data Sample Summary by Country and Year

Country	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
Advanced Economies	815	1101	1426	1762	2017	2573	2938	3262	3477	3508	3662	3727
USA	4218	4530	4908	4893	4677	4537	4373	3967	3686	3504	3521	3422
Japan	32	31	32	31	32	1732	2238	2297	2263	2321	2425	2496
Country	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Advanced Economies	3871	3808	3623	3280	3371	3502	3535	3459	3497	3420	3289	3215
USA	3331	3223	3042	2816	2741	2683	2634	2581	2616	2505	2355	2012
Japan	2564	2564	2474	2220	2187	2221	2289	2301	2345	2372	2374	2401

Table 6. Investment Rate by Country and Year Group

Country	Time Period	Min.	P25	P50	Mean	P75	Max.	MAD
Advanced Economies	1990-1999	0.01	0.05	0.08	0.11	0.13	0.89	0.05
Advanced Economies	2000-2007	0.01	0.03	0.06	0.09	0.10	0.89	0.04
Advanced Economies	2008-2017	0.01	0.03	0.05	0.07	0.08	0.89	0.04
USA	1990-1999	0.01	0.04	0.07	0.11	0.13	0.89	0.06
USA	2000-2007	0.01	0.03	0.05	0.08	0.09	0.89	0.04
USA	2008-2017	0.01	0.02	0.04	0.07	0.08	0.89	0.03
Japan	1990-1999	0.01	0.02	0.04	0.05	0.06	0.66	0.03
Japan	2000-2007	0.01	0.02	0.04	0.05	0.06	0.89	0.03
Japan	2008-2017	0.01	0.02	0.03	0.05	0.06	0.89	0.02

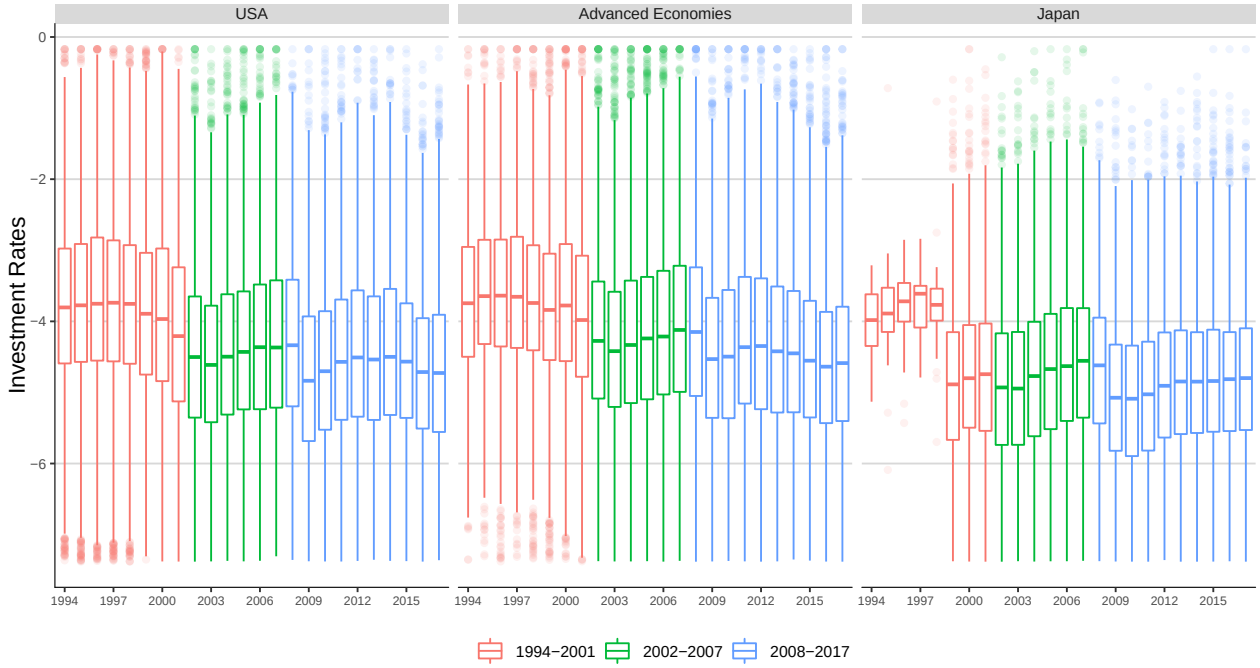
Note: *Investment Rates decline over time secularly across the distribution of firms. Japan's investment rates, however, show a degree of consistency, albeit at very low levels.*

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

Country	Time Period	Min.	P25	P50	Mean	P75	Max.	MAD
Advanced Economies	1990-1999	-3.88	0.03	0.08	0.06	0.14	1.86	0.08
Advanced Economies	2000-2007	-3.99	0.02	0.09	0.06	0.16	1.86	0.10
Advanced Economies	2008-2017	-3.98	0.05	0.10	0.11	0.17	1.86	0.09
USA	1990-1999	-3.99	-0.04	0.07	-0.03	0.14	1.86	0.13
USA	2000-2007	-4.00	-0.03	0.08	-0.04	0.15	1.86	0.13
USA	2008-2017	-3.97	0.03	0.09	0.01	0.16	1.86	0.10
Japan	1990-1999	-1.96	0.03	0.06	0.07	0.10	1.76	0.05
Japan	2000-2007	-3.56	0.03	0.06	0.08	0.11	1.87	0.06
Japan	2008-2017	-3.47	0.04	0.07	0.12	0.13	1.86	0.06

Note: *Cash flow rates increase across country groups and percentiles over time.*

Figure 10. Boxplot Investment Rates by Country Group



Note: *Sample size for Japan prior to 1999 is small. For each box plot the lower and upper hinges correspond to the first and third quartiles (the 25th and 75th percentiles). The upper whisker extends from the hinge to the largest value no further than 1.5 x IQR from the hinge (where IQR is the inter-quartile range, or distance between the first and third quartiles). The lower whisker extends from the hinge to the smallest value at most 1.5 * IQR of the hinge. Data beyond the end of the whiskers are "outliers" and are plotted individually.*

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

Country	Time Period	Min.	P25	P50	Mean	P75	Max.	MAD
Advanced Economies	1990-1999	0.08	0.63	0.94	1.67	1.59	32.68	0.57
Advanced Economies	2000-2007	0.08	0.64	0.96	1.48	1.56	33.56	0.58
Advanced Economies	2008-2017	0.08	0.62	0.93	1.39	1.50	33.13	0.56
USA	1990-1999	0.08	0.77	1.27	2.45	2.49	33.59	0.95
USA	2000-2007	0.08	0.74	1.21	2.02	2.18	33.17	0.88
USA	2008-2017	0.08	0.78	1.19	1.83	1.98	33.26	0.75
Japan	1990-1999	0.12	0.49	0.67	1.09	0.93	29.06	0.30
Japan	2000-2007	0.08	0.49	0.67	0.87	0.93	28.51	0.30
Japan	2008-2017	0.08	0.46	0.63	0.80	0.87	21.58	0.29

Note: *Q values stagnate or decline across countries and years, depending on the percentile of the distribution.*

B Hierarchical Model: Additional details and findings

B.1 Technical Model Specification and Method: Bayesian Hierarchical Model

Our hierarchical model, a 'mixed, fixed and random coefficient model (Greene 2003; Sims 2010; Hsiao 2014; Meager 2019),[41] allows for the degree of variation within our *country* and *year* groups to be estimated directly from the data; rather than imposed *a priori* as a constraint either by assuming no relevant differences between clusters of countries and years within each group (complete pooling), or by assuming no relatedness between countries or years within each group (no pooling, complete independence).

Each group's parameters are drawn from a common prior distribution and estimated together so that the inferences for each country (or year) can potentially 'learn' from one another, rather than estimated in isolation (McElreath 2018).[42] This joint estimation approach produces a lower *total* mean squared error for the sum of the parameters than a maximum likelihood estimator which estimates each parameter separately (James and C. Stein 1961; Kreft and De Leeuw 1998; Lehmann and Casella 1998).[43] Equation 10 can formally be written in a hierarchical form as:

$$\log(y_i) \sim \mathrm{t}_\nu(\mu, \sigma_y^2, \nu_y), \tag{13}$$

$$\mu_{[i]} = X_i^0 \beta^0 + X_i \beta_{t,c,j[i]} + \rho \epsilon_{i,t-1}, \qquad \text{for } i \in 1:n \tag{14}$$

$$\beta_{t,c,j} \sim \mathrm{MVN}(M_\beta, \Sigma^\beta_{t,c,j}), \qquad \text{for } t, c, j \in 1: T, C, J, \tag{15}$$

Equation 13 shows that our regression model is specified in log-level form. By making our dependant variable roughly normal, this dramatically improves sampling efficiency and reduces heteroskedasticity.[44] We use a symmetric student-t distribution t_ν, with the degree of freedom ν, as our likelihood function.[45] The mean of the investment function (eq.14) is the location parameter μ of the t-likelihood, and estimated as the combination of the fixed effect and random effect coefficients. X_i^0 are the fixed effect predictors, with parameter estimates β^0 from the pooled, population-level regression. X_i are the

[41] They are a natural extension of 'analysis of variance' (ANOVA) models (Malinvaud 1980; Gelman 2006).

[42] The extent to which one country's inference learns from another country's is based partly 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.

[43] 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).

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

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

3 random, group-level, predictors with parameter estimates $\beta_{t,c,j[i]}$, varying for each 'cluster' within each group of countries and years (and country:years). The time- and country-level group regressions contain 24 and 18 clusters, respectively, such that $T = 24$ and $C = 18$, and the country:year level contains $J = 24$ x $18 = 432$ clusters. The country:year group coefficients are country-specific time effects (or equivalently time-specific country effects).[46] For each of the three groups (t, c, j), $\beta_{t,c,j}$ is a vector of length 3 random effects corresponding to the tth c^{th} or j^{th} row of β. Finally, $\epsilon_{i,t-1}$ is the error term at time $t-1$, where ρ represents the estimated AR(1) error process. This estimates the degree of auto-correlation in the error term, and, therefore, the state-dependence of the investment rate over time.[47]

For each group t, c, j, eq. 15 estimates the 3 random effects of our model $\beta_{t,c,j}$, as deviations around $M_\beta = \{\mu_\alpha, \mu_q, \mu_{cf}\}$, the grand mean of each of our 3 random effect predictors, drawn from a common multivariate normal (MVN) distribution.[48] The variance-covariance matrix Σ_β, is estimated separately for each t, c, j group of random effect parameters, with the 3 variance parameters in each group $\sigma_{\alpha,q,cf}$, determining the extent of variability in parameter estimates across countries, years, or country:years.

As the key quantities of interest of our investment model, *cash flow*, Q (Market-to-book or MTB ratio), and the *intercept* are estimated as both *fixed effects* and *random effects*, as recommended by Schmidt-Catran and Fairbrother (2015), among others. They are included in every level of our model and are the only predictors for the country, year, and country:year group regressions. In our 'fixed' population regression level, we also include a firm size dummy, an industry dummy, a capacity utilization dummy (a capital-output ratio), and a net external financing (EF) dummy, telling us if the firm's demand intercept is that of a net external 'borrower' or 'releaser' of funds.[49]

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

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

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

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

B.2 Hierarchical Priors and Variance-Covariance Structure

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

$$\begin{pmatrix} \alpha_{t,c,j} \\ \beta^q_{t,c,j} \\ \beta^{cf}_{t,c,j} \end{pmatrix} \sim \text{MVNormal}\left[\begin{pmatrix} \mu_\alpha \\ \mu_q \\ \mu_{cf} \end{pmatrix}, \quad \Sigma^\beta_{t,c,j}, \right], \tag{16}$$

Each group t, c, j has its own variance-covariance matrix (though we do not write it out 3 times). Within each group, the variance-covariance matrix (eq. 17) is $\Sigma^\beta = \mathrm{D}(\sigma)\,\Omega\,\mathrm{D}(\sigma)$, where $\mathrm{D}(\cdot)$ has the standard deviation of each of the 3 random effect variables along the diagonal:

$$\Sigma^\beta_{t,c,j} = \begin{pmatrix} \sigma_{\alpha_{t,c,j}} & 0 & 0 \\ 0 & \sigma_{\beta^q_{t,c,j}} & 0 \\ 0 & 0 & \sigma_{\beta^{cf}_{t,c,j}} \end{pmatrix} \Omega \begin{pmatrix} \sigma_{\alpha_{t,c,j}} & 0 & 0 \\ 0 & \sigma_{\beta^q_{t,c,j}} & 0 \\ 0 & 0 & \sigma_{\beta^{cf}_{t,c,j}} \end{pmatrix}. \tag{17}$$

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

$$\Omega_{t,c,j} = \begin{pmatrix} 1 & \rho_{\alpha_{t,c,j},\beta^q} & \rho_{\alpha_{t,c,j},\beta^{cf}_{t,c,j}} \\ \rho_{\alpha_{t,c,j},\beta^q_{t,c,j}} & 1 & \rho_{\beta^q_{t,c,j},\beta^{cf}_{t,c,j}} \\ \rho_{\alpha_{t,c,j},\beta^{cf}} & \rho_{\beta^q_{t,c,j},\beta^{cf}_{t,c,j}} & 1 \end{pmatrix}. \tag{18}$$

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

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

$$\sigma_{\alpha_{t,c,j}},\ \sigma_{\beta^q_{t,c,j}},\ \sigma_{\beta^{cf}_{t,c,j}} \sim \text{Cauchy}(0, 2), \tag{20}$$

$$\Omega_{t,c,j} \sim \text{LKJcorr}(5)\,. \tag{21}$$

The prior for the variables' population means M_β, follows a normal distribution centered at zero with

a reasonably informative standard deviation of 0.5. This allows for an equal probability of negative and positive parameter values. The full list of priors can be found in Appendix B. Our model is not sensitive to the priors chosen for several reasons. Firstly, our priors overlap sufficiently with the inference from our likelihood, i.e. our data. Secondly, our large sample ensures our priors are unlikely to overwhelm our likelihood. Even though the number of parameters we estimate is large at 1,466 (excluding group predictors) the same data points are used for more than one regression if the firm belongs to more than one group.[50] Thirdly, our priors are only informative enough to help aid in the convergence properties of the model.

Lastly, 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 prior, we have the following joint posterior parameter distribution, with N number of observations, K number of predictors and, L number of groups:

$$\begin{aligned} p(\theta|y) &\propto p(y|\theta)\, p(\theta|\phi)\, \mathrm{p}(\phi) \\ &\propto \underbrace{\prod_{l=1}^{L} \text{student-t}(y_{.l}|\beta_l, \nu, \sigma_y)}_{\text{Likelihood}} \underbrace{\prod_{l=1}^{L} \text{MVN}(\beta_l|\boldsymbol{M}_{\boldsymbol{\beta}}, \boldsymbol{\Sigma}^{\boldsymbol{\beta}})}_{\text{Prior}} \underbrace{p(\boldsymbol{M}_{\boldsymbol{\beta}}, \boldsymbol{\Sigma}^{\boldsymbol{\beta}})}_{\text{Hyper prior}} \end{aligned} \tag{22}$$

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

[50] 432×3 random country:year effects, 18×3 random country effects, 24×3 random year effects, 3×3 variance parameters per group, 3×3 correlation parameters per group, 2 t-distribution parameters, 23 population level predictors, and 1 AR process coefficient.

B.3 Priors

$$M_\beta \sim \mathrm{N}(0, 0.5), \tag{23}$$

$$\alpha^0 \sim \mathrm{N}(0, 1.5), \tag{24}$$

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

$$\log(Q)^0 \sim \mathrm{N}(0.3, 0.3), \tag{26}$$

$$\nu \sim \mathrm{Gamma}(2, 0.1), \tag{27}$$

$$\sigma_y,\ \sigma_{\alpha,q,cf\in t},\ \sigma_{\alpha,q,cf\in c},\ \sigma_{\alpha,q,cf\in j} \sim \mathrm{Cauchy}(0, 2), \tag{28}$$

$$\mathbf{R} \sim \mathrm{LKJcorr}(5)\,. \tag{29}$$

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

B.4 Model Fit

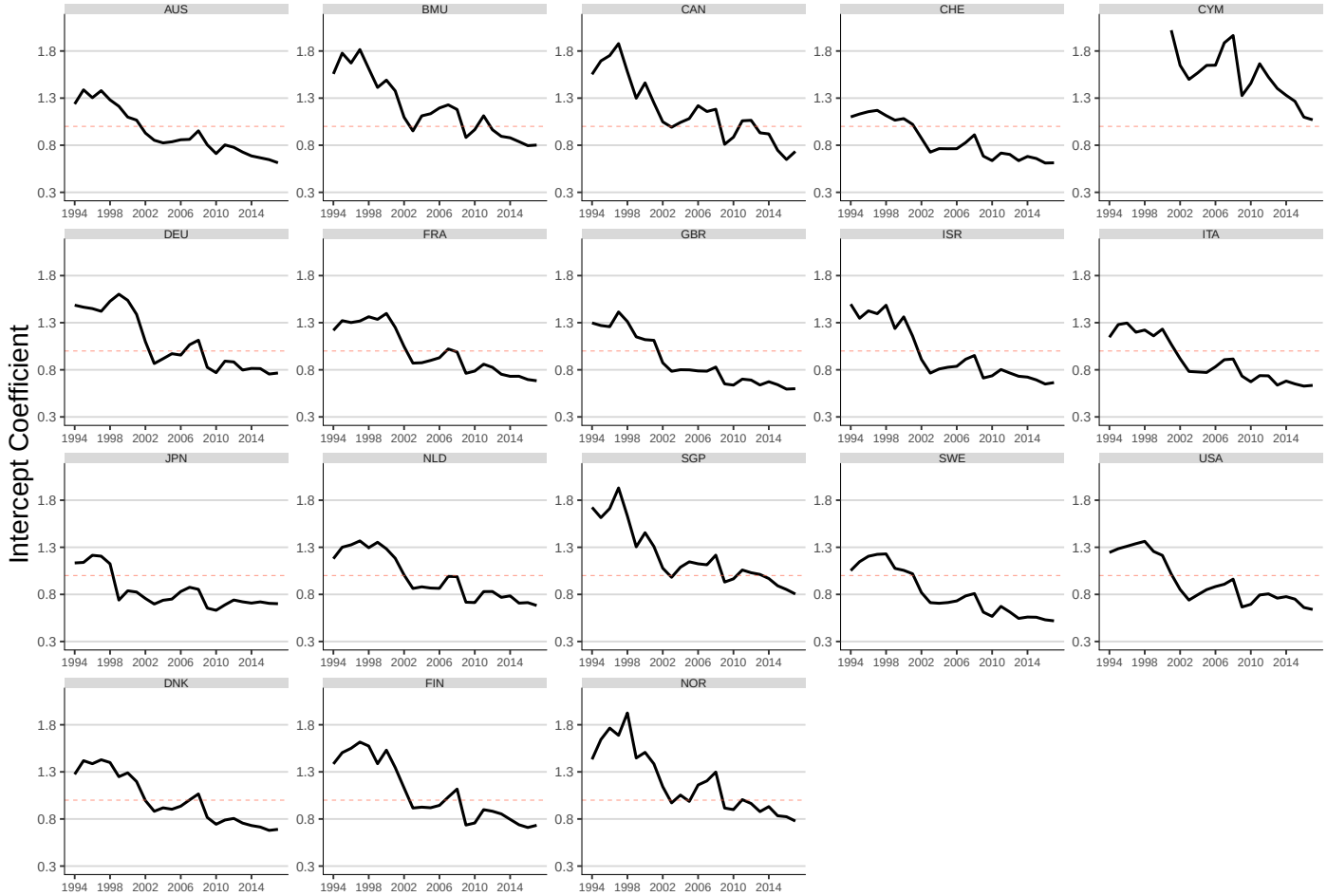
Table 9. Model Fit: Bayesian R^2 by Country and Year Groups

Year	R2	Est.Error	Q2.5	Q97.5
1994	0.12	0.00	0.11	0.13
1995	0.12	0.00	0.11	0.13
1996	0.13	0.00	0.12	0.13
1997	0.12	0.00	0.11	0.13
1998	0.10	0.00	0.10	0.11
1999	0.21	0.00	0.20	0.22
2000	0.19	0.00	0.18	0.20
2001	0.16	0.00	0.15	0.17
2002	0.15	0.00	0.14	0.15
2003	0.15	0.00	0.14	0.16
2004	0.15	0.00	0.15	0.16
2005	0.15	0.00	0.14	0.15
2006	0.14	0.00	0.13	0.15
2007	0.15	0.00	0.14	0.16
2008	0.14	0.00	0.13	0.15
2009	0.15	0.00	0.14	0.16
2010	0.18	0.00	0.17	0.19
2011	0.20	0.00	0.19	0.21
2012	0.17	0.00	0.16	0.18
2013	0.16	0.00	0.15	0.17
2014	0.15	0.00	0.14	0.15
2015	0.13	0.00	0.12	0.14
2016	0.12	0.00	0.12	0.13
2017	0.13	0.00	0.13	0.14

Country	R2	Est.Error	Q2.5	Q97.5
USA	0.47	0.00	0.46	0.47
JPN	0.42	0.00	0.42	0.42
GBR	0.48	0.00	0.48	0.49
CAN	0.50	0.00	0.49	0.50
AUS	0.45	0.00	0.45	0.46
CYM	0.37	0.00	0.36	0.37
FRA	0.47	0.00	0.47	0.48
DEU	0.46	0.00	0.46	0.47
SGP	0.39	0.00	0.39	0.40
BMU	0.38	0.00	0.38	0.39
SWE	0.49	0.00	0.49	0.50
ISR	0.50	0.00	0.49	0.50
CHE	0.48	0.00	0.47	0.48
ITA	0.43	0.00	0.43	0.44
NLD	0.51	0.00	0.51	0.52
NOR	0.44	0.00	0.43	0.45
DNK	0.45	0.00	0.44	0.46
FIN	0.49	0.00	0.48	0.50

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*

Figure 11. Intercept Coefficients of All Random Effects Combined, 1994-2017



Note: *Plotting the exponentiated random effect intercepts from all three levels of our model combined. Investment rates decline for advanced economies as a secular tendency. For the U.S.'s random effect intercept dips below one (dotted pink line) around 2000, indicating declining investment rates. Tax haven countries have higher predicted investment rates indicating the importance of partial pooling of firm-level investment data. Some of the Cayman Island's plot is cut off since its intercept starts very high.*

C 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 attenutation.[51] 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; Richardson and Gilks 1993; Gelman, Carlin, et al. 2013). 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 $\widetilde{Q}$ measured without error. We assume classical measurement error such that $Q = \widetilde{Q} + \epsilon$. This implies greater variability in the observed surrogate, Q, than true $\widetilde{Q}$. The error is assumed to be homoskedastic with zero mean and identity covariance matrix independent of true covariates, $\text{Var}(\epsilon|\widetilde{Q}) = \tau_{me}\boldsymbol{I}$, where τ_{me} governs the variance of the measurement error ϵ. This implies that surrogate Q is an unbiased version of the true covariate $\widetilde{Q}$, hence $E(Q) = E(\widetilde{Q})$.

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

[51] This is called a 'sensitivity analysis'.

model $log(Q) = log(\widetilde{Q}) + \epsilon$.

This leads to the following measurement error model on the fixed effect and random effect Q values:[52]

$$Q_{ij} \sim \mathcal{N}(\widetilde{Q}_{ij}, \tau_{me}), \tag{30}$$

$$Q_i \sim \mathcal{N}(\widetilde{Q}_i, \tau_{me}). \tag{31}$$

For computational purposes we apply this measurement error correction model to a single random-effects level version of our hierarchical model, with only random effects being estimated for the 432 country:year clusters.[53]

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 effects 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:

$$h(y, q, \tilde{q}, z) = h(y|q, \tilde{q}, z)\ h(q, \tilde{q}, z) \tag{32}$$

$$= h(y|q, z)\ h(q, \tilde{q}, z) \tag{33}$$

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

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):

$$f(y|\tilde{q}, z; \theta) \propto \int\ f(y|q, z; \beta)\ f(q|\tilde{q}, z)\ d\eta(q). \tag{35}$$

[52]We 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 $\widetilde{Q}$. The uncertainty of the measurement error model will partially be reflected in the estimate of the population parameters of perfectly measured $\widetilde{Q}$, and in particular in σ_Q

[53]The findings do not change materially when applied to the full model.

This leads to the following model:

$$y_i \sim \mathrm{t}_\nu \left(X^0_{i-Q}\beta^0 + X_{i-Q}\beta_{j[i]} + \widetilde{Q}^0_i\beta^0 + \widetilde{Q}_i\beta_{j[i]},\, \sigma^2_y,\, \nu_y \right) \quad \text{for } i = 1, \ldots, n, \tag{36}$$

$$Q_{ij} \sim \mathcal{N}\left(\widetilde{Q}_{ij}, \tau_{me}\right), \tag{37}$$

$$Q_i \sim \mathcal{N}\left(\widetilde{Q}_i, \tau_{me}\right), \tag{38}$$

$$\beta_j \sim \mathrm{MVN}\left(M_\beta, \Sigma_\beta\right) \quad \text{for } j = 1, \ldots, J. \tag{39}$$

We provide no additional ('exposure') model for true Q - which does not contribute very much 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:[54] Our priors are as follows:

$$\alpha \sim \mathrm{Normal}(0, 1.5), \tag{40}$$

$$\beta^0_\alpha \sim \mathrm{Normal}(0, 0.5) \tag{41}$$

$$\beta^0_{\widetilde{Q}} \sim \mathrm{Normal}(\tau, 0.3), \tag{42}$$

$$\mu_\alpha, \mu_{\beta^{CF}} \sim \mathrm{Normal}(0, 1), \tag{43}$$

$$\mu_{\widetilde{Q}} \sim \mathrm{Normal}(0.5, 0.5), \tag{44}$$

$$\nu \sim \mathrm{Gamma}(2, 0.1), \tag{45}$$

$$\sigma_\alpha, \sigma_{cf}, \sigma_y \sim \mathrm{HalfCauchy}(0, 2), \tag{46}$$

$$\sigma_{\widetilde{Q}} \sim \mathrm{HalfCauchy}(0, 1), \tag{47}$$

$$\mathbf{R} \sim \mathrm{LKJcorr}(5)\,. \tag{48}$$

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

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

$\tau = \{0.1, 0.3, 0.5, 0.7\}$. This is called a sensitivity analysis.[55]

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

		Non ME		**ME .1**		**ME .3**		**ME .5**		**ME .7**	
	Variable	Est.	Est.Err.	Est.	Est.Err.	Est.	Est.Err.	Est.	Est.Err.	Est.	Est.Err.
Fixed Effect	α	-2.84	0.09	-2.85	0.05	-2.85	0.05	-2.86	0.05	-2.88	0.05
	γ^{eb}	0.15	0.00	0.15	0.00	0.15	0.00	0.15	0.00	0.15	0.00
	β^{cf}	0.06	0.04	0.04	0.01	0.05	0.01	0.05	0.01	0.06	0.01
	β^{q}	0.18	0.01	0.18	0.00	0.20	0.01	0.28	0.01	0.54	0.02
Country:Year Random Effect	σ_{α_j}	0.07	0.00	0.30	0.01	0.30	0.01	0.29	0.01	0.29	0.01
	$\sigma_{\beta^{cf}_j}$	0.13	0.01	0.19	0.01	0.19	0.01	0.19	0.01	0.19	0.01
	$\sigma_{\beta^{q}_j}$	0.02	0.00	0.05	0.00	0.05	0.00	0.15	0.01	0.36	0.02
Student-t Parameters	σ	0.51	0.00	0.51	0.00	0.50	0.00	0.48	0.00	0.43	0.00
	ν	3.98	0.04	3.98	0.04	3.93	0.04	3.75	0.04	3.34	0.04

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.*

As expected the size of the fixed effect value of Q, β^q, increases as the value of τ increases, with strongly non-linear effects, almost doubling in size from 0.28 ($\tau = 0.5$) to 0.54 ($\tau = 0.7$).

The variation in the random effects of Q, $\sigma_{\beta^q_j}$, increases strongly too as τ increases, from 0.02 ($\tau = 0.1$) to 0.36 ($\tau = 0.7$), indicating that the lack of variability in Q across time and country might be an artifact of measurement error.

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

[55] In 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 $\tau = SD(Q|\widetilde{Q})/SD(Q)$ can be interpreted as the magnitude of the measurement error relative to the variability in X, and the relative bias is defined as $(Q - \widetilde{Q})/\widetilde{Q}$ or 1 minus the attenuation factor $Q/\widetilde{Q} = 1/(1+\tau^2)$. $\tau = 0.1$ 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 $\rho = COR(\widetilde{Q}, z)$, worsening as ρ increases, such that bias with a single additional regressor we have: $Q/\widetilde{Q} = 1/\left(1 + \frac{\tau^2}{1+\rho^2}\right)$. For the Z univariate case see Gustafson, equation 2.7 where $Q/\widetilde{Q} = 1/(1+\tau^2 K)$ where K is a complex expression including a correlation matrix for Z and a vector of correlation between X and Z.

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

D FINCF: Further Analysis

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.[56] 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).[57] They come up with several important empirical findings which support our conclusions.[58]

D.1 FINCF Visual Description

Figure 12 shows a clear difference in the distribution of investment rates for firms who are net external borrowers of funds and firms who are net external releasers of funds. This indicates that it is not just differences in surplus cash flow rates driving this trend but also structurally weaker investment opportunities for these firms. We confirm this in the 'DNA' graphs below.

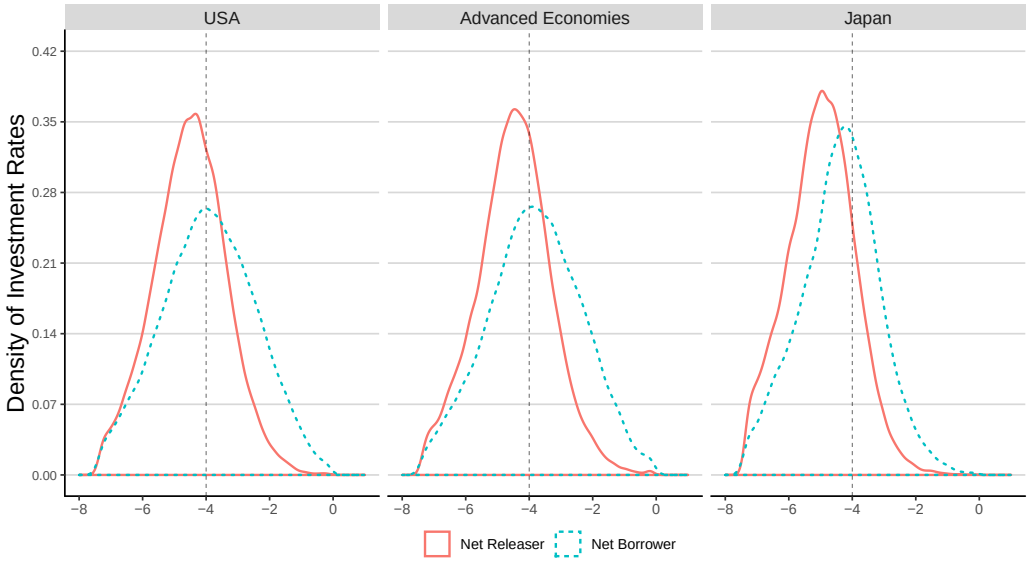
The DNA graphs in Figure 13 show changes in our key quantities of interest over time by FINCF percentile and country grouping. Each DNA dot ('atom') shows the median value of the variable in question for a specific FINCF firm percentile (unless stated otherwise). While the different coloured strands reflect different time periods. Strands loosen or tighten over time. Vertical lines for each time period show the median pooled value. These vertical lines show that median cash flow rates for our

[56] Frank 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.

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

[58] They 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.

Figure 12. Investment Rates by FINCF and Country Grouping



Note: *Kernel density approximation of firm-level investment rates on log2() 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 4.06% (.029 MAD), compared to an investment rate of 6.46% (.058 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.*

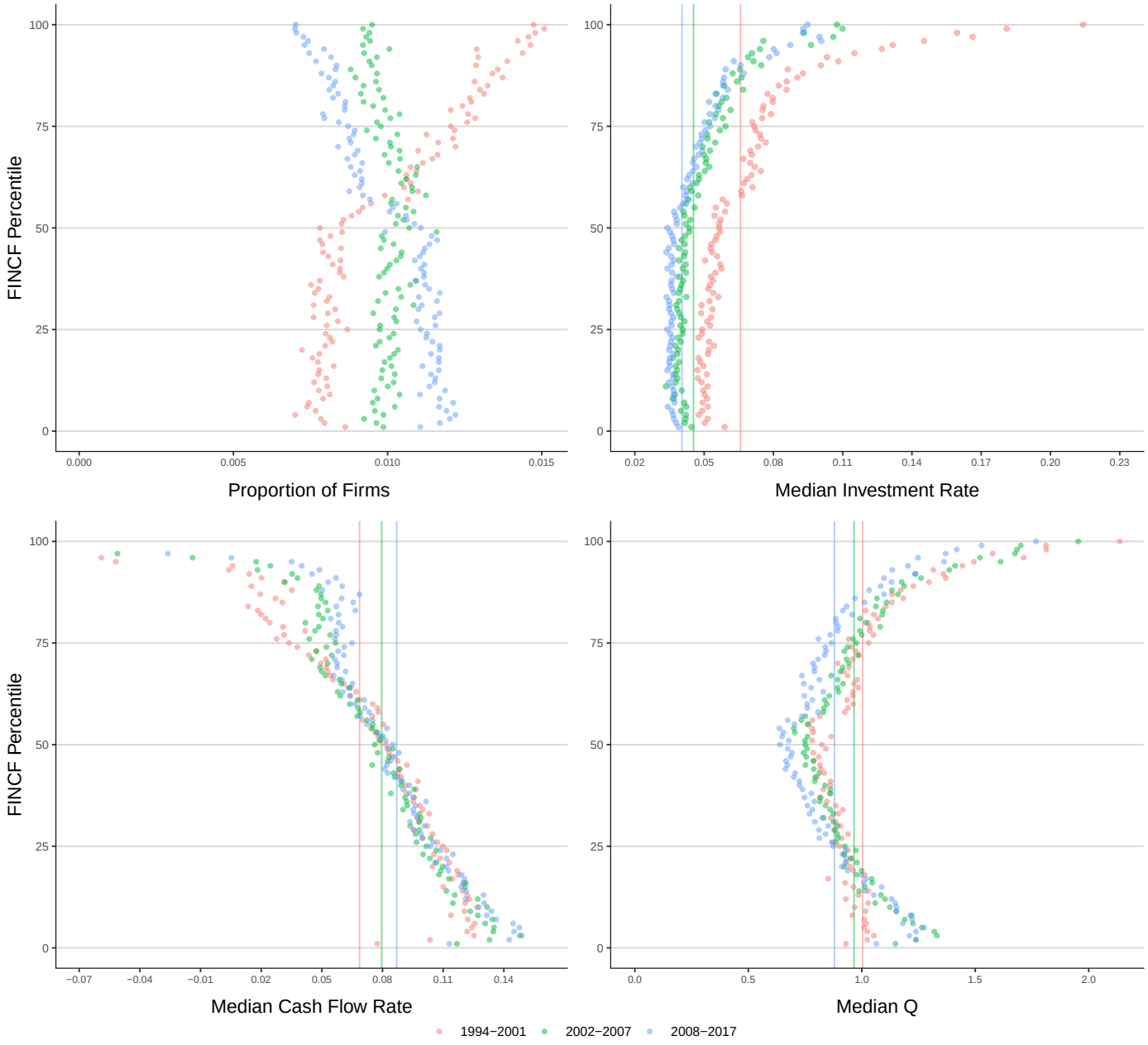
pooled sample have increased even as raw Q values and investment rates have declined. The DNA graphs allow us to explore this variation in greater detail across the FINCF bins.

We see an increase over time in the proportion of total firms that are large net external releasers of funds (percentiles 50 → 0) and a decline in the proportion of firms that are net external borrowers (percentiles 50 → 100). This is reflected in a shifting out - an increase - in the proportion of mid-tier FINCF firms (percentiles 75 → 10), but a shift in (decrease in the proportion of) the largest net releasers of funds (percentiles 10 → 0) and the largest net borrowers of funds (percentiles 10 → 0).

With respect to investment opportunities (bottom right hand graph Figure 13): 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). 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 scale.

Note that, as per Figure 13 (top right hand graph), investment rates tend to be higher for firms that borrow more and release less (percentiles 50 → 100). Investment rates have shifted inwards for all

Figure 13. Cash Flow, Q, Investment Rate, and proportion of observations by FINCF Bin.



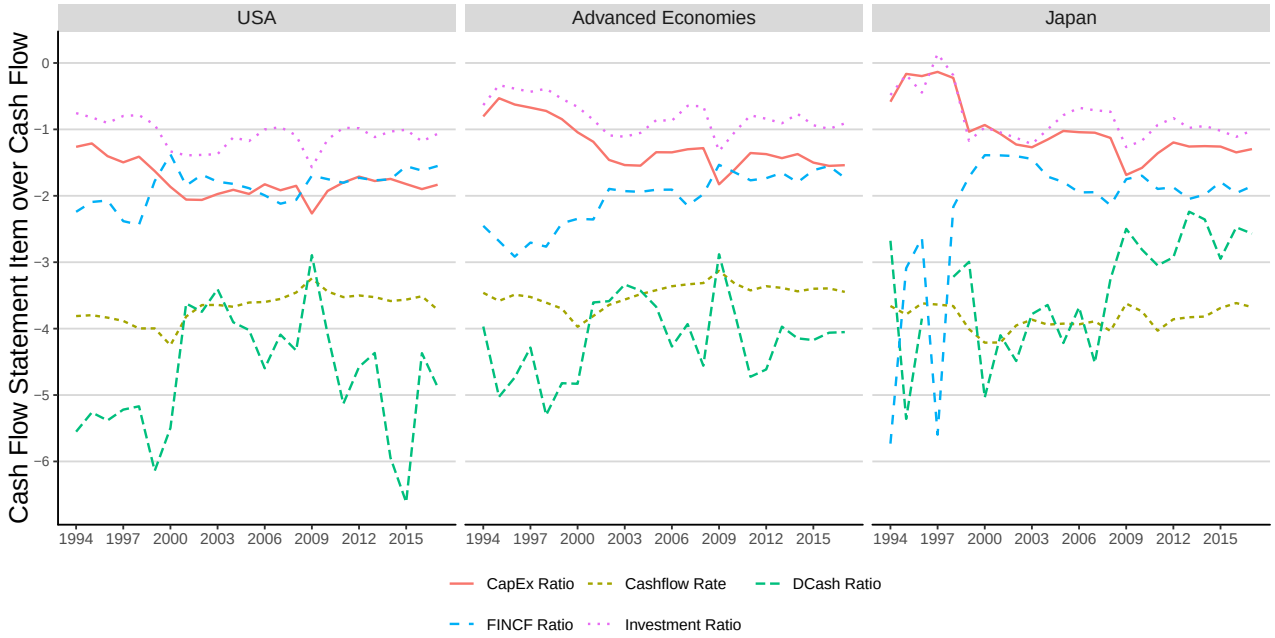
Note: *Large net external releasers of funds tend to be percentiles* $50 \rightarrow 0$ *(bottom of y-axis); firms that are net external borrowers tend to be percentiles* $50 \rightarrow 100$ *(top of y-axis). Bin widths calculated on pooled unstratified sample.*

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 → 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.)

Median cash flow rates are highest (around 14%) for firms that release the most (Figure 13 bottom left hand graph), 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). Profitability 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 → 100) and for firms that release the most (top 5 percentiles). They have increased from 6.8% to 7.9% to 8.7% post-crisis for advanced economy firms. 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

D.2 Alternative Explanations for FINCF and the Other Cash Flow Statement Items

Figure 14. Uses of cash flow by cash flow statement activity on Log2() scale



Note: *Showing Log2(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'. 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.*

Firms' increasing tendency to retain cash flow (CHECH) has accompanied the increase in the release of funds externally through FINCF (Figure 14). 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. 2001, 1999). 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. 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.

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).[59] 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).[60] 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

[59] Even 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.

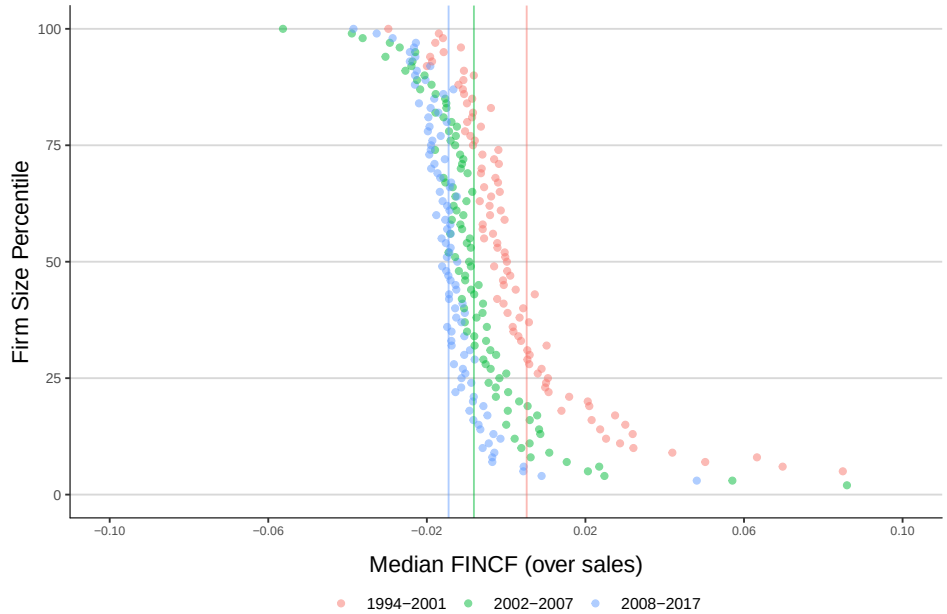
[60] Firms that are very large net external 'borrowers' of funds, tend to have very low leverage levels, though, since they are young firms. This makes sense, since firms with low and negative levels of cash flow are almost always net 'borrowers' of external funds, while firms with high levels of cash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

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 Savings (profits less dividends) − 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 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.3 Life Cycle of the Firm and FINCF

Figure 15. FINCF by Firm Size



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 ($0 \rightarrow 50$ on y-axis) in their infancy with plenty of investment opportunities but negative cash flow borrow more (relative to sales), while larger ($50 \rightarrow 100$), mature, firms tend to release more as their investment opportunities tend to fall short of their by now large cash flow rates. Some values cut off for top and bottom percentiles to reduce graph sale.*

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 (H. DeAngelo, L. DeAngelo, and Stulz 2006; H. DeAngelo, L. DeAngelo, Skinner, et al. 2009; Damodaran 2010).[61] Figure 15 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 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 is a feature across all firm sizes. Secondly, Table 4 shows that firms

[61] The shortening of firms' life cycle may be speeding this up (Damodaran 2015).

in our non-U.S. sample do not display this same decline in public listing as in the U.S.. This decline begins in 1996 in our specific U.S. sample. Outside of the U.S. listing have not been declining until more recently (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.