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Firm selection and corporate cash holdings[☆]

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ABSTRACT

Since the early 1980s, the composition of US public firms has progressively shifted toward less profitable firms with high growth potential (Fama and French, 2004). We estimate a dynamic corporate finance model to quantify the role of this selection mechanism for the secular trend in cash holdings among US public firms. We find that an increase in the precautionary savings motive—primarily driven by the decline in initial profitability among R&D-intensive new lists—explains about 50% of the upward trend in cash holdings. This selection mechanism also explains part of the upward trend in sales growth volatility.

1. Introduction

Why do US public firms hold much more cash since the early 1980s? A large literature in corporate finance has dedicated itself to answering this question. The evidence suggests many different drivers for higher cash holdings including riskier cash flows (Opler et al., 1999; Bates et al., 2009), lower opportunity cost of holding cash (Azar, Kagy and Schmalz, 2016), taxes (Butters, 1949; Foley et al., 2007), agency frictions (Dittmar and Mahrt-Smith, 2007; Nikolov and Whited, 2014), and a change in production technologies (Brown and Petersen, 2011; Falato, Kadyrzhanova and Sim, 2013; Falato and Sim, 2014; Gao, 2015; Zhao, 2020; He and Wintoki, 2016; Lyandres and Palazzo, 2016).

In this paper, we quantitatively assess the role of selection of different types of firms into US equity markets. We are motivated by the following three stylized facts. First, the secular increase in cash holdings among US public firms is driven by firms going public with progressively higher cash balances over time (i.e., selection effect). Second, once public, firms experience a decrease in their cash-to-asset ratio (i.e., within-firm effect). Third, when

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we decompose the change in average cash holdings into a within-firm effect and a selection effect, we find that most of the change in cash holdings is due to a selection effect. The latter is almost entirely driven by R&D-intensive firms.

We build on Riddick and Whited (2009) to quantify the importance of the selection mechanism. We keep the model purposefully simple to focus on a few important drivers of higher cash ratios: standard neoclassical investment dynamics and selection. Our model features decreasing returns to scale in production, an idiosyncratic productivity process, and capital adjustment costs on the production side. To finance investments, firms have two options. They can issue equity or accumulate cash internally (retained earnings), both at a cost. Each period a random fraction of incumbents exists. The mass of exiting firms is replaced by an identical mass of heterogeneous entrants. Entrants receive different productivity signals and therefore endogenously choose different levels of cash and capital.

Three model ingredients are key to capture the stylized facts in the data: decreasing returns to scale in production, a precautionary savings motive due to financing costs, and mean reversion in the productivity process. When the productivity signal at entry is low, entrants are well below their long-run productivity and hence far from their long-run optimal scale. In this case, entrants choose high cash levels at entry to avoid incurring equity issuance costs in the future to finance their growth (positive selection effect). After entry, these firms mean revert to their long-run scale (i.e., grow larger) and their precautionary savings motive decreases, thus leading to a smaller cash-to-asset ratio (negative within-firm effect).

The goal of our paper is to explore the quantitative implications of the simple mechanism described above. Given the empirical support for cohort and firm-industry effects, we allow for variation by time and industry and estimate most parameters at the cohort and industry level using a simulated method of moments estimation (SMM), akin to Warusawitharana and Whited (2015). Our model features two industries that represent R&D-intensive firms and non-R&D-intensive firms. While the production and financing technologies are identical across industries, their parametrization can differ. For each industry and cohort, we separately estimate the parameters governing the production process, financing costs, and the firm selection process. To identify the parameters of interest, we include a large set of moments based on quantities that we can reasonably calculate with our model: the cash-to-asset ratio, the sales growth rate, the investment-to-asset ratio, and the equity issuance-to-asset ratio. These moments are calculated using all firms that become public during the 1974-1978 period (baseline cohort) and are calculated separately for R&D-intensive and non-R&D-intensive firms for all subsequent five-year cohorts over the period 1979-2003.

Overall, the estimated model does a good job in reproducing the data moments. The majority of the model-generated moments are very similar in magnitude to their empirical counterparts, and many of them are also statistically indistinguishable. For example, across cohorts and industries, the model replicates the average equity issuance size of mature firms, the average sales growth rate, and the average investment-to-asset ratio at entry. In all industries and cohorts, firms grow much faster when they enter compared to when they have been public for ten years. More importantly and in line with the data, the model generates an increasing trend in both the cash-to-asset ratio and the dispersion in the sales growth rate at entry for firms belonging to the R&D-intensive group.

The estimated parameter values are in the ballpark of previous studies. For example, we find that relative to non-R&D-intensive firms, firms in R&D-intensive industries tend to be smaller and more volatile (0.24 versus 0.20) and feature lower persistence of the productivity process (0.50 versus 0.70) and lower production function curvature (0.86 versus 0.59). These estimates are consistent with the ones in Hennessy and Whited (2007), who find that, relative to large firms, smaller firms have a larger volatility parameter (0.16 versus 0.09), a smaller persistence parameter (0.50 versus 0.79), and a larger return-to-scale parameter (0.69 versus 0.58). Although we allow for variation by cohort, we find no systematic trend over time in most of the model's parameters for both industries. The two notable exceptions are the parameters governing the average productivity at entry and the cash flow volatility for R&D-intensive firms. These firms experience a decline in the average signal and an increase in the cash flow volatility.

We assess how much of the secular increase in cash holdings from 1979 to 2003 can be explained by our model.[1] We assume that firms across both industries (R&D-intensive and non-R&D-intensive) and all cohorts have identical exit probabilities but are replaced by new entrants according to the industry composition at entry observed in the data. We find that our estimated neoclassical investment model, augmented by a choice of cash holdings and capital at entry, generates an increase of the cash-to-asset ratio of about 80% versus an increase of 160% in the data. At the same time, our model can generate a secular increase in sales growth volatility consistent with the empirical evidence in Davis et al. (2007). In our simulation, sales growth volatility increases by 44% during the period 1979-2003, while in the data the increase is 88%. In short, we show that a canonical neoclassical investment model, augmented to allow for firm selection, can explain half of the percentage increase in both average cash holdings and sales growth volatility among US public firms.

The model explains these two trends with two main channels. Over time, firms in the R&D-intensive sector have gone public with increasingly lower initial productivity and increasingly higher cash flow volatility. Both channels contribute to an increase in the precautionary savings motive of firms, thereby leading to higher cash holdings over time. To isolate their individual importance, we conduct several counterfactual experiments. Specifically, we investigate the model's implication for the rise in average cash holdings and sales growth volatility when only selected forces of the model operate.

[1] We end our analysis in the early 2000s because cash levels stayed fairly constant after 2003 in the data.

Our first counterfactual exercise aims at isolating the importance of firm selection. To this end, we only allow for changes in the parameters governing the distribution of firms at entry (selection), while we keep all other parameters at their baseline cohort values. In this case, the model still generates about 65% of the change in cash holdings relative to the fully estimated model (i.e., firm selection alone explains the majority of the secular increase in cash holdings in our model economy). When we only shut off firm selection and allow all other parameters to take their estimated values, the model fails to generate any increase in cash holdings over time. Interestingly, the effect on sales growth dispersion is also subdued, as the model generates only 70% of the full model's response. That is, selection alone generates 30% of the full model's response for a rise in sales growth dispersion.

Next we conduct a similar set of counterfactual exercises to focus on the quantitative strength of a rise in cash flow volatility (Opler et al., 1999; Bates et al., 2009). When we only allow the cash flow volatility parameter to change over time, the model generates a third of the rise in cash holdings and two-thirds of the rise in sales growth volatility relative to the full model's response. When we allow both the selection parameters and the cash flow volatility parameters to change (while keeping all other variables at their baseline values), the model generates an increase of 102% in cash, closer to the increase in cash holdings of 160% in the data. This shows that a selection mechanism in conjunction with higher cash flow volatility goes a long way to quantitatively explain the secular trends in the data. In sum, our model and the empirical evidence suggests that a selection mechanism plays an important role for the rise in the US.

One noteworthy shortcoming of our model is that its firms deplete their cash holdings much faster compared to the data. This lowers its potential to fully match the rise in cash holdings. In other words, the negative within-firm effect is too strong in our model. We purposefully kept our model fairly simple and abstracted from many of the proposed mechanisms that would make firms deplete their cash holdings less aggressively such as agency conflicts, firm-level changes of cash flow uncertainty, firm-level changes in production techniques and capital types. We conclude by discussing how incorporating those features will likely strengthen the model's ability to quantitatively match the data.

Our paper relates to a large literature on the drivers of the increase in cash holdings among US publicly listed firms.[2] We are most closely related to the literature in dynamic corporate finance that quantifies corporate cash policies (e.g., Gamba and Triantis, 2008; Riddick and Whited, 2009; Anderson and Carverhill, 2012; Nikolov and Whited, 2014) as well as the secular increase in cash holdings (e.g., Falato et al., 2013; Gao, 2015; Zhao, 2020; Armenter and Hnatkovska, 2017; Chen et al., 2017). The firm's optimization problem in our model is based on Riddick and Whited (2009). Our stylized model provides one of the first dynamic corporate finance models that explicitly allows for the presence of various selection mechanisms and is qualitatively consistent with the stylized facts we show in Section 2.

In this paper, we argue that selection is a key driver for the secular increase in the cash-to-assets ratio. We are not the first to point out that newly listed firms in R&D-intensive industries appear to play a role.[3] Fama and French (2004) notes that the 1980s and 1990s experienced a surge in initial public offerings (IPOs) and showed that the new firms were markedly different from older firms. Bates et al. (2009) find that high-tech, nondividend payers, and recently listed firms have successively higher cash ratios, but they also find an increase in the nonhigh-tech sectors. Booth and Zhou (2013) present evidence that the increase in the average cash-to-assets ratio is due to changing firm characteristics of high-tech firms that went public after 1980. Graham and Leary (2018) also find that average cash holdings began to rise in about 1980 even though within-firm cash balances declined over this period. They also attribute the post-1980 rise in average cash balances to changes in sample composition due to new health and tech Nasdaq firms going public with large cash balances.[4] Dittmar and Duchin (2010) also show a robust negative within-firm trend for the cash-to-asset ratio among US publicly listed firms.

We contribute to this literature by quantifying the role of firm selection in explaining the secular upward trends in cash holdings and sales growth volatility among US publicly listed firms. Relative to the reduced-form approach of this prior literature, our estimated dynamic corporate finance model allows us to isolate the firm selection mechanism. In particular, we can distinguish sample composition effects from changes in expected profitability at entry. Our approach also lets us isolate the quantitative strength of changes in the cash flow volatility parameter for cash holdings, as proposed by Bates et al. (2009) and others. In our model, higher cash flow uncertainty alone accounts for 15% of the rise in cash holdings. Selection and a rise in cash flow uncertainty together can explain 64% of the upward trend in cash.

The paper is organized as follows. We first show motivational evidence about cash holdings of US firms in

[2] The literature on the determinants of cash holdings is extensive and ranges over many decades. A classic motive for holding cash is transaction costs (e.g., Baumol, 1952; Tobin, 1956; Miller and Orr, 1966; Vogel and Maddala, 1967). Other motives include taxes (e.g., Foley et al., 2007), precautionary savings (e.g., Froot et al., 1993; Kim et al., 1998), and agency costs (e.g., Jensen, 1986; Dittmar and Mahrt-Smith, 2007; Nikolov and Whited, 2014). Opler et al. (1999) provide an extensive test of these different motives. In the last decade, the secular increase in cash holdings has received much attention and spurred many explanations that are not based on sample selection, for example, a tax-based explanation by Foley et al. (2007) and Faulkender and Petersen (2012); a precautionary savings motive by Bates et al. (2009), McLean (2011), and Zhao (2020); operative changes by Falato et al. (2013) and Gao (2015); the cost of carrying cash (e.g., Azar et al., 2016; Curtis et al., 2017).

[3] Several papers find a positive relationship between cash and R&D expenditures (e.g., Opler and Titman, 1994; Opler et al., 1999; Brown and Petersen, 2011; Falato and Sim, 2014, He and Wintoki, 2016; Lyandres and Palazzo, 2016; Malamud and Zucchi, 2016 among many others).

[4] Seventy percent of the R&D-intensive entrants in our sample are listed on Nasdaq, while 20% are listed on the NYSE and the remainder on Amex.

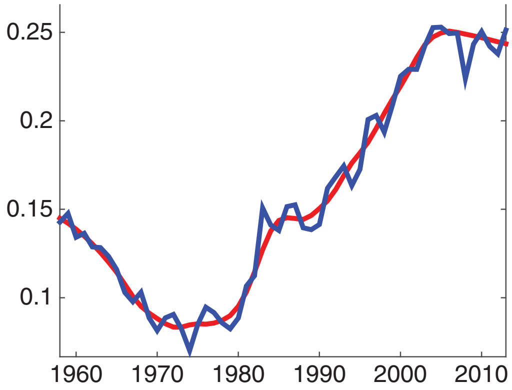

Fig. 1. Average cash-to-assets ratio of US-listed firms. This figure reports the average cash-to-assets ratio of US public companies over the period 1958-2013.

Section 2. Section 3 presents the model, and Section 4 discusses our estimation. In Section 5 we discuss how much of the secular trend in cash holdings our model replicates. Section 6 isolates the quantitative strength of the selection mechanism and contrasts it with several other potential mechanism. In Section 7, we discuss additional mechanisms that we could not directly quantify and conclude in Section 8.

2. Stylized facts about cash holdings of US public firms

In this section, we present stylized facts that inform our modeling choices and analysis. Over the period from 1979 until 2003, the average cash-to-asset ratio of US public firms increased. Fig. 1 shows the average cash-to-assets ratio for US public companies over the period from 1958 to 2013. As described by Bates et al. (2009), the secular increase began in 1979. The average cash-to-asset ratio increased from 8% in 1979 to 25% in 2013. In what follows, we show that this secular increase is the byproduct of R&D-intensive firms entering U.S. equity markets with progressively larger cash balances.[5]

2.1. Cohort effects and cash at entry

Fig. 2 shows the cash-to-asset ratio at IPO for different cohorts over time. Since the late 1970s, firms have gone public with higher and higher cash balances, suggesting a mechanism that centers around decisions at entry, such as how much capital and cash to choose.[6]

To investigate the importance of the entry margin on the average cash-to-asset ratio, we follow a similar approach as Brown and Kapadia (2007). Using firm-level data from Compustat, we estimate the following panel regression model:

[5] Our definition classifies firms as R&D-intensive firms when they operate in an industry where R&D expenditures are at least 2% of assets (see Online Appendix A.1). The stylized facts are robust to defining R&D intensity at the firm level.

[6] We show in Fig. B.4 in the online appendix that the increase in the cash-to-asset ratio occurs before firms go public.

Table 1
Estimating the entry cohort effect.

	Pooled OLS I	All firms II	Non-R&D-intensive III	R&D-intensive IV
t	0.415***	−0.000	−0.033*	0.017
	(0.019)	(0.019)	(0.019)	(0.032)
1959-1963		−1.521*	−0.931	−1.811
		(0.916)	(1.103)	(1.499)
1964-1968		−1.335	−0.322	−2.274
		(0.921)	(1.148)	(1.407)
1969-1973		−0.932	−1.130	0.705
		(0.840)	(0.952)	(1.473)
1979-1983		6.288***	2.445**	8.547***
		(0.980)	(1.113)	(1.519)
1984-1988		7.970***	1.263	13.711***
		(1.000)	(0.993)	(1.602)
1989-1993		10.739***	0.527	19.177***
		(1.053)	(1.004)	(1.608)
1994-1998		13.513***	2.183**	22.126***
		(1.043)	(1.074)	(1.560)
1999-2003		23.835***	7.186***	29.465***
		(1.299)	(1.562)	(1.705)
2004-2008		16.569***	2.678**	28.328***
		(1.513)	(1.326)	(2.222)
2008-2013		14.255***	3.667	22.919***
		(3.805)	(2.606)	(5.731)
Constant	11.678***	11.349***	10.270***	13.022***
	(0.342)	(0.719)	(0.817)	(1.210)
Observations	76,872	76,872	38,553	38,319
R-squared	0.031	0.108	0.016	0.163

We estimate the following baseline linear equation:

$$CH_{i,t} = \alpha + \beta t + \sum_{k \in \{K\}} \gamma_k \times I_{i \in k} + \varepsilon_{i,t}.$$

The dependent variable is the cash-to-assets ratio defined as Compustat item CHE divided by Compustat item AT and expressed in percentage terms. The sample includes Compustat firm-year observations from 1979-2013 with at least five years of observations and positive values for assets and sales, excluding financial firms (SIC codes 6000 to 6999) and utilities (SIC codes 4000 to 4999). Differently from the regression in Table 2, we exclude firms that entered Compustat before 1959. In column 1, we run pooled OLS regressions, and we normalize the year 1979 to zero. In column 2, we report the results with cohort fixed effects. In column 3, we report the results with cohort fixed effects only for the R&D-intensive sector, whereas in column 4, we report the results with cohort fixed effects only for the non-R&D-intensive sector. We report standard errors that are clustered at the firm level. * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level.

$$CH_{i,t} = \alpha + \beta t + \sum_{k \in \{K\}} \gamma_k \times I_{i \in k} + \varepsilon_{i,t},$$

where $CH_{i,t}$ is the cash-to-asset ratio of firm i at time t, β is the time trend coefficient, γ_k is a cohort fixed effect estimated for K cohorts, and $I_{i \in k}$ is an indicator function that is one when firm i is a member of cohort k and zero otherwise. Table 1 presents the results of this regression. In Column 1, we show results for a pooled ordinary least squares (OLS) regression without cohort fixed effects. The time trend β in the cash-to-asset ratio is economically large (0.415) and significant. The second column runs the model with cohort fixed effects. In contrast to the pooled model, the estimated time trend is zero and insignificant. Beginning with the 1979-1983 cohort, the estimated cohort fixed effects become significantly bigger, and their evolution mimics the evolution of the average cash holdings at

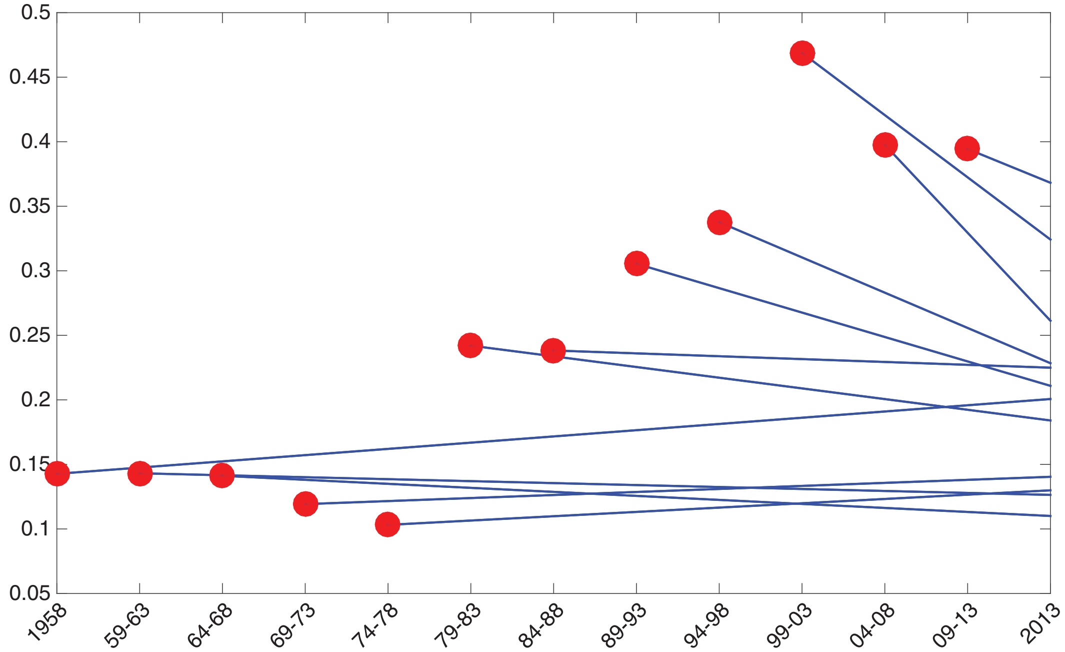

Fig. 2. Average cash holdings at entry (1959-2013). The figure reports the evolution of the cash-to-assets ratio around IPO for US public companies for 11 five-year cohorts over the period 1959-2013. The red dot denotes the average cash ratio at entry for each cohort. The first observation denotes the average cash holdings of incumbent firms in 1958. The straight line connects the initial average cash holdings to the average holding in 2013 for each cohort. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

entry depicted in Fig. 2. This suggests that the time trend in cash ratios of Compustat firms is due to a change at the entry margin.

In Columns 3 and 4, we separately estimate cohort fixed effects for R&D-intensive and non-R&D-intensive firms. In both cases, no significant differences exist in cohort fixed effects among the first four cohorts. For non-R&D–intensive firms (Column 3), only the 1999-2003 cohort has a significantly (at the 1% level) higher cash balance at entry compared to the 1974-1978 cohort.[7] From 1979 onwards, the cohort fixed effects for R&D-intensive firms (Column 4) are always significantly different from the excluded cohort (the intercept, i.e., the 1974-1978 cohort). In addition, starting with the 1984-1988 cohort and up to the 1999-2003, cohort the fixed effect becomes significantly larger (i.e., the difference in the fixed effect between two successive cohorts is positive and significantly different from zero). The magnitude of the cohort fixed effects is always much higher relative to non-R&D-intensive firms, furthering the evidence of a minor role played by this sector in determining the secular increase in cash holdings.

[7] During the first half of the 2000s, two events had a significant impact on corporate cash holdings: the Sarbanes-Oxley Act and the 2003 dividend tax cut. Bargeron et al. (2010) show a significant increase in cash holdings following the introduction of the Sarbanes-Oxley Act. Officer (2011) shows a large increase in cash holdings in anticipation of the dividend tax cut.

2.2. Negative within-firm time trend of the cash-to-asset ratio

The previous section presented evidence for a positive trend in cash ratios at entry. This section studies the firm-level (within-firm) trend of the cash-to-asset ratio. Fig. 2 shows that at the time of IPO, firms have higher cash balances than during later stages. This implies that the cash-to-asset ratio decreases over time at the firm level.

To show this, we first estimate the time trend in the cash-to-assets ratio using all firms over the period 1979-2013. The resulting trend is positive: cash holdings represented around 11% of total assets for the typical firm in 1979, and they have increased by 14 percentage points over the subsequent 35 years (Column 1 of Table 2). Column 2 of Table 2 shows the differences in the time trend across sectors by including a dummy variable that takes a value of zero if a firm is non-R&D-intensive and one otherwise. The estimated slope for the R&D sector is one order of magnitude larger than the estimated slope for the non-R&D sector (66 b.p. versus. 6 b.p.). The implied increase in cash holdings for the non-R&D sector over the 35-year period is very small (around 2%), while cash holdings in the R&D sector surged from an average value of 14% in 1979 to an average value of 35% in 2013. The secular increase in the cash-to-assets ratio appears to be a phenomenon that pertains almost exclusively to the R&D-intensive sector.

Pooled OLS regressions allow us to identify R&D-intensive firms as the driver of the secular increase in cash holdings. However, the cash-to-assets ratio is fairly persistent (see Lemmon et al., 2008), and pooled OLS regressions are not conclusive with regard to each firm's individual

Table 2
Estimating the time trend.

	Pooled OLS		Firm-by-firm							
	All I	All II	All III	All IV	Young V	Young VI	Mature VII	Mature VIII	Old IX	Old X
Trend	0.418*** 0.007	0.055*** 0.006	−0.497*** 0.034	−0.267*** 0.048	−0.461*** 0.037	−0.239*** 0.053	−0.226*** 0.026	−0.115*** 0.037	0.005 0.239	0.001 0.033
Trend X R&D		0.605*** 0.013		−0.463*** 0.068		−0.447*** 0.075		−0.224*** 0.052		0.007 0.048
R&D dummy		4.579*** 0.253		20.711*** 0.587		20.760*** 0.642		0.180*** 0.000		11.100*** 0.910
Constant	10.661*** 0.123	9.371*** 0.122	21.920*** 0.325	11.640*** 0.413	21.581*** 0.350	11.276*** 0.453	20.234*** 0.387	11.446*** 0.505	14.648*** 0.474	9.510*** 0.619
Observations	85,947	85,947	(5,496; 16)		(5,496; 5)		(3,614; 9)		(1607; 13)	
Adjusted R^2	0.035	0.185	0.295		0.418		0.312		0.291	

We estimate the following baseline linear equation:

$$CH_{i,t} = \alpha + \beta t + \varepsilon_{i,t}.$$

The dependent variable is the cash-to-assets ratio defined as Compustat item CHE divided by Compustat item AT and expressed in percentage terms. The sample includes Compustat firm-year observations from 1979-2013 with at least five years of observations and positive values for assets and sales, excluding financial firms (SIC codes 6000 to 6999) and utilities (SIC codes 4000 to 4999). We also sort firms into R&D- versus non-R&D-intensive, as discussed in Section 2.3. In columns 1 and 2, we run pooled OLS regressions and we normalize the year 1979 to zero. In columns 3-10, we run a linear regression for each firm in our sample and set the time variable equal to zero the first year the firm appears in the sample. Young firms are firms that have been public for at most 5 years, mature firms are firms that have been public for more than 5 years but less than 16 years, and old firms are firms that have been public for at least 16 years. For the firm-by-firm regressions, we report the number of individual firms in the sample together with the average number of observations for each firm. The reported R^2 for the firm-by-firm regressions is the average R^2 across all the regressions. We report robust standard errors. * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level.

cash-to-assets evolution. In fact, incumbent R&D-intensive firms could have indeed increased their cash-to-assets ratios over time. To address the persistence issue, we perform firm- by-firm regressions and report average values of the estimated coefficients. We set the time variable equal to zero the first year the firm appears in the sample. In this way, we control for the cash holdings at entry at the firm level. The results show a negative change in average cash holdings for incumbents. The estimated yearly within-firm change in average cash holdings over 35 years is -50 b.p. (Column 3). Column 4 shows that R&D-intensive firms start with much larger cash balances and deplete cash faster than non-R&D-intensive firms.[8]

The data show that a positive time trend in average cash holdings exists despite a negative time trend within firms. This feature is a result of newly listed firms increasing their cash holdings at entry faster than the rate at which incumbents deplete theirs.

2.3. The importance of R&D-intensive firms for the secular trend in cash

Decomposing firms into sectors shows that in fact only R&D-intensive firms increased their cash holdings over this time (see Fig. 3). Before 1979, R&D-intensive firms and all other firms had very similar cash-to-asset ratios. During that time, non-R&D-intensive firms dominated the sample of public firms. After 1979, their dominance quickly waned such that by 2013, over 55% of all firms in Compustat operated in the R&D-intensive sector (see left panel of Fig. 4). IPOs from R&D-intensive firms grew from 35% to 65% over the same period. Interestingly, new cohorts of R&D-intensive firms went public with more and more cash on their balance sheets (relative to assets) than the preceding cohorts (see right panel of Fig. 4). There is no such increase in the cash-to-asset ratio at entry of non-R&D-intensive firms. This sectoral difference in the cash-to-asset ratio trend suggests a sector specific mechanism as opposed to one that relies on an economy-wide change in the environment of firms.

We directly measure the contribution of sample selection to the secular increase in average cash holdings. Using a simple accounting decomposition, we find selection that contributes by more than 200%, whereas the within-firm change in cash holdings contributes a negative 117%.

The accounting decomposition allows us to isolate the part of the change in the average cash-to-assets ratio coming from changes within incumbent firms from changes due to new firms (entrants). The change in the average cash-to-assets ratio ΔCH_t between time $t-1$ and t can be written as

$$\Delta CH_t = \underbrace{\left(\frac{N_t^I}{N_t} CH_t^I - \frac{N_t^I}{N_{t-1}} CH_{t-1}^I\right)}_{\text{within change}} + \underbrace{\left(\frac{N_t^E}{N_t} CH_t^E - \frac{N_{t-1}^X}{N_{t-1}} CH_{t-1}^X\right)}_{\text{selection effect}},$$

where the first term is the change in average cash holdings due to incumbents (within change), and the second term is the change in average cash holdings due to the se-

[8] We also show (Columns 5-8) that (i) both young and mature firms witness a reduction in the cash-to-asset ratio after an IPO, (ii) young firms display a faster reduction than mature firms, and (iii) the estimated slope for R&D-intensive firms is much larger than the one for non-R&D-intensive firms. No significant time trend in cash holdings exists for old firms (see Columns 9 and 10) regardless of the sector.

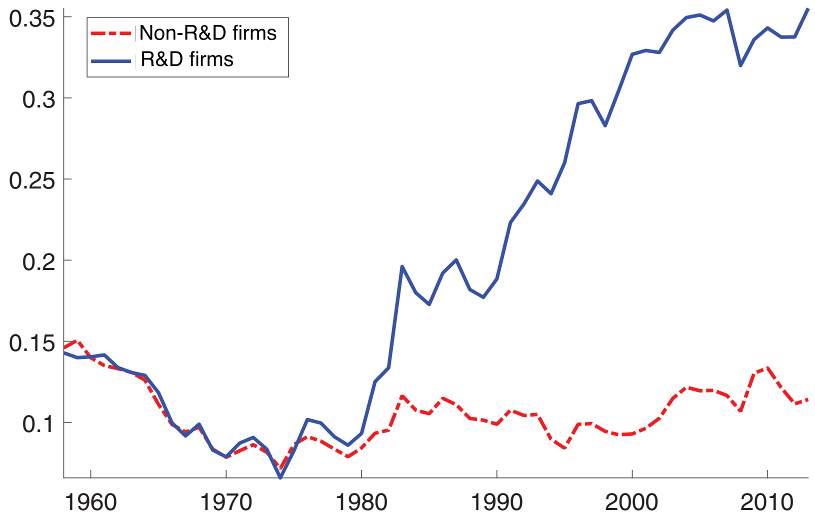

Fig. 3. Average cash-to-assets ratio of US listed firms by sector. This figure reports the average cash-to-assets ratio of R&D-intensive and non-R&D-intensive firms over the period 1958-2013. An R&D-intensive firm belongs to an industry (three-level digit SIC code) whose average R&D investment amounts to at least 2% of assets over the sample period.

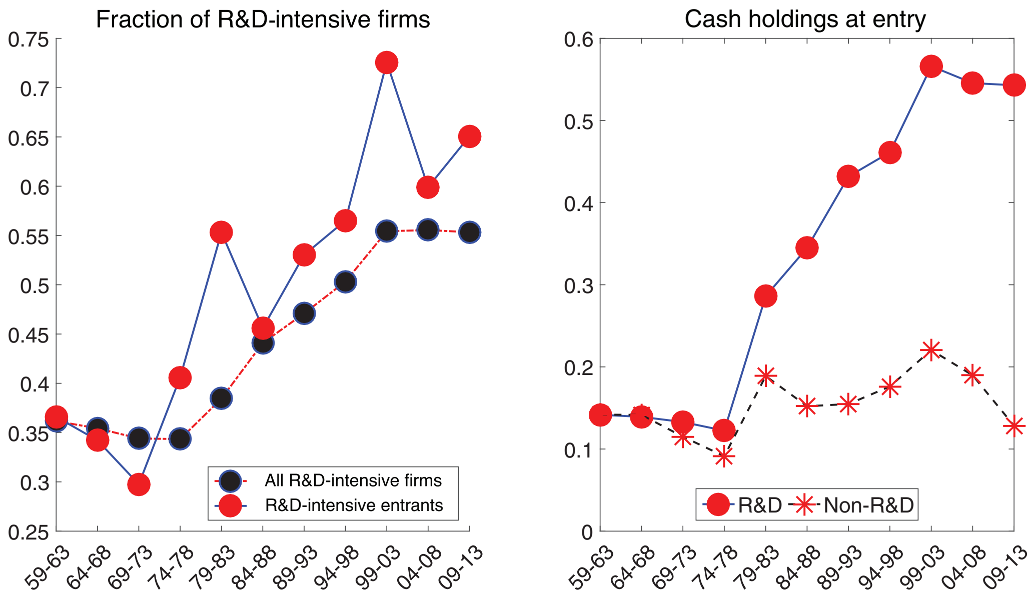

Fig. 4. Industry composition of US public firms (1959-2013). The left panel of this figure presents the share of R&D-intensive firms in Compustat (in darker color with a dashed line) and the share of R&D-intensive entrants (in red with a solid line). The right panel shows the average cash-to-assets ratio at entry of R&D-intensive and non-R&D-intensive firms. An R&D-intensive firm belongs to an industry (three-level digit SIC code) whose average R&D investment amounts to at least 2% of assets over the sample period. We group firms into cohorts of five years starting from 1959. We define as entrant a firms that reports a year-end value of the stock price for the first time (item *PRCC_C*). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

lection effect. N^j denotes the number of incumbents ($j = I$), entrants ($j = E$), and exitors ($j = X$).[9]

The selection effect can be further split between the selection effect generated by R&D-intensive firms and the selection effect generated by non-R&D-intensive

[9] More precisely, consider the change in average cash holdings between time t and time $t-1$: $\Delta CH_t = CH_t - CH_{t-1}$. Let N_t^I be the firms publicly traded between time $t-1$ and t (the incumbents), and let N_{t-1}^X be the firms that exit between time $t-1$ and t. Then the average cash holdings at time $t-1$ are $\frac{N_t^I}{N_{t-1}} CH_{t-1}^I + \frac{N_{t-1}^X}{N_{t-1}} CH_{t-1}^X$, where $N_{t-1} = N_t^I + N_{t-1}^X$, CH_{t-1}^I is the average cash holdings of incumbents at time $t-1$ and CH_{t-1}^X is the average cash holdings at time $t-1$ of firms that exit between time $t-1$ and t. Let N_t^E be the firms that enter into Compustat at time t. Then the average cash holdings at time t are $\frac{N_t^I}{N_t} CH_t^I + \frac{N_t^E}{N_t} CH_t^E$, where $N_t = N_t^I + N_t^E$, CH_t^I is the average cash holdings of incumbents at time t and CH_t^E is the average cash holdings at time t of firms that enter at time t.

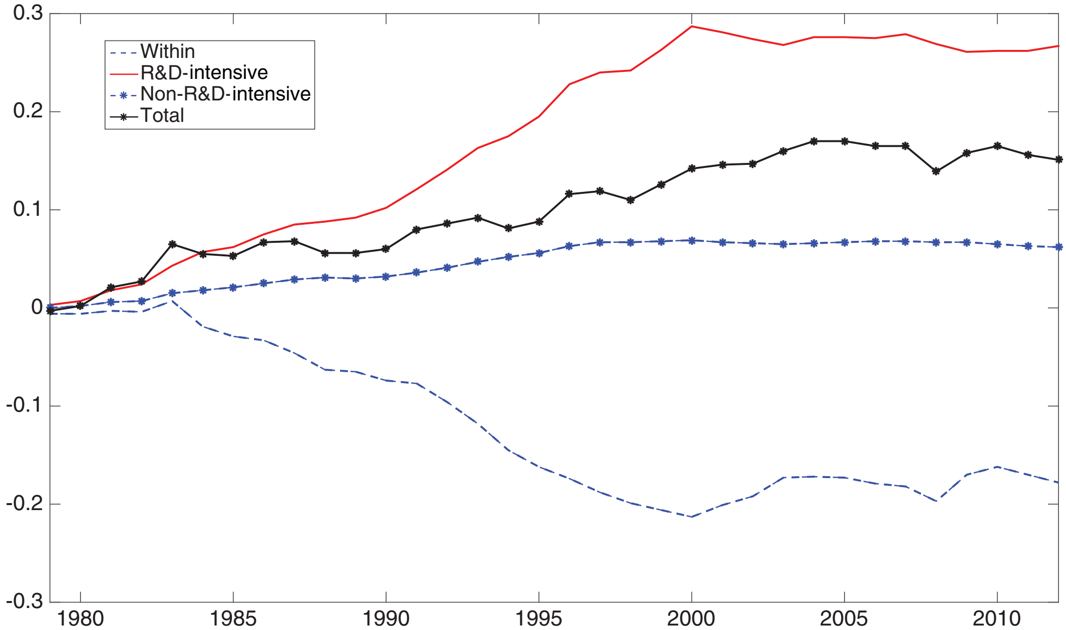

Fig. 5. Cash change decomposition. This figure reports the cumulative change in average cash holdings over the sample period together with its three components: the cumulative change due to incumbents (labeled "within"), the cumulative change due to R&D-intensive entrants, and the cumulative change due to non-R&D-intensive entrants.

firms:

$$\Delta CH_t = \left(\frac{N_t^I}{N_t}CH_t^I - \frac{N_t^I}{N_{t-1}}CH_{t-1}^I\right) + \sum_{i=\{R\&D;nonR\&D\}}\left(\frac{N_t^{E_i}}{N_t}CH_t^{E_i} - \frac{N_{t-1}^{X_i}}{N_{t-1}}CH_{t-1}^{X_i}\right).$$

In Fig. 5, we plot the cumulative change in average cash holdings over time, whereas Table B.1 in the online appendix reports the quantities.[10] The selection effect due to R&D-intensive entrants accounts for more than 200% of the secular increase in cash holdings, whereas the contribution of non-R&D-intensive entrants is less than 40%, and the within change contributes a -117% to the secular increase in cash holdings. This result not only reemphasizes the importance of a selection mechanism but also shows that most of the selection mechanism is driven by R&D-intensive firms.

3. Model

The empirical analysis highlights three main stylized facts. First, the secular increase in cash holdings among US public firms is driven by firms going public with progressively higher cash balances over time. Second, once public, firms experience a decrease in their cash-to-asset ratio. Third, when we decompose the change in average cash holdings into a within-firm effect and a selection effect, we find that most of the change in cash holdings is due to a selection effect almost entirely driven by R&D-intensive firms. In this section, we develop a heterogeneous firm model to illustrate how these three stylized facts naturally arise when we allow for changes in the firm selection process in an otherwise standard neoclassical investment setup. We keep the model purposefully simple to focus on a few drivers: standard neoclassical investment dynamics and selection.

To this end, we augment the setup in Riddick and Whited (2009) to allow for the entry of firms with progressively higher cash balances. Specifically, we assume that a constant fraction of firms exits exogenously each period and exitors are replaced by an identical mass of new entrants in the stock market. These new entrants are heterogeneous in their profitability and choose, upon entry, an initial amount of cash to keep as a buffer and an initial capital stock.

To replicate the stark sectoral difference in the secular increase in cash holdings shown in Fig. 3, we assume firms belong to one of two sectors labeled as the industry 0 and industry 1. In both sectors, firms use a decreasing returns-to-scale technology with capital as the only input. Firms can finance themselves with equity or with internal funds. We estimate the model at the industry-cohort level and use it as a laboratory to understand the importance of firm selection in shaping the secular increase in cash holdings by performing a battery of counterfactual exercises.

3.1. Incumbent problem

This section presents the incumbent problem that is identical across both sectors and cohorts of firms.

[10] In Online Appendix B, we show that our results are robust to value-weighted cash ratios. Defining entry based on the IPO dates are provided by Jay Ritter (http://bear.warrington.ufl.edu/ritter/ipodata.htm) delivers similar results.

Technology. Firms produce using the decreasing returns-to-scale production function $y_t = pe^{z_{t+1}k_t^{\alpha}}$, where p is a scale parameter and z_{t+1} is the firm-level revenue total factor productivity (TFPR) that evolves according to

$$z_{t+1} = \rho z_t + \sigma\epsilon_{t+1},$$

where $\rho \in (0, 1)$, $\sigma > 0$, and $\epsilon_{t+1} \sim N(0, 1)$ is identically and independently distributed over time and across firms. In what follows, we will use the terms TFPR and productivity interchangeably. The law of motion for the capital stock is $k_{t+1} = (1-\delta)k_t + x_t$, where δ is the depreciation rate and x_t is the capital investment at time t that entails an adjustment cost equal to

$$\phi(k_{t+1}, k_t) = \eta\left(\frac{k_{t+1} - (1-\delta)k_t}{k_t}\right)^2 k_t.$$

Financing. Firms can finance their operations internally by transferring cash from one period to the next at an accumulation rate $1 + \widehat{r}$ lower than the (gross) risk-free rate $1 + r$. In particular, we assume $\widehat{r} = \nu r$, where $\nu \in (0, 1)$. Firms can also raise external resources by issuing equity. Equity financing is costly: raising equity (i.e., having a negative dividend $d_t < 0$) requires the payment of $H(d_t)$, where $H(d_t) = -f_e - \kappa|d_t|$.

Incumbent's problem. The incumbent firm can use the total resources available to distribute dividends (d_t), invest in capital (x_{t+1}), and pay the adjustment cost ($\phi(k_{t+1}, k_t)$) or to accumulate cash internally $\left(c_{t+1}/\widehat{R}\right)$. If the initial net worth w_t is not enough to cover the firm's investment and financing needs, it issues equity (i.e., d_t is negative) and pays an equity issuance cost equal to $f_e + \kappa d_t$. In what follows, $\mathbf{1}_{[d_t \le 0]}$ is an indicator function that takes the value of one only if the firm needs to issue equity at time t. Choosing cash holdings (c_{t+1}) and investment (x_{t+1}) determines the next-period net worth (w_{t+1}). Each period, the firm faces an exogenous exit probability, λ.[11] Upon exit, the firm recovers its net worth (w_{t+1}). and depreciated capital stock ($(1-\delta)k_{t+1}$).

Let $V_t = V(k_t, c_{t,} z_t)$ be the value of the firm, and then the time t value of an incumbent firm solves the functional equation below:

$$V_t \equiv \max_{c_{t+1 \ge 0}, x_{t+1}} d_t + H(d_t)\mathbf{1}_{[d_t \le 0]} + \frac{1-\lambda}{R}E_t[V_{t+1}] + \frac{\lambda}{R}E_t[w_{t+1} + (1-\delta)k_{t+1}], \tag{1}$$

subject to the law of motion for firm-level TFPR and

$$d_t = w_t - \frac{c_{t+1}}{\widehat{R}} - x_{t+1} - \phi(k_{t+1}, k_t), \tag{2}$$

$$k_{t+1} = (1-\delta_j)k_t + x_{t+1}, \tag{3}$$

$$w_{t+1} = pe^{z_{t+1}}k_{t+1}^{\alpha} + c_{t+1}. \tag{4}$$

Eq. 2 is the firm's budget constraint, Eq. 3 is the law of motion for the capital stock, and Eq. 4 shows what determines the firm's net worth next period.

3.2. Entry

Every period, a constant fraction of firms λ exogenously exits the economy. The mass of exiting firms is replaced by an identical mass of heterogeneous entrants. While the decision to enter is itself not endogenous, firms can choose their initial capital stock and cash holdings at entry. Specifically, following Clementi and Palazzo (2016), we introduce heterogeneity in firms at entry assuming that each potential entrant receives a signal q about its future productivity. This signal follows a Pareto distribution $q \sim Q(q)$ over the interval $[\underline{q}, +\infty]$, whose shape is governed by the parameter ξ. Conditional on q, an entrant chooses capital and cash balances to maximize the value function below

$$V^E(q_t) = \max_{c_{t+1}, k_{t+1}} \left\{-k_{t+1} - \frac{c_{t+1}}{\widehat{R}} + \frac{1}{R}E[V(k_{t+1}, c_{t+1}, z_{t+1})|q_t]\right\}, \tag{5}$$

where the next-period idiosyncratic shock depends on q in the following fashion: $z_{t+1} = \rho \log q_t + \sigma\epsilon_{t+1}$.[12]

3.3. Model implications for cash holdings

In our setup, a firm's investment and financing policies are the result of a standard firm-optimization model. That is, given the parameters, both entrants and incumbents maximize firm value by choosing cash balances and capital stock.

The implied optimal cash retention policy for the incumbent firm is standard (e.g. Riddick and Whited, 2009). Large incumbent firms are characterized by high productivity and large installed capital. These firms have a low precautionary savings motive because, in expectation, they can generate large cash flows and have low investment needs. Given the mean-reverting nature of the firm-level productivity process, these firms expect to disinvest in the near future, so the benefit of holding cash is very low. Conversely, small firms, given their low productivity and low installed capital, tend to keep large cash balances relative to their capital. These firms expect to grow fast in the near future, and the benefit of holding cash is large given the high probability of financing investment with costly external equity.

[11] This assumption is innocuous in the context of our exercise. Fig. B.3 in the online appendix shows the average cash holdings for exiting firms is very close to the average cash holdings of incumbent firms. This feature of the data can be replicated by an i.i.d. exit process. In the data as well as in the model, we allow exit to be defined in a broader sense that includes firms disappearing from the data or the model due to acquisitions and mergers, bankruptcy, or going private.

[12] Two things are worth noting. First, ours is not an industry equilibrium model since the mass of entrants and exitors is not pinned down by an equilibrium condition. Second, our entry mechanism is not a model of the going-public decision problem. Our mechanism conveniently allows for the replacement of exiting firms with an equal mass of firms that differ in their initial productivity, capital stock, and cash balances. However, the selection mechanism that drive our results will also operate in a more realistic setup along the lines of Clementi (2002).

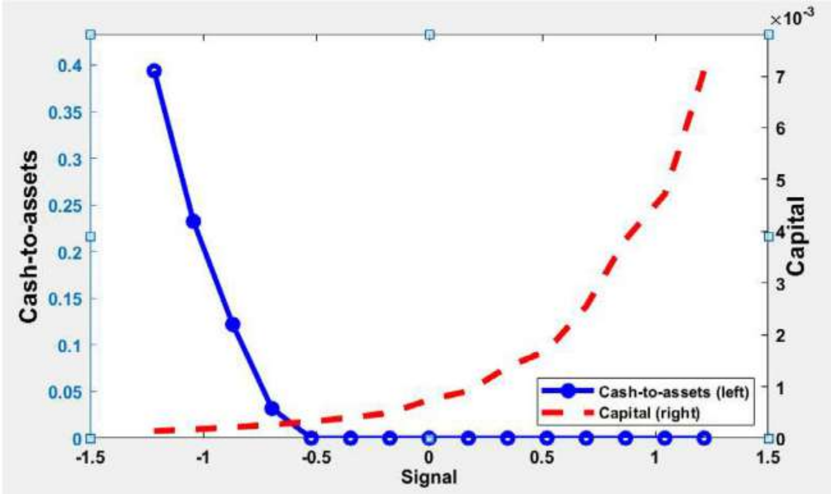

Fig. 6. Entry margin This figure reports the optimal cash-to-assets ratio (solid blue lien, left) and capital (dashed red line, right) at entry as a function of the (log) quality signal. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

A similar argument can be made for entering firms. When an entrant receives a large signal q, it decides to invest a lot in productive capital and to carry no cash balances, given that going forward this firm expects low growth and large cash flows. Conversely, when an entrant receives a low signal q, it expects to grow in the near future and decides to carry some cash to minimize the cost of future external financing. Everything else being equal, the lower the signal and the higher the precautionary saving motive at entry, the higher cash balance relative to capital. This mechanism, depicted in Fig. 6, makes clear that initial firm-level TFPR is a key dimension that influences the average cash holdings for entering firms.

The entry margin alone has the qualitative ability to generate a secular increase in cash together with a negative within-firm trend. For this to be the case, it is sufficient that entering firms have a progressively lower average signal. In what follows, we quantify the contribution of a choice of cash at entry and compare it to other channels that might also have contributed to the secular increase in cash holdings.

4. Model estimation

In this section, we estimate the model's parameters. For each industry and cohort, we estimate key parameters governing the production process, financing costs, and firm selection process. To identify the parameters of interest, we include a large set of moments based on quantities that we can reasonably calculate with our model. Since the empirical evidence highlights the importance of cohort and industry effects, we conduct our estimation at the cohort and industry level. We estimate our model on data from Compustat from 1974 to 2003. We choose 2003 as an ending point, because the rise in average cash holdings leveled off in 2003, as shown in Fig. 1. We first discuss our estimation and identification strategy. Then we present the estimation results.

4.1. Estimation strategy

Our stylized economy depends on 13 parameters of which we estimate 8 and take the remaining 5 from other studies. Specifically, we estimate 8 parameters for a baseline cohort and 7 parameters for 5 additional cohorts across two different industries. Thus, effectively, we estimate a total of 78 structural parameters and take 5 from other studies.

Following Riddick and Whited (2009), we set the depreciation rate δ equal to 0.15 and the interest rate r equal to 4%. We choose a proportional equity issuance cost κ equal to 0.07. This value is less conservative than 0.053, the value used by Riddick and Whited (2009), but well within the range of estimates by Hennessy and Whited (2007). The scaling parameter p pins down the average firm size, and we set it to 0.07.[13] The last parameter that we do not estimate is the exit rate λ. We choose a value of 8% to generate an age and industry distributions close to the ones observed in our sample over the period 1979–2003.[14]

We use SMM to estimate eight structural parameters:

- The returns-to-scale parameter α, the convex adjustment cost parameter η, the persistence of the TFPR pro-

[13] In the case without frictions, the optimal capital choice is pinned down by the following Euler equation: $r+\delta = p\alpha k_{t+1}^{\alpha-1} e^{\rho z_t + 0.5\sigma^2}$. For given values of r, δ, ρ, and σ, the optimal capital stock depends on the current productivity shock and the scale parameter. If we want the optimal capital to be 1 for a particular value of z_t, then the scale parameter must satisfy $p = \frac{r+\delta}{\alpha e^{\rho z_t + 0.5\sigma^2}}$. We choose $p = 0.07$ so that the optimal capital is approximately 1 when $r = 0.04,\ \delta = 0.15,\ \rho = 0.7,\ \sigma = 0.12,\ \alpha = 0.66$, and the productivity shock is fairly large ($z_t = 2$).

[14] Age is the year from entry in the model and year from IPO in the data. An exit rate of 8% delivers the following age distribution in the model: 34% of firms are below age 6; 22% of firms between 6 and 10; 15% of firms between 11 and 15; 10% of firms between 16 and 20; and 19% of firms larger than 20. For the same age bins, our data generate the following percentages over the period 1979-2003: 31%, 19%, 13%, 10%, and 27%. The model-implied industry distribution is discussed in Section 5.

cess ρ and its volatility σ. These parameters govern production technology.

- The financing cost parameters ν and f_e, which determine the cost of accumulating cash and the fixed equity issuance cost, respectively.
- The lower bound and the shape parameter of the Pareto distribution, $\underline{q}$ and ξ, which drive the selection of average productivity at entry.

We follow a standard SMM estimation procedure (see, e.g., Warusawitharana and Whited, 2015) by estimating the parameters at the cohort level. That is, we first estimate a baseline case using a balanced cohort of firms that went public during the period 1974-1978 and survived at least ten years. Then, given the heterogeneity across industries and cohorts shown in the empirical section, we estimate the parameters using a balanced panel of firms that survived at least ten years across two industries and for each of the following five cohorts of entrants: 1979-1983, 1984-1988, 1989-1993, 1994-1998, and 1999-2003. For the industry-cohort estimation, we do not directly estimate the shape of the Pareto distribution ξ. We assume that this value does not change across industries and cohorts and it is equal to the estimated value using entrants over the period 1974-1978. The details of the estimation strategy are discussed in Online Appendix C.

4.2. Identification Strategy

Naturally, the quality of the estimation procedure hinges on choosing moments that are informative about the structural parameters we estimate. Since we do not want to tilt our estimation results toward any specific outcome, we choose as many moments as we can reasonably calculate with our model. Our moments are based on the cash-to-asset ratio, sales growth, investment-to-asset ratio, and the equity-to-asset ratio. We calculate the moments at the industry and cohort level. That is, for each industry (R&D-intensive and non-R&D-intensive) and cohort (baseline, 1979-1983, 1984-1988, 1989-1993, 1994-1998, and 1999-2003), we define an industry-cohort as a balanced panel of firms of length ten years that went public during the cohort window and belong to one of the industries. Online Appendix A.2 contains more details.

To capture the documented dynamics of the cash-to-asset ratio both in the cross-section (i.e., secular increase) and within the firm (i.e., negative average trend), we calculate moments both at the time of entry into the sample and at age ten, when a firm has matured. We choose more moments than needed to identify the parameters. Therefore, our model is overidentified and bound to fail in matching some dimensions of the data. The details of our identification strategy are as follows.

The following four moments help us identify the four production technology parameters: the average change in the sales growth rate, the average firm-level sales growth volatility, the average firm-level sales growth autocorrelation, and the average firm-level investment-to-asset ratio volatility. The average firm-level sales growth volatility and autocorrelation are directly informative about the autocorrelation (ρ) and volatility (σ) of the idiosyncratic productivity shock process. The autocorrelation pins down the degree of comovement of firm-level sales growth rates across periods. If ρ is close to zero, i.e., there is no persistence in the productivity process, the sales growth rate reverts quickly to its long-run average. If ρ is close to one, i.e., the productivity process is highly persistent, a mature firm's sales growth rate is close to its sales growth rate ten years ago. Since we pinned down the optimal scale of the firm via the scale parameter p, the production curvature (i.e., returns-to-scale) parameter α governs the change in the marginal productivity of a firm over its lifetime. For $\alpha < 1$, the marginal productivity declines over the firm's lifetime when its capital stock grows, meaning that the within-firm change in the sales growth rate is informative for identifying α. Last, we use the investment rate volatility to identify the adjustment cost parameter η. Intuitively, firms with higher adjustment costs adjust their investments less in response to productivity shocks (i.e., they have a lower investment rate volatility).

We include the average size of equity issuances and the average cash-to-asset ratio at entry to identify the two financing cost parameters: the fixed equity issuance cost f_e and the cost of carrying cash ν. Higher values for these parameters depress the amount of equity or internal financing.

The distribution of productivity at entry is important for pinning down firms' sales growth rates. Because of decreasing returns to scale in production, smaller firms have more volatile growth rates and, conditional on survival, grow faster. In our setup, the initial firm size distribution (i.e., the distribution of firms over the productivity space) depends on $\underline{q}$ and ξ, the parameters governing the Pareto distribution.[15] A larger average expected signal (i.e., higher $\underline{q}$ or lower ξ) causes our model to generate a lower average growth rate in sales, while a larger signal dispersion (i.e., higher $\underline{q}$ or lower ξ) causes a larger dispersion in sales growth rates among entrants. For this reason, we use the average and volatility of the sales growth at entry to identify $\underline{q}$ and ξ.[16]

We also include five additional moments. To study how well the model replicates firms' investment rates both at entry and ten years after, we include the average investment rate at entry and the within-firm change in this variable over ten years. To explore the model's ability in delivering a negative within-firm trend in cash holdings, we include the within-firm change in the cash-to-asset ratio during the first ten years after entry. In addition, we also assess the model's ability to replicate the observed patterns in the volatility and autocorrelation of cash holdings.

4.3. Baseline cohort estimation

Panel A of Table 3 compares the model-generated moments with their empirical counterparts, while Panel B

[15] The average signal is given by $\frac{\underline{q}\xi}{\xi-1}$, while the signal's variance is given by $\frac{\underline{q}^2\xi}{(\xi-1)^2(\xi-2)}$.

[16] We calculate real sales growth by netting out nominal GDP growth from nominal sales growth. In this way we remove the effect of inflation and aggregate economic growth, two forces not present in our stationary setup.

Table 3
Simulated moments estimation: baseline cohort.

Panel A: Moments

Moments	Data	Model	$t-stat$
	N=532		
Average cash holdings at entry	0.118	0.110	1.486
Average change in cash holdings	−0.018	−0.061	7.264
Volatility cash holdings	0.057	0.053	2.093
Autocorrelation cash holdings	0.276	0.282	−0.368
Average issue size at year 10	0.022	0.022	−0.067
Mean sales growth at 2	0.152	0.167	−1.152
Volatility sales growth at entry	0.086	0.054	3.426
Average change in sales growth	−0.136	−0.141	0.292
Volatility sales growth	0.191	0.175	2.941
Autocorrelation sales growth	0.053	−0.002	3.530
Average investment rate at entry	0.108	0.082	4.003
Average change in investment rate	−0.050	−0.056	0.746
Volatility investment rate	0.088	0.104	−5.972

Panel B: Parameter estimates

Parameter	Point estimate	S.E.
σ	0.156	0.002
ρ	0.649	0.009
α	0.694	0.011
η	0.092	0.009
ξ	11.804	14.640
$\log(\underline{q})$	−0.774	0.156
ν	0.851	0.034
f_e	0.093	0.057

This table reports the simulated and actual moments (Panel A) together with the estimated structural parameters (Panel B) using a balanced panel of firms belonging to the 1974-1978 cohort. The balanced panel is composed of all the firms that entered our sample of publicly listed firms during the period 1974-1978 and have ten consecutive years of observations on total assets (Compustat item *at*); revenues (item *sale*); cash (item *che*); net property, plant, and equipment (item *ppent*); common shares outstanding (item *csho*); sale of common and preferred stock (item *sstk*); and market price at the calendar year end (item *prcc_c*). In Panel A, we also report the number of firms in the sample (N) and the t-statistics for the difference between model-generated and actual moments. The estimated parameters in Panel B are the following: the volatility (σ) and persistence (ρ) of the TFPR process; the returns-to-scale parameter α; the convex adjustment cost parameter η; the shape parameter (ξ) and the lower bound ($\underline{q}$) of the Pareto distribution; the internal accumulation wedge ν; and the fixed equity issuance cost and f_e. For each estimated parameter, we report the associated standard error, whose calculation is described in Online Appendix C.2.

tabulates the parameter estimates. Overall, the model does a pretty good job in reproducing the moments in the data. In addition, 6 out of 13 moments are also statistically indistinguishable from their data counterparts (i.e., the average cash-to-asset at entry, the cash holdings autocorrelation, the average equity issue size for mature firms, the average sales growth rate for entering firms, the average within-firm change in sales growth rate, and the average within-firm change in the investment-to-asset ratio). Although statistically distinguishable, the model delivers magnitudes of the cash-to-asset ratio volatility, investment rate volatility, sales growth volatility, and investment-to-asset ratio at entry that are very close to the data. For instance, the sales growth volatility is 0.191 in the data and 0.175 in the model.

The model struggles along two dimensions. It generates a much faster decline in cash holdings over the lifetime of a firm compared to the data. While both the data and the model have similar average cash holdings at entry, the decline in this quantity is much faster in the model. The average cash-to-asset ratio in the data is only 0.02 lower after ten years, while in the model it falls from 0.11 at entry to an average value of 0.05 after ten years (an average negative change of 0.06). In addition, the model fails to generate the small positive autocorrelation in firms' sales growth rate. In our sample, the average firm has a sales growth rate autocorrelation of 0.05 (calculated using the first ten years after an IPO), while in the model the autocorrelation is zero. These two shortcomings of the model permeate also to the industry-cohort estimation as discussed in Section 4.4.

We list the parameter estimates in Panel B of Table 3. All parameters are statistically significant except for the parameter governing the shape of the Pareto distribution (more on this below). The estimated parameters for the production technology process driving the firm-level TFPR are in line with estimates from previous studies. For example, Hennessy and Whited (2007) estimate a value of 0.684 for the persistence parameter, a value of 0.118 for the conditional volatility parameter, and a value of 0.627 for the curvature of the production function. Our estimates for these parameters are 0.649, 0.156, and 0.694, respectively. The convex adjustment cost η is not directly comparable across studies given its dependence on the scale of the economy. In our estimation, this parameter is positive and precisely estimated.

The estimated parameters for the Pareto distribution imply an average productivity signal value of $(\frac{\xi}{\xi-1})\underline{q} = 0.504$, a value well below 1, the unconditional mean of e^z. A significant estimate for the average productivity at entry highlights that the distribution of firms at entry matters for the success of our model in replicating important dimensions of the data. Note that the Pareto shape parameter estimate is not significant. This is also true if we had estimated this parameter at the industry-cohort level. For this reason, we choose not to estimate this parameter for each industry-cohort separately but instead use the imprecisely estimated baseline value of 11.804 for all cohorts and industries.[17]

The estimated value for the cost of carrying cash ν is 0.851. This means that cash carried on the firm's balance sheet delivers a return of 3.4% instead of 4% the risk-free rate. A wedge of 0.851 is consistent with values used in other studies. For example, in Hennessy and Whited (2005) the wedge implied by the average realized corporate tax rate (30%) and the tax rate on interest income (25%) is $\frac{(1-\tau_c)}{(1-\tau_i)} = \frac{1-0.30}{1-0.25} = 0.933$, while in Hennessy and Whited (2005) the wedge implied by the maximum corporate tax rate (40%) and the tax rate on

[17] Because of linearity, a 10% increase in $\underline{q}$ from its estimated value causes the average signal to increase by 10%, while a 10% increase in ξ from its estimated value causes the average signal value to increase by a meager 0.8%. So changes in $\underline{q}$ have a large impact on expected value of the idiosyncratic shock at entry, given the expected productivity at entry is $\rho \log \underline{q}$. At the same time, the signal volatility plays a smaller role relative to σ in determining the dispersion of idiosyncratic shock at entry, thus preventing the identification of ξ.

interest income (29%) is $\frac{(1-\tau_c)}{(1-\tau_i)} = \frac{1-0.40}{1-0.29} = 0.845$. The fixed cost of issuing equity f_e is positive and marginally significant, a result in line with Hennessy and Whited (2007).[18]

4.4. Industry-cohort estimation

In this section, we discuss the estimation at the industry-cohort level. Table 4 presents cohort level results for the non-R&D-intensive sector (called industry 0), and Table 5 presents the analog results for the R&D-intensive sector (called industry 1).

Our simple model replicates qualitatively the strikingly different dynamics in cash holdings at entry across the two different industries in the data. It also captures the dynamics of sales growth volatility across industries and cohorts. Fig. 7 compares the model-generated trends of cash holdings at entry (top panel) and sales growth volatility (bottom panel) with the actual data. It shows that our simple model with an entry margin goes a long way to qualitatively account for the data. However, our model does not quite quantitatively match the increase in cash holdings at entry for industry 1 cohorts after 1983. In particular, the largest difference to the data is in the industry 1 cohort of 1994-1998. The model generates only an average cash-to-asset ratio at entry of 0.322, while the corresponding value in the data is 0.426. The sales growth volatility of post 1983 cohorts in industry 1 are also slightly lower compared to the data. This limits the extent to which the model can fully account for the secular increase in cash holdings, as we discuss in Section 5.

Turning to the other moments in the industry-cohort level estimation (Tables 4 and 5), we find that our model replicates the data well. Specifically, the majority of moments are statistically indistinguishable from the data. For example, across cohorts and industries, the model replicates the average equity issuance size of mature firms, the sales growth rate, and the average investment-to-asset ratio at entry. The average investment-to-asset ratio at entry is larger for industry 0 cohorts compared to industry 1 cohorts but is declining for all industries over time. In all industries and cohorts, firms grow much faster when they enter compared to when they have been public for ten years. Our model generates these different dynamics with firms that have below long-run average TFPR when they decide to enter the sample and operate with decreasing returns to scale in production. Firms with a low TFPR are smaller and, conditional on surviving, grow faster given the curvature of their production function. As the firm-level TFPR reverts to its long-run average value, firms grow larger at a progressively slower pace.

As in the baseline model, our model struggles to replicate two moments of the data. For all industries and cohorts, firms' cash holdings decline twice as fast over the first ten years after an IPO as in the data. The sales growth rate autocorrelation is positive in the data and negative for industry 1 cohorts in the model. However, its magnitude is very small, less than 0.1 in absolute value in the model and the data. In addition, we find that the volatility in cash holdings and sales growth rates at entry is too low, while the model-implied investment rate volatility is too high relative to the data. In the latter case, a higher value of the investment adjustment cost parameter η could generate a lower investment rate volatility (closer to the data) in our model. However, a higher investment adjustment cost parameter causes firms to reduce their investment size and, as a consequence, to reduce their average cash holdings (e.g., Riddick and Whited, 2009).

The second panel of Tables 4 and 5 shows that most parameters are statistically significant. The only exception is the fixed equity issuance cost that is significant in four out of five cases for industry 0 and insignificant for cohorts in industry 1. For both industries, the estimated average productivity signal at entry $\underline{q}$ is smaller than in the baseline cohort. Moreover, for industry 1 and recent cohorts, especially for the 1984-1988, 1989-1993, and 1999-2003 cohorts, the estimated average productivity signal is particularly low. This means that firms in industry 1 go public with a very low average productivity signal (relative to the baseline and industry 0). These firms are far away from their optimal size. Given fixed issuance costs, they have high incentives to enter the sample with a large amount of cash on their balance sheets.

Aside of the parameter governing firms' entry decisions, the other parameter estimates for industry 1 are also interesting. Relative to industry 0, we estimate a higher volatility of the productivity process (σ) for all cohorts in industry 1. We also find that the persistence parameter (ρ) is, on average, much lower than for industry 0 (0.497 versus 0.700). Interestingly, we estimate a lower production function curvature for industry 1 firms (i.e., $\alpha = 0.857$ compared to $\alpha = 0.594$ in industry 0). These estimates are consistent with the ones in Hennessy and Whited (2007), who find that, relative to large firms, smaller firms have a larger volatility parameter (0.160 versus 0.086), a smaller persistence parameter (0.498 versus 0.791), and a larger return-to-scale parameter (0.693 versus 0.577). In our model, the average size of firms in industry 1 is about one-quarter the average size of firms in industry 0. It is worth noting that the estimated value of the persistence parameter is pretty stable across cohorts within each industry, with the notable exception of a sharp drop in the estimated ρ for the 1999-2003 cohort in industry 0. This is not the case for the volatility parameter that closely mimics the dynamics of sales growth volatility in Fig. 7. Hence, while we do not have an increasing trend in σ for firms in industry 0, we have a steady increase for firms in industry 1, for which σ goes from 0.209 for the 1979-1983 cohort to 0.275 for the 1999-2003 cohort. Remarkably, we find no clear trend in the estimated cost of carrying cash ν over time. However, firms in industry 0 earn only 3.1 cents on each dollar saved internally, while firms in industry 1 earn 3.5 cents.

[18] This parameter is difficult to identify because it determines the extensive margin of equity issuance. The standard error calculation are based on changes in the model's behavior to a small variation in the parameter. However, a tiny variation in the fixed cost of equity issuance does little to change the behavior of the model. We experimented with setting the fixed equity issuance cost parameter to zero. This reduced the average cash at entry to 0.09 and the average issue size in year 10 to 0.0015 while leaving the other moments unchanged.

Table 4
Simulated moments estimation: industry 0.

Moments	1979-1983			1984-1988			1989-1993			1994-1998			1999-2003		
	Data	Model N=116	t-stat	Data	Model N=205	t-stat	Data	Model N=197	t-stat	Data	Model N=236	t-stat	Data	Model N=86	t-stat
Average cash holdings at entry	0.194	0.185	(0.50)	0.154	0.143	(0.96)	0.152	0.146	(0.48)	0.171	0.146	(2.06)	0.136	0.098	(1.99)
Average change in cash holdings	−0.083	−0.132	(2.82)	−0.054	−0.097	(3.72)	−0.073	−0.108	(2.65)	−0.049	−0.130	(6.08)	0.014	−0.077	(4.80)
Volatility cash holdings	0.085	0.084	(0.15)	0.070	0.067	(0.92)	0.070	0.070	(−0.12)	0.078	0.070	(2.23)	0.074	0.057	(2.58)
Autocorrelation cash holdings	0.287	0.376	(−2.63)	0.281	0.307	(−1.01)	0.267	0.284	(−0.66)	0.310	0.403	(−4.18)	0.270	0.252	(0.46)
Average issue size at year 10	0.021	0.021	(0.07)	0.020	0.020	(0.09)	0.019	0.019	(0.04)	0.015	0.015	(−0.05)	0.019	0.019	(0.03)
Mean sales growth at 2	0.186	0.199	(−0.36)	0.198	0.181	(0.71)	0.232	0.201	(1.29)	0.287	0.263	(1.06)	0.166	0.209	(−1.29)
Volatility sales growth at entry	0.142	0.098	(2.097)	0.113	0.068	(2.997)	0.111	0.091	(1.942)	0.124	0.115	(0.683)	0.093	0.062	(1.466)
Average change in sales growth	−0.127	−0.142	(0.33)	−0.126	−0.119	(−0.25)	−0.183	−0.167	(−0.51)	−0.222	−0.212	(−0.37)	−0.178	−0.198	(0.45)
Volatility sales growth	0.259	0.254	(0.30)	0.195	0.195	(−0.03)	0.227	0.236	(−0.93)	0.237	0.233	(0.38)	0.213	0.163	(2.80)
Autocorrelation sales growth	0.100	0.052	(1.46)	0.139	0.017	(5.04)	0.107	0.029	(2.94)	0.160	0.012	(6.55)	0.101	−0.026	(3.22)
Average investment rate at entry	0.157	0.147	(0.46)	0.116	0.102	(1.10)	0.149	0.124	(1.54)	0.142	0.140	(0.12)	0.132	0.119	(0.50)
Average change in investment rate	−0.106	−0.083	(−0.94)	−0.044	−0.040	(−0.24)	−0.080	−0.083	(0.17)	−0.094	−0.086	(−0.46)	−0.115	−0.104	(−0.43)
Volatility investment rate	0.140	0.174	(−3.43)	0.113	0.124	(−1.67)	0.130	0.146	(−2.04)	0.110	0.130	(−2.98)	0.088	0.092	(−0.41)

	σ	ρ	α	η	$\log(\underline{q})$	ν	f_e
1979-1983	0.246	0.795	0.493	0.051	−1.087	0.869	0.246
	0.007	0.017	0.005	0.000	0.144	0.018	0.114
1984-1988	0.186	0.774	0.606	0.072	−1.015	0.767	0.044
	0.003	0.009	0.017	0.007	0.027	0.007	0.042
1989-1993	0.221	0.721	0.592	0.044	−0.865	0.732	0.048
	0.005	0.014	0.007	0.006	0.039	0.052	0.015
1994-1998	0.215	0.717	0.564	0.071	−1.224	0.701	0.098
	0.002	0.013	0.000	0.032	0.198	0.032	0.060
1999-2003	0.125	0.498	0.715	0.056	−0.873	0.776	0.248
	0.005	0.016	0.024	0.002	0.161	0.160	1.785

This table reports the simulated and actual moments (Panel A) together with the estimated structural parameters (Panel B) using a balanced panel of firms in the non-R&D-intensive sector belonging to the following five cohorts: 1979-1983, 1984-1988, 1989-1993, 1994-1998, and 1999-2003. For each cohort, the balanced panel is composed of non-R&D-intensive firms that entered our sample of publicly listed firms and have ten consecutive years of observations on total assets (Compustat item *at*); revenues (item *sale*); cash (item *che*); net property, plant, and equipment (item *ppent*); common shares outstanding (item *csho*); sale of common and preferred stock (item *sstk*); and market price at the calendar year end (item *prcc_c*). In Panel A, we also report the number of firms in each cohort (N) and the t-statistics for the difference between model-generated and actual moments. The estimated cohort-level parameters in Panel B are the following: the volatility (σ) and persistence (ρ) of the TFPR process; the returns to scale parameter α; the convex adjustment cost parameter η; the shape parameter, (ξ) and the lower bound ($\underline{q}$) of the Pareto distribution; the internal accumulation wedge ν; and the fixed equity issuance cost and f_e. The parameters are separately estimated for each cohort. For each estimated parameter, we report the associated standard error, whose calculation is described in Online Appendix C.2.

Table 5
Simulated moments estimation: industry 1.

Moments	1979-1983			1984-1988			1989-1993			1994-1998			1999-2003		
	Data	Model N=172	*t*-stat	Data	Model N=227	*t*-stat	Data	Model N=213	*t*-stat	Data	Model N=306	*t*-stat	Data	Model N=199	*t*-stat
Average cash holdings at entry	0.283	0.298	(−0.75)	0.368	0.313	(2.98)	0.412	0.348	(3.14)	0.426	0.322	(6.30)	0.526	0.428	(4.67)
Average change in cash holdings	−0.093	−0.201	(5.22)	−0.114	−0.210	(6.27)	−0.110	−0.224	(5.92)	−0.097	−0.230	(9.09)	−0.172	−0.264	(4.42)
Volatility cash holdings	0.122	0.094	(5.26)	0.120	0.099	(4.74)	0.131	0.105	(5.30)	0.132	0.103	(7.64)	0.142	0.127	(3.00)
Autocorrelation cash holdings	0.333	0.380	(−1.70)	0.333	0.467	(−5.61)	0.337	0.455	(−4.89)	0.327	0.500	(−8.25)	0.322	0.552	(−9.38)
Average issue size at year 10	0.015	0.015	(0.07)	0.069	0.069	(0.04)	0.061	0.061	(−0.02)	0.063	0.062	(0.09)	0.055	0.055	(−0.03)
Mean sales growth at 2	0.263	0.254	(0.27)	0.319	0.328	(0.38)	0.279	0.293	(−0.47)	0.297	0.309	(−0.46)	0.346	0.325	(0.51)
Volatility sales growth at entry	0.187	0.109	(2.233)	0.206	0.164	(2.228)	0.181	0.164	(0.955)	0.209	0.155	(3.152)	0.329	0.188	(5.469)
Average change in sales growth	−0.195	−0.227	(0.88)	−0.205	−0.279	(1.99)	−0.243	−0.261	(0.47)	−0.186	−0.271	(2.59)	−0.325	−0.289	(−0.84)
Volatility sales growth	0.270	0.24	(2.35)	0.286	0.268	(1.34)	0.323	0.308	(1.11)	0.336	0.274	(5.14)	0.321	0.315	(0.48)
Autocorrelation sales growth	0.061	−0.047	(4.32)	0.095	−0.071	(6.68)	0.084	−0.156	(9.05)	0.077	−0.094	(8.59)	0.07	−0.089	(6.85)
Average investment rate at entry	0.117	0.114	(0.27)	0.081	0.081	(−0.02)	0.068	0.062	(0.76)	0.078	0.085	(−1.02)	0.048	0.057	(−1.30)
Average change in investment rate	−0.099	−0.089	(−0.84)	−0.045	−0.037	(−1.00)	−0.047	−0.033	(−1.41)	−0.069	−0.051	(−2.55)	−0.044	−0.022	(−2.96)
Volatility investment rate	0.093	0.111	(−4.20)	0.073	0.093	(−6.07)	0.07	0.089	(−5.36)	0.061	0.092	(−11.41)	0.048	0.097	(−15.22)

	σ	ρ	α	η	$\log(\underline{q})$	ν	f_e
1979-1983	0.209	0.513	0.823	0.062	−0.830	0.876	0.032
	0.005	0.011	0.013	0.002	0.023	0.013	0.326
1984-1988	0.229	0.511	0.850	0.179	−1.340	0.862	0.039
	0.002	0.012	0.012	0.005	0.089	0.012	0.037
1989-1993	0.263	0.461	0.888	0.165	−1.219	0.892	0.000
	0.008	0.012	0.002	0.004	0.059	0.002	0.001
1994-1998	0.236	0.494	0.851	0.159	−1.216	0.869	0.026
	0.005	0.008	0.001	0.071	0.050	0.035	0.005
1999-2003	0.275	0.505	0.872	0.192	−1.361	0.900	0.001
	0.005	0.008	0.005	0.022	0.092	0.101	0.001

This table reports the simulated and actual moments (Panel A) together with the estimated structural parameters (Panel B) using a balanced panel of firms in the R&D-intensive sector belonging to the following five cohorts: 1979-1983, 1984-1988, 1989-1993, 1994-1998, and 1999-2003. For each cohort, the balanced panel is composed of R&D-intensive firms that entered our sample of publicly listed firms and have ten consecutive years of observations on total assets (Compustat item *at*); revenues (item *sale*); cash (item *che*); net property, plant, and equipment (item *ppent*); common shares outstanding (item *csho*); sale of common and preferred stock (item *sstk*); and market price at the calendar year end (item *prcc_c*). In Panel A, we also report the number of firms in each cohort (N) and the t-statistics for the difference between model-generated and actual moments. The estimated cohort-level parameters in Panel B are the following: the volatility (σ) and persistence (ρ) of the TFPR process; the returns to scale parameter α; the convex adjustment cost parameter η; the shape parameter (ξ) and the lower bound ($\underline{q}$) of the Pareto distribution; the internal accumulation wedge ν; and the fixed equity issuance cost and f_e. The parameters are separately estimated for each cohort. For each estimated parameter, we report the associated standard error, whose calculation is described in Online Appendix C.2.

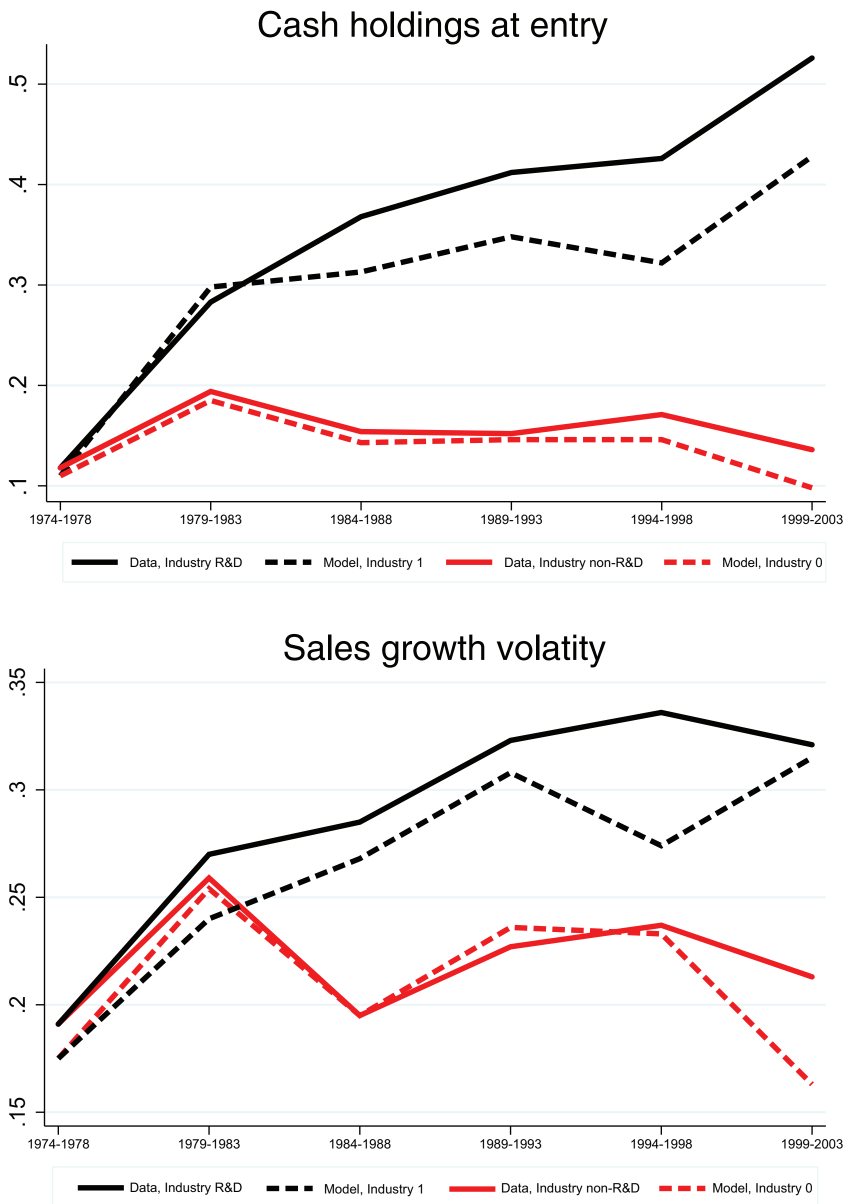

Fig. 7. Secular trends: model versus data. This figure reports model-generated average cash-to-asset ratio at entry (top panel) and average firm-level sales growth volatility (bottom panel) and compares these quantities with their empirical counterparts. The quantities are reported for each cohort, starting from the 1974-1978 one, and across two industries. The black lines refer to industry 1 in the model and R&D-intensive industry in the data, while the red lines refer to industry 0 in the model and non-R&D-intensive industry in the data. Solid lines refer to actual data, while dashed lines refer to model-generated data. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

5. Analysis

In this section, we explore the model's ability to reproduce the secular increase in cash during the period 1979-2003. To this end, we simulate the model economy with 4,000 firms. In each period, a firm can exit the sample exogenously with a 8% probability. The exiting firms are replaced by an equal number of entering firms that choose initial capital and cash balances according to Eq. 5. We first simulate the economy using the estimated parameters for the baseline cohort for 350 periods. We found this was long enough to reach a stationary distribution. Then, we simulate a period of length 25 years and let firms of different industries and cohorts enter over time. The fraction of entrants belonging to either industry reflects the composition at entry observed in the data and reported in Table 6. We perform 50 simulations, and all model-based reported moments are averaged over these simulations.

We focus our discussion on two trends among publicly traded firms: the secular increase in cash (Bates et al., 2009) and the increase in firm-level sales growth rate volatility (Davis et al., 2007). How much of these trends can our model explain? In Table 7, we report the following

Table 6
Entrants distribution.

Cohort	1974-1978	1979-1983	1984-1988	1989-1993	1994-1998	1999-2003
Industry 1 (ω)	0.33	0.55	0.45	0.52	0.55	0.74
Industry 0 (1-ω)	0.67	0.45	0.55	0.48	0.45	0.26

This table reports the composition on firms entering in U.S. public equity markets during the period 1974-2003 across six cohorts of entrants: 1974-1978, 1979-1983, 1984-1988, 1989-1993, 1994-1998, and 1999-2003. For each cohort, we report the fraction of firms belonging to the R&D-intensive industry (ω) and the fraction of firms belonging to the non-R&D-intensive industry $(1-\omega)$.

Table 7
Cash and volatility dynamics.

Year5	Sample composition		Cash-to-asset		Cash-to-asset (Ind. 0)		Cash-to-asset (Ind. 1)		Sales growth vol	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model
1974-1978	0.336	0.330	0.085	0.071	0.085	0.071	0.085	0.071	0.172	0.176
1979-1983	0.376	0.381	0.108	0.090	0.095	0.066	0.126	0.102	0.223	0.192
1984-1988	0.434	0.417	0.140	0.096	0.108	0.068	0.182	0.110	0.286	0.215
1989-1993	0.467	0.443	0.153	0.104	0.101	0.068	0.210	0.130	0.269	0.228
1994-1998	0.500	0.476	0.182	0.105	0.092	0.060	0.270	0.135	0.306	0.244
1999-2003	0.554	0.543	0.221	0.127	0.097	0.044	0.322	0.187	0.324	0.254
Difference	0.218	0.213	0.136	0.056	0.012	−0.027	0.237	0.116	0.152	0.078
% change	65%	65%	160%	78%	14%	−38%	278%	163%	88%	44%

This table reports simulated quantities across 50 simulations. For each simulation, we simulate a panel with 4,000 firms. In each period, a firm can exit the sample exogenously with a 8% probability and is replaced by a new entrant, which chooses initial capital and cash balances according to Eq. 5. We first simulate the economy using the estimated parameters for the baseline cohort for 350 periods. Then, we simulate a period of length 25 years and let the firms of different industries and cohorts enter over time with composition at entry dictated by the quantities in Table 6. We report the model-generated quantities together with their empirical counterparts. All quantities are calculated at an annual frequency and are averaged over a five-year period. The first two columns report the fraction of incumbents firms belonging to the R&D-intensive industry in the data (Column 1) and to industry 1 in model (Column 2). Columns 3 and 4 report the cash-to-asset ratio's cross-sectional average. Columns 5 and 6 report the cash-to-asset ratio's cross-sectional average for firms belonging to the non-R&D-intensive industry in the data (Column 5) and to industry 0 in model (Column 6). Columns 7 and 8 report the cash-to-asset ratio's cross-sectional average for firms belonging to the R&D-intensive industry in the data (Column 7) and to industry 0 in model (Column 8). Columns 9 and 10 report the average firm-level sales growth rate volatility. All model-based quantities are averaged over the 50 simulations.

cross-sectional moments averaged over a five-year horizon across all concurrent cohorts: the average industry composition, average cash holdings across all firms, cash holdings for each industry, and the cross-sectional sales growth volatitity. In the data, the change in cash holdings between the 1974-1978 cohort and the 1999-2003 cohort is 0.136, an increase of 160%. Our estimated model can generate a level change of 0.056, which correspond to an increase of 78%. That is, our model captures a large fraction of the secular trend in cash generating about 40% of the level change (0.056 versus 0.136) and about 50% of the percentage change (78% versus 160%). Note that our choice of an exogenous exit rate of 8% allows us to generate an industry composition that is very close to the data. This is important to properly assess the ability of our model to reproduce the observed secular trend in cash holdings. An exit rate that is too low would tilt the distribution of firms toward industry 0 firms and generate a much lower average cash-to-asset in the cross-section.

There are several reasons why the model cannot fully account for the secular time trend in cash. We highlighted in our prior estimation result discussion that firms in our model deplete cash twice as quickly as in the data. This depresses the average cash holdings of firms. Moreover, our model generates a slightly lower amount of cash holdings for industry 0 entrants of the 1994-1998 and 1999-2003 cohorts (see Table 4). As a consequence, cash holdings of firms in industry 0 decline over time, while the data feature a modest increase. However, the negative change in cash holdings for industry 0 firms is more than compensated by the positive change for industry 1 firms. Our model generates about 50% of the level change in industry 1 firms' cash holdings (0.116 versus 0.237) and about 60% of the percentage change (163% versus 278%). However, 50% of the level increase in cash holdings at entry for firms in industry 1 is too small to explain the entire increase in cash holdings over this time period.

In the last two columns of Table 7, we compare the cross-sectional sales growth volatility of the model with the data. To this end, we calculate the cross-sectional dispersion in the sales growth rate each year and report its average over a five-year period. Our simulated economy not only can generate a secular increase in cash holdings, it also generates a monotonically increasing cross-sectional dispersion in sales growth rates. The magnitude of such an increase is quite large. Our model generates about 50% of both the level change (0.078 versus 0.152) and the percentage change (44% versus 88%). This result is not merely an artifact of our estimates for the volatility of the productivity process σ. There is no trend in industry 0 estimates of σ. We estimate that the 1999-2003 cohort has only a 30% higher volatility parameter than the 1974-1978 cohort in industry 1 (0.275 versus 0.209). Moreover, 46% of firms during 1999-2003 period do not operate in industry 1, nor are all firms in industry 1 of the 1999-2003 cohort. In the following section, we show that the entry margin mechanism also independently contributes to a higher sales growth volatility.

Table 8
The role of selection.

	Cash-to-asset				Sales growth dispersion			
	Model (1)	$\underline{q}$ fixed (2)	$(\omega, \underline{q})$ fixed (3)	only $(\omega, \underline{q})$ (4)	Model (5)	$\underline{q}$ fixed (6)	$(\omega, \underline{q})$ fixed (7)	only $(\omega, \underline{q})$ (8)
1974-1978	0.071	0.071	0.071	0.071	0.176	0.176	0.176	0.176
1979-1983	0.090	0.095	0.080	0.082	0.192	0.196	0.193	0.181
1984-1988	0.096	0.076	0.069	0.097	0.215	0.210	0.208	0.189
1989-1993	0.104	0.079	0.070	0.094	0.228	0.221	0.218	0.189
1994-1998	0.105	0.077	0.064	0.109	0.244	0.236	0.230	0.193
1999-2003	0.127	0.094	0.064	0.107	0.254	0.246	0.231	0.199
Difference	0.056	0.023	−0.008	0.035	0.078	0.070	0.055	0.022
% change	78%	32%	−11%	50%	44%	40%	31%	13%

This table reports simulated quantities across 50 simulations. For each simulation, we simulate a panel with 4,000 firms. In each period, a firm can exit the sample exogenously with a 8% probability and is replaced by a new entrant, which chooses initial capital and cash balances according to Eq. 5. We first simulate the economy using the estimated parameters for the baseline cohort for 350 periods. Then, we simulate a period of length 25 years and let the firms of different industries and cohorts enter over time with composition at entry dictated by the quantities in Table 6. The first four columns report the cash-to-asset ratio's cross-sectional average, while the last four columns report the average firm-level sales growth rate volatility. Columns 1 and 5 report quantities calculated using the parameters estimated using SMM. Columns 2 and 6 report quantities from a model in which all parameters are kept at their estimated values except for $\underline{q}$. Columns 3 and 7 report quantities from a model in which all parameters are kept at their estimated values except for $\underline{q}$ and the fraction of entrants from industry 1, kept at its baseline value (0.33). Columns 4 and 8 report quantities from a model in which all parameters are set to their baseline value except for the composition at entry and $\underline{q}$. All are averaged over the 50 simulations.

6. Counterfactuals

What are the drivers of the secular trend in cash holdings in our model? A close inspection at the estimated parameters in Table 5 suggests that two forces might play a crucial role in generating a secular increase in cash holdings. First, the process for the firm-level productivity is characterized by an increasing value of the volatility parameter across cohorts belonging to industry 1. A larger σ increases the precautionary need for cash reserves. Second, for all the cohorts in industry 1, the estimated lower bound of the average productivity signal at entry is much lower compared to the baseline. The mean reversion in the productivity process means that firms with low initial productivity expect a larger increase in productivity and therefore expect larger incentives to accumulate cash for future investments compared to firms with initially high productivity. Hence, a decline in the average productivity signal at entry contributes to the secular increase in cash holdings. In what follows, starting with the entry margin mechanism (i.e., selection), we try to understand how important these two forces are in shaping the dynamic evolution of average cash holdings.

6.1. Selection

Using the model, we explore the quantitative role of selection in causing the secular trend in the data. In Table 8, we report the results of the following counterfactual exercises. The first exercise simulates the data from the model in which all parameters are kept at their estimated values except for $\underline{q}$. For all industries and cohorts, we set $\underline{q}$ to its estimated value in the baseline cohort, reported in Table 3. To study the importance of composition, in addition to keeping $\underline{q}$ at its baseline value, the second counterfactual exercise also keeps the fraction of entrants from industry 1 at its baseline value (0.33) for all subsequent cohorts. For this last counterfactual exercise in this section, we keep all the parameters at their baseline value but allow $\underline{q}$ and the fraction of industry 1 entrants to take their estimated values. We look at the effects of our experiments both on cash holdings and on sales growth volatility.

With the first counterfactual exercise, we study the role of changes in the entry margin through changes in the cohort-specific average productivity signal for the secular increase in cash. Column 2 of Table 8 shows that without a change in the entry margin, the model generates only 40% of the level change (0.023 versus 0.056) and the percentage change (32% versus 78%) relative to the full model's response. While the entry margin has a sizable impact on the trend in cash holdings, it has a marginal effect on the trend in sales growth volatility. Column 6 shows that without $\underline{q}$ at work, the model can still generate about 90% of the overall change in the sales growth volatility.

In the second exercise, we not only shut off the entry margin but also keep the fraction of industry 1 firms at the baseline level, allowing us to assess the overall effect of firm selection on the secular increase in cash. Column 3 of Table 8 shows that the model without selection produces a slightly declining trend in average cash holdings. When the fraction ω of industry 1 entrants stays at the baseline level, a counterfactually large fraction of low cash holdings firms enter over time. As a consequence, the fraction of industry 0 incumbents is much higher, thus contributing to keep the average cross-sectional cash holdings at a lower value. Even the effect on the cross-sectional volatility of sales growth rates is considerable. Without selection at work, the model can generate only 70% of the overall change (Column 7).

In the last exercise, we let selection be the only force at work. All parameters are set to their baseline value except for the composition at entry and $\underline{q}$. Column 4 of Table 8 shows that selection alone can explain about 60% of the change in cash holdings (0.035 versus 0.056). In addition, selection alone can also generate a secular trend in the sales growth rates dispersion and be responsible for

Table 9
The role of cash flow volatility.

	Panel A: Cash flow volatility					
	Cash-to-asset			Sales growth dispersion		
	Model (1)	σ fixed (2)	only σ (3)	Model (4)	σ fixed (5)	only σ (6)
1974-1978	0.071	0.071	0.071	0.176	0.176	0.176
1979-1983	0.090	0.082	0.085	0.192	0.184	0.191
1984-1988	0.096	0.087	0.083	0.215	0.190	0.208
1989-1993	0.104	0.088	0.088	0.228	0.190	0.218
1994-1998	0.105	0.085	0.094	0.244	0.192	0.229
1999-2003	0.127	0.113	0.088	0.254	0.197	0.229
Difference	0.056	0.042	0.017	0.078	0.021	0.053
% change	78%	59%	24%	44%	12%	30%

	Panel B: Selection and cash flow volatility					
	Cash-to-asset			Sales growth dispersion		
	Model (1)	(σ, ω, $\underline{q}$) fixed (2)	only (σ, ω, $\underline{q}$) (3)	Model (4)	(σ, ω, $\underline{q}$) fixed (5)	only (σ, ω, $\underline{q}$) (6)
1974-1978	0.071	0.071	0.071	0.176	0.176	0.176
1979-1983	0.090	0.064	0.097	0.192	0.180	0.195
1984-1988	0.096	0.049	0.123	0.215	0.177	0.221
1989-1993	0.104	0.048	0.125	0.228	0.178	0.233
1994-1998	0.105	0.040	0.139	0.244	0.178	0.247
1999-2003	0.127	0.040	0.144	0.254	0.180	0.256
Difference	0.056	−0.031	0.072	0.078	0.004	0.080
% change	78%	−44%	102%	44%	2%	45%

This table reports simulated quantities across 50 simulations. For each simulation, we simulate a panel with 4,000 firms. In each period, a firm can exit the sample exogenously with a 8% probability and is replaced by a new entrant, which chooses initial capital and cash balances according to Eq. 5. We first simulate the economy using the estimated parameters for the baseline cohort for 350 periods. Then, we simulate a period of length 25 years and let the firms of different industries and cohorts enter over time with composition at entry dictated by the quantities in Table 6. The first three columns report the cash-to-asset ratio's cross-sectional average, while the last three columns report the average firm-level sales growth rate volatility. Columns 1 and 4 in both Panel A and Panel B report quantities calculated using the parameters estimated using SMM. In Panel A, Columns 2 and 5 report quantities from a model in which all parameters are kept at their estimated values except for σ, while Columns 3 and 6 report quantities from a model in which all parameters are set to their baseline value except for σ. In Panel B, Columns 2 and 5 report quantities from a model in which all parameters are kept at their estimated values except for σ, $\underline{q}$, and the fraction of entrants from industry 1, kept at its baseline value (0.33). Columns 3 and 6 in Panel B report quantities from a model in which all parameters are set to their baseline value except for σ, $\underline{q}$, and composition at entry. All are averaged over the 50 simulations.

about 30% of the difference between the 1999-2003 and 1974-1978 cohorts (Column 8).

Overall, the counterfactual exercises reported in Table 8 provide strong support to the idea that the entry margin played an important role in explaining the secular increase in cash during the period 1979-2003. In addition, our exercises show that firm selection can also partially explain the secular increase in sales growth rates volatility as shown by Davis et al. (2007).

6.2. Cash flow volatility

In this section, we explore the question of whether a change in firms' cash flow volatility could have explained the increase in firms' cash holdings, as suggested by Bates et al. (2009). In addition, we study its role for the increase in firms' sales growth volatility. To this end, we conduct two counterfactual exercise whose results we present in Panel A of Table 9. First, we allow all parameters to change at the industry-cohort level except for σ (firms' productivity volatility), which is kept at its baseline values. For the second exercise, we only allow σ to vary at the cohort-industry. All other parameters remain at their baseline values, meaning that we also keep entrants' industry composition fixed at the value $\omega = 0.33$.

In Column 2, we show that just by shutting off the volatility parameter σ, i.e., keeping it fixed at its baseline level, the model still generates a sizable secular increase in cash holdings. The overall change in average cash holdings between the 1979-1983 and the 1999-2003 cohorts is 0.042, a value almost twice as large as the one that we obtained by keeping $\underline{q}$ fixed (0.023). In other words, shutting off σ as a model force does not take away the model's ability to explain the increase in cash holdings over time. However, it is a major driving force behind the increase in the average sales growth volatility. Column 5 shows that keeping σ at its baseline level produces only an increase of 0.02 (12%) in firms' average sales growth volatility.

We find similar implications if we only allow σ to vary. In Column 3 we show that the model generates only a relatively small fraction of the change in firms' cash holdings over time (i.e., it explains only around 10% of the increase in the data). Column 6 shows the implications for the sales growth volatility. When we allow only σ to change over time, the model generates an increase of 30%. Recall that the full model generates an increase of 44% in the sales growth volatility. That is, while the model's main force in explaining the secular trend in the sales growth volatility is coming from changes in the cash flow volatility itself, other model forces such as selection explain a sizable amount. These results support the idea that an increase in precautionary saving motives—driven by an increase in firm-level cash flow volatility—are much less important for driving the secular increase in cash than firm selection. However, without the estimated progressive increase in σ, the model could not come close to replicating the secular increase in the sales growth volatility.

The results thus far suggest that both an increase in firms' cash flow volatility and changes at the entry margin are important forces for the two secular trends we focus on. In the last set of counterfactual exercises (Panel B of Table 9), we explore their role jointly. First, we allow all parameters to change except composition, $\underline{q}$, and the firm-level volatility parameter σ. Then, we analyze the economy where the only moving parts are composition, the Pareto lower bound, and the firm-level volatility parameter σ.

When we shut down both the firm selection force and the cash flow volatility force of the model, our model produces a negative trend in cash holdings (Column 2). In fact, the economy looks very similar to industry 0 (see Table 7), for which we have no trend in σ across cohorts and little movements in the lower bound of the average productivity signal at entry. Without these two forces, the model produces no change in the average sales growth volatility. Connecting with our previous results, this implies that selection alone also contributes to the trend in the sales growth volatility. That is, keeping only σ constant still produces a small increase as shown in Column 5 of Panel A.

We also analyze an economy where the only moving parts are the industry compositions at entry, the average productivity signal at entry, and the firm-level cash flow volatility. In this case, the economy generates a larger change in average cash holdings (0.072 versus 0.056, Column 3) and a similar change in the sales growth volatility (0.080 versus 0.078, Column 6). It seems puzzling at first that these three forces alone generate a much larger increase in cash holdings than our full model (102% versus 78%). In this experiment we keep the productivity process persistence parameter ρ fixed at its baseline value (0.649) for industry 1 firms. Our estimation finds that this parameter decreases over time. By keeping it at the baseline level in this experiment, it delivers a lower expected productivity at entry ($\rho \times \log q$), which translates in a higher choice of cash balances at entry.[19]

Our counterfactual analysis leads us to conclude that both selection and cohort variation in the parameter governing the volatility of the productivity shock (σ) are essential ingredients to generate two much talked about secular trends among publicly traded US firms. In our model economy, selection is the major force for an increase in the cash-to-asset ratio over time. But the cash flow volatility is critical for explaining the rise in the sales growth volatility.

[19] It is useful to remember that $\log q$ is, on average, negative.

7. Discussion

Our estimation results in Tables 4 and 5 studies the quantitative strength of two mechanisms—selection and a change in cash flow volatility—for the secular increase in cash holdings. We singled out these two mechanisms because our estimation found no clear time trend in any of the other parameters. These two forces alone generate an increase in cash holdings of 78% compared to an increase of 168% in the data. The main reason our model cannot explain all of the increase in cash holdings is due to the fact that firms in our model deplete cash too fast. While in the data the within-firm trend of cash holdings is negative, our model implies a much faster depletion of cash holdings at the firm level compared to the data. This limitation of our model naturally suggests a role for complementary explanations, including corporate taxes (Foley et al., 2007), a decline in interest rates and therefore the opportunity cost for holding cash (Azar et al., 2016), agency frictions (Dittmar and Mahrt-Smith, 2007; Nikolov and Whited, 2014), adoption of just-in-time production (Gao, 2015) and intangible capital (Falato et al., 2013). In isolation, most of these complementary explanations would generate a secular increase in cash holdings via a positive within-firm effect. This would help our model to generate a slower mean reversion in cash holdings. In what follows, we briefly discuss how adding these additional forces relate to our analysis.

As shown by Foley et al. (2007), tax considerations are one of the reasons large multinational firms hold on to significant cash balances abroad. Foley et al. (2007) also show that the cash holdings of technology firms, i.e., firms with more flexibility to shift profits to low tax locations, are especially sensitive to tax rates. This explanation could serve as an additional force to drive differences between R&D-intensive firms and non-R&D–intensive firms. With this additional feature, our model might generate higher cash holdings for industry 1 firms ex-ante.

In a standard economic model, the opportunity cost of money is the short-term risk-free rate. Azar et al. (2016) show that a higher risk-free rate is correlated with lower corporate cash balances. In other words, while the risk-free rate has been falling over the last 30 years, corporate cash balances have been rising. Without any additional assumption, a decline in the opportunity costs of carrying cash affects all firms. This explanation alone can therefore not explain why R&D-intensive entrants have higher cash balances. It also cannot explain the negative trend within firms (Table 2). Yet, if cash balances are particularly important for R&D-intensive firms to circumvent financing constraints, then, effectively, R&D-intensive firms might become more sensitive to changes in the opportunity cost of holding cash. In our estimation exercise (see Tables 4 and 5), we do not allow the interest rate to vary over time, but we allow ν—the cost of carrying cash—to vary at the cohort and industry level. Within industry 1, the cost of carrying cash ν does not vary by cohort in our estimation, suggesting that this has not been a major driver for the change in cash holdings at the cohort level over time. Augmenting our setup to include a negative time trend in the risk-free rate might help in generating a slower mean reversion in cash holdings.

Agency frictions as discussed by Dittmar and Mahrt-Smith (2007) and Nikolov and Whited (2014) also play an important role in the rise of cash holdings. Nikolov and Whited (2014) show that for larger firms, agency frictions such as a lower share of managerial firm ownership are relevant for the upward trend in cash. They also find, however, that agency frictions are less important for smaller firms that play a prominent role in the selection mechanism. This suggests a complementary role of agency frictions to the selection and rise in cash flow volatility mechanism and likely helps the model to better match the upward trend in cash holdings.

Last, several papers (Falato, Kadyrzhanova and Sim, 2013; Falato and Sim, 2014; Gao, 2015) suggest a change in production technologies as a driver for the secular increase in cash. The empirical evidence in these papers is more supportive of a within-firm effect, meaning that new production technologies are adopted by existing firms. But unless one controls for cohort effects, the changes in the production technology could also emerge from new firms that progressively enter the sample with new production technologies. In addition, while we do not allow for changes in the functional form of the production function or its capital input type, we find no clear time trend for its parameters over industries and cohorts. Modeling tangible and intangible capital as production factors and studying their role in conjunction with selection is beyond the scope of this paper. Incorporating a capital type choice along the lines of Falato, Kadyrzhanova and Sim (2013) would likely boost the model's ability to quantitatively match the secular rise in cash holdings.

8. Conclusion

In this paper, we estimate a standard neoclassical investment model—augmented to allow for an entry margin—to investigate the role of firm selection as an important driver of higher average cash-to-asset ratios. Our model can account for roughly half of the increase in cash holdings of US public companies over the period 1979-2003. Using our model, we quantify the role of firm selection in conjunction with other mechanisms, such as a rise in cash flow volatility and the cost of carrying cash. Our estimation identifies cash flow volatility and the average TFPR of newcomers into US equity markets as an important forces behind the secular increase in the average cash-to-asset ratio. More than a shift in the composition of R&D-intensive firms, a shift toward smaller, riskier, initially less productive, but higher growth potential, firms is the key driver of higher cash balances. In addition, our results further show that entry margin decisions matter for the rise in sales growth volatility, alone explaining 15% of the increase in the data.

To focus primarily on a selection mechanism, we made many simplifying assumptions with our model. Our model leaves 50% of the increase in cash holdings in the data unexplained. Several papers in the literature have presented evidence that show the importance of explanations complementary to firm selection and a rise in cash flow volatility. For future work, it would be interesting to augment our setup to explicitly account for these complementary explanations.

While beyond the scope of this paper, an open research question is why in recent years R&D-intensive firms went public at smaller size, with lower initial productivity, and hence less profitability. This model mechanism is consistent with the evidence of Fama and French (2004) who suggest that more favorable IPO conditions allowed smaller and less profitable firms to go public (i.e., "a downward shift in the supply curve for new list equity funding" Fama and French, 2004, page 233). Such a change could have been instigated by relaxing the Employment Retirement Income Security Act's (ERISA) "Prudent Man" Rule passed by Congress in 1979 that allowed pension funds to invest in riskier ventures (Longstreth, 1987), such as smaller, less profitable firms with higher growth option value. The ensuing improvement in equity funding conditions for this type of firms might have particularly benefited R&D-intensive firms that are often risky ventures.

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