Essays in financial economics

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This dissertation contains three essays in financial economics. The first essay investigates why firms become less dynamic in the subsequent years after going public. The second essay is inspired by the financial crisis of 2008. It shows that there is not enough information production about the underlying risks of innovative financial products in the run-up to financial crises, leading to overinvestment. The third essay is a survey about the emerging literature on safe assets, which play a crucial role in shaping credit expansion and risk taking in the financial sector.

Pascal Golec (1990) obtained a Bachelor in Economics and Business at the University of Zurich. After completing an MPhil in Finance at the Tinbergen Institute in 2014, he continued to pursue a PhD at the University of Amsterdam.
Essays in Financial Economics

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Essays in Financial Economics

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Faculteit Economie en Bedrijfskunde
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Introduction

This thesis contains three *Essays in Financial Economics*. In the first essay, I document that in the subsequent years after firms go public, they gradually cut the rate at which they invest. Interestingly, over half of the decline in investment is unrelated to their size or profitability. This fact is at odds with standard economic theory, where the decline in investment after going public simply reflects firms’ gradual growth path towards their efficient scale.

I build a dynamic investment model which features different sources of the decline in investment conditional on size and profitability. Firms grow towards their efficient scale, learn about their efficient scale, become more rigid, experience mean-reversion in productivity and decline in volatility of productivity. I then estimate the parameters of the model using data on U.S. public firms. The joint dynamics of investment, profitability and market valuation allow me to differentiate between the sources and infer their contribution towards the decline in conditional investment. I find that the unique combination of growing towards the efficient scale and increasing rigidity, as well as learning and decreasing volatility of productivity all explain roughly a third of the decline in investment unrelated to size or profitability. I also revisit interpretations of different phenomena, such as why firms’ market-to-book ratio declines, why their profitability declines and why firms react less to fundamentals in the subsequent years after they go public.

The second essay is inspired by how the recent financial crisis in 2008 came as a surprise. There, the riskiness of asset-backed securities and the underlying mortgages only came to light when U.S. house prices declined nationwide and foreclosures rapidly increased. A common view is that these securities are optimally designed to be opaque so as to limit the amount of information trading parties can produce about the underlying assets. This facilitates trade because there is little fear of being exploited in case the other party knows more.

I show theoretically that issuers of asset-backed securities may be tempted to obscure too much information. In my model opaqueness also has a dark side: if trading parties do not acquire information, then the prices of the securities are also less informative. This can lead to booms fueled by ignorance due to a lack of knowledge whether assets are toxic. The reason opacity is excessive is a free-riding problem, which arises when issuers’ assets are exposed to similar risks, for example how sensitive they are to house prices. On the one hand, all of them would benefit from outsiders producing information. But individually they worry too much about obscuring information to make their own securities easily tradable, because that makes their funding cheap. The model suggests regulations that incentivize information production, which would limit overinvestment.
In the third essay (together with Enrico Perotti), we survey the emerging literature on safe assets. At the core is the recognition of investors’ fundamental demand for safety, distinct from the demand for assets that are easily tradable. We report that considerable evidence has emerged on a strong and stable demand for safe assets. Periods of low supply of government debt, the safest asset, tend to incentivize the financial sector to produce (quasi-) safe assets in the form of short-term debt to meet the demand. On the asset side, this appears to be associated with an expansion in credit and an increase in net long-term investment. We review recent theoretical advances highlighting how pressure to satisfy this demand for safety, a source of cheap funding, leads to contractual forms that ultimately create and propagate risk. This had major implications in the financial crisis of 2008, where uninsured bank debt turned out not to be safe at all. Risk-intolerant investors fled into government debt, leaving the financial system short of funding. We conclude the survey with insights for financial stability and regulatory policy emerging from the literature. Of particular importance is the role of government debt as a financial stability tool.
Chapter 1

Why do firms become less dynamic after they go public? Evidence from structural estimation

1.1 Introduction

In the subsequent years after going public, firms cut investment. This is not all that surprising however. An important reason firms do an initial public offering (IPO) is because they discover major growth opportunities, and therefore want to raise capital to be able to grow. The fact that their investment declines after going public could simply reflect their gradual growth path towards their new efficient scale (Clementi, 2002). With convex adjustment costs, early on they grow faster when their marginal product of capital is high, and later on more slowly when it is low.

Interestingly, over half of the investment decline is unrelated to profitability or size, so it can not only be about firms growing towards their efficient scale. What then is the explanation for the conditional investment decline? While there is an understanding that firms become more rigid (Asker et al., 2014), are learning Pástor et al. (2008) and become less profitable after they go public (Chemmanur et al., 2009), the relative importance of the different factors is yet unknown.

This paper quantifies the contributions of five sources towards the conditional investment decline. In addition to growing towards their efficient scale (GTES), rigidity, learning and declining profitability, I also consider the role of decreasing shock volatility as firms age and interactions between the different sources.

Measuring the relative importance of these mechanisms represents a challenge. Investment is endogenous, and firms’ rigidity and their beliefs are hard to measure. Although one can estimate the reasons’ directional effects using reduced-form empirical techniques, evaluating their magnitudes requires estimating or calibrating an economic model.

These challenges lend themselves to a structural estimation approach. I present a dynamic firm investment model which focuses on firms’ life after going public. The model is a convex adjustment cost framework that I extend across five dimensions. (i) Firms’ capital stock at IPO is lower than what is long-term efficient, i.e., they are growing towards their efficient scale (GTES), (ii) they are learning about their efficient scale, (iii) their volatility of productivity declines over time, (iv) their adjustment costs
increase over time, i.e., they become more rigid and (v) their productivity is abnormally high at the time of IPO and then reverts to the mean.¹

I estimate the model using the simulated method of moments (SMM) and Compustat data on U.S. public firms. Although the model contains different sources for the decline in conditional investment, they all generate different predictions for the joint dynamics of investment, Tobin’s Q and profitability. These predictions enable the estimation procedure to separate them from one another. The model fits the dynamics well. With the estimated model in hand, I decompose the fitted conditional investment decline into the different sources.

Estimates indicate that no single source alone is responsible for the decline in conditional investment. There are three important mechanisms at work, each contributing roughly one third. Interestingly, one is an interaction of two sources, GTES and increasing rigidity, which explains 31 percent of the decline in conditional investment. The fact that profitability and size explain almost half of the decline in both investment and also Tobin’s Q implies that GTES must be important. I also find that firms’ adjustment costs increase by a factor of 3.5 during the first several years after going public. In the model they must increase quite substantially to fit the declining sensitivity of investment to profitability. This allows firms to grow faster towards their efficient scale than they could otherwise. To build intuition, it is useful to compare two otherwise identical firms which are at different points in their post-IPO life-cycle. Both have the same marginal product of capital and profitability, but the firm that recently went public will invest more aggressively, due to lower adjustment costs. Thus there is a discrepancy in their investment rates that is not explained by profitability or size.

Learning about the efficient scale accounts for 37 percent of the conditional investment decline. To match the pronounced decline in Q conditional on size and profitability in the data, the option value from learning must be pretty high in the model. Intuitively, firms earlier in their post-IPO life-cycle are more uncertain about their efficient scale, so there is (still) a chance of learning to in fact be highly productive or unproductive. The option value comes from productivity being skewed, so the upside is more valuable. Skewness in productivity implies that firms which revise their beliefs upwards invest more than firms which revise their beliefs downward divest. The result is a positive net investment on average, the magnitude of which decreases as firms over time gradually learn about their efficient scale. Interestingly, firms learn mostly from sources other than their productivity, as the conditional Q in the data declines too fast compared to how noisy firms’ productivity is.

Decreasing shock volatility over time accounts for the remaining 32 percent of the decline in conditional investment. This mechanism also operates through skewness in productivity, similarly to learning. When the volatility of productivity is high, firms react more to positive productivity shocks than negative because there is a higher chance that another productivity shock next period could produce abnormally high profits. Since the volatility of productivity is correlated with the time since IPO but not with productivity itself, this mechanism also generates a declining conditional investment pattern.

This paper contributes to different literatures. In the firm dynamics literature, it

¹ Section 1.3.4 contains a discussion about other potential explanations that a priori can be ruled out in explaining the conditional investment decline.
is well known that conditional on size, young firms grow faster and conditional on age, small firms grow faster (see Decker et al. (2014) for a review). These results come from data on private companies and the focus is in employment growth. My contribution to that literature is twofold. First, I quantify which mechanisms are important in generating the conditional growth relationship in the context of public firms, capital investment and time since IPO rather than age. It turns out that focusing on public firms is what enables me to do this analysis in the first place, since accounting for the dynamics of Q is important to distinguish between some of the mechanisms. Second, although not the focus of this paper, to my knowledge I am the first to theoretically propose GTES in combination with increasing rigidity as an explanation for the conditional investment decline.

There is a literature on the (operational) underperformance of firms after they go public (e.g., Jain and Kini (1994); Chemmanur et al. (2009)). My contribution is to quantify the relative importance of the two main explanations provided in the literature. According to the theory of Pástor et al. (2008), it is optimal for firms to go public when their expected future profitability is sufficiently high, i.e., after a sequence of positive productivity shocks. The post-IPO drop in operating performance then simply reflects mean-reversion in productivity. This is in contrast to the theory of Clementi (2002), which attributes the drop in operating performance to firms growing towards their efficient scale. There, when firms discover a growth option, their capital stock is relatively low compared to their productivity and profitability is high. As they grow, profitability decreases. I find that 55% of the decline in profitability post-IPO is driven by GTES, and 45% by mean-reversion in productivity, validating both theories. It would be difficult to obtain these estimates without a structural model, because productivity is hard to measure.

The paper also contributes to the literature on learning, an important mechanism in my model. My contribution is twofold. First, I revisit two measures previously interpreted as evidence of learning. Pástor and Veronesi (2003) interpret the decline in Q in the years after IPO, conditional on other observables, as evidence of learning. I find that indeed, 66 percent of the decline is due to learning, most of the rest coming from growth options related to declining volatility. Moyen and Platikanov (2013) interpret the decline in the sensitivity of investment to profitability as evidence of learning. I find that only 20 percent of that decline is related to learning, the rest coming mostly from increasing rigidity. Second, I am the first to quantify how much firms learn about their efficient scale of operations after going public and how this affects investment. There are papers quantifying learning in other contexts, for example entrepreneurial choice (Catherine, 2018), learning about CEO quality (Taylor, 2010), learning about disaster risk (Hennessy and Radnaev, 2016), or learning about trading skills (Linnainmaa, 2011). The paper closest to mine on the learning front is David et al. (2016), who study how much firms learn and the relationship with misallocation across firms. While in their model firms learn about future shocks and are in a steady state, I explicitly study how firms gradually learn about their (persistent) quality post-IPO and the dynamics thereof.

The remainder of the paper is organized as follows. The next section describes the data and documents the (conditional) investment decline. In section 1.3 I present the model. In section 1.4 I discuss the estimation of the model while in section 1.5
decompose the conditional investment decline into different mechanisms. I perform robustness exercises in section 1.6. Section 1.7 concludes.

1.2 Stylized facts

This section first describes the data and construction of variables. Then I document the (conditional) investment decline in the subsequent years after firms go public.

1.2.1 Data and summary statistics

The data source is the annual Compustat database. Compustat contains financial data on (most) publicly listed U.S. firms. An observation is defined at the firm-year-since-IPO level. The data source for the IPO date is also Compustat.\(^2\) In the data, years since IPO is correlated with fiscal year for observations with long time since IPO. If there are structural shifts in firm dynamics over time, this could introduce bias. To mitigate this bias, I remove observations with more than 20 years since IPO.

Furthermore, I remove all regulated utilities (SIC 4900-4999), financial firms (SIC 6000-6999), and quasi-governmental and nonprofit firms (SIC 9000-9999). I also remove firm-year observations with missing capital stock (\(ppeg\)), assets (\(at\)), operating income (\(oibdp\)) and sales (\(sale\)). Furthermore I also remove observations with negative sales, negative capital stock and negative assets. Compustat sometimes also includes a few observations before firms go public, which I delete too. All ratios are winsorized at the 1% level. In line with the corporate investment literature I remove firms from the sample if their capital stock in any one year is smaller than one million (2010) dollars.\(^3\)

<table>
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<tr>
<th>Table 1.1: Summary Statistics</th>
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<tr>
<td>Obs.</td>
</tr>
<tr>
<td>-----------------------------</td>
</tr>
<tr>
<td>Fiscal year</td>
</tr>
<tr>
<td>Years since IPO</td>
</tr>
<tr>
<td>investment rate</td>
</tr>
<tr>
<td>scaled operating income</td>
</tr>
<tr>
<td>sales-to-capital ratio</td>
</tr>
<tr>
<td>capital stock (millions)</td>
</tr>
<tr>
<td>log of Q</td>
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This Table reports the summary statistics used in the analysis. For each variable, I present its mean, median, 25th and 75th percentiles, and its standard deviation, as well as the number of non-missing observations for this variable. All variables are defined in Table A.31. The sample period is from 1960 to 2018.

The final sample is a panel data set with 65'816 firm-year-since-IPO observations

\(^2\) I find that this source practically has the same coverage as the widely used data collected by Jay Ritter, available on his website.
\(^3\) All dollar variables are deflated by the CPI index provided by the St. Louis Fed (2010 dollars).
from 1960 to 2018. Table 1.1 reports the summary statistics. The firms in the sample are skewed in size and being public are obviously large, the average capital stock being 1370 million dollars and the median being 59 million dollars. They are also rather profitable, operating income being 29% of the capital stock on average. Q, the ratio of market valuation to the capital stock, is also pretty high. It is an unbalanced panel. On average 12% of firms exit the sample in a given year, so the sample is skewed towards observations with fewer years since IPO.

1.2.2 Declining investment

Figure 1.1: Investment decline after IPO.

The dashed lines plots the investment rate and the solid lines plots the conditional investment rate, for the data (circles) and a standard neoclassical model with convex adjustment costs (squares) (Clementi, 2002; Cooper and Haltiwanger, 2006). Conditional investment is the age dummies obtained from regressing the investment rate on years-since-IPO dummies, the log capital stock, the log sales-to-capital ratio, scaled operating income and squared terms thereof while using firm fixed effects (column 2 in Table A.32).

The dashed blue line in Figure 1.1 shows that firms’ capital investment rate decreases in the subsequent years after they go public. The solid blue line plots firms conditional investment rate, which is obtained by regressing the investment rate on years-since-IPO dummies while also controlling for size and two different measures of profitability. The area under the conditional investment curve is 60 percent of the area under the unconditional investment curve. More than half of investment can thus not be explained by size or profitability. The red lines are obtained from simulating a standard convex adjustment cost model (see e.g., Clementi (2002); Cooper and Haltiwanger (2006)) where firms start with a lower than steady-state capital stock. This produces a declining investment pattern, due to a decreasing marginal product of capital as they converge to their steady state capital stock. I obtain the solid red line by running the

---

4 Figure A.41 shows that most initial public offerings in the sample are concentrated in the period from the mid eighties to 2001 when the dot-com bubble burst.
conditional investment regression on the sample obtained from the simulated model. No matter the parameter values in the convex adjustment model, the line is always flat. Intuitively, the state variables in that model are only productivity and the capital stock, so all the variation in investment is soaked up by profitability (which is highly correlated with productivity) and size.

1.3 The model

In this section I present a dynamic investment model which contains different sources of the conditional decline in investment. The model is a neoclassical convex adjustment cost model (see e.g., Cooper and Haltiwanger (2006)). It starts at a point in time which corresponds to the IPO. I extend it model across five dimensions. First, I assume that firms start with a smaller than efficient capital stock. Even though the model of Clementi (2002) where firms grow towards their efficient scale can not explain the conditional investment decline, it can explain the unconditional investment decline. Omitting this (likely) first-order mechanism could introduce a bias when I estimate the model. Furthermore it could interact with other sources. Second, the firm dynamics literature proposes learning as a source for the conditional investment decline in the context of private firms (see e.g., Jovanovic (1982); Arkolakis et al. (2018)). In the model I therefore assume that firms are learning about their efficient scale. Third, according to the theory of Pástor et al. (2008), firms optimally choose to go public when their productivity is temporarily high. This implies that after the IPO it tends to revert back to the mean. Although this mechanism is not an obvious source for the conditional investment decline, including it in the model allows me to quantify the sources of the post-IPO underperformance documented in the literature (Jain and Kini, 1994). Therefore I assume that firms start on average with an abnormally high productivity. Fourth, Asker et al. (2014) show that public firms invest less and respond less to profitability than (similar) private firms, and interpret this as differences in adjustment costs. It is possible that this phenomenon reflects the process of firms gradually becoming more rigid after they go public. Therefore I assume in the model that firms’ adjustment costs increase over time. Fifth, in the data firms’ volatility of profitability decreases in the subsequent years after they go public. Thus I assume that the volatility of productivity decreases over time.

After presenting the model, I also provide intuition behind how learning and volatility can produce the conditional investment pattern. Finally, I discuss other potential mechanisms and why I chose to omit them.

1.3.1 Cash flows

I begin by laying out my assumptions about cash flows. Consider an infinitely lived firm making capital investment decisions in discrete time. The firm operates at decreasing returns to scale. Sales at time $t$ are $A_tK_t^\alpha$. The variable $A_t$ reflects the time-varying productivity or demand for the firm’s products, $K_t$ is the capital stock and $\alpha$ the returns

---

\[^5\text{I am agnostic about the sources of increasing rigidity, for example short-termism (Holmström, 1999) or organizational rigidity (Ferreira et al., 2012).} \]
to scale parameter. Log productivity is the sum of a transitory component \( z_t \) and a permanent component \( \mu \), i.e., \( \ln A_t \equiv a_t = z_t + \mu \). The transitory component follows an AR(1) process with decreasing volatility:

\[
\begin{align*}
z_{t+1} = \rho_z z_t + \varepsilon_{z,t+1}, \quad \text{where} \quad \varepsilon_{z,t+1} & \sim N(0, f_z(t)\sigma^2_z) \\
\text{and} \quad f_z(t) & = 1 + \frac{b_z}{1 + t},
\end{align*}
\]

where \( \rho_z \) is the autocorrelation coefficient and \( \varepsilon_{z,t+1} \) is an independently distributed random variable with a normal distribution. It has mean 0 and a variance that depends on \( t \). The function \( f_z(t) \) is a scaling factor which is decreasing in time \( t \). It converges to one, which means that the variance of \( \varepsilon_{z,t+1} \) converges to \( \sigma^2_z \). The parameter \( b_z \) determines by how much volatility decreases over time.

Firm investment in physical capital is defined as:

\[
I_t = K_{t+1} - (1 - \delta)K_t, \tag{1.3}
\]

where \( \delta \) is the depreciation rate of capital. When the firm invests, it incurs adjustment costs, which can be thought of as profits lost as a result of the process of investment. These adjustment costs are convex in the rate of investment net of depreciation and increase over time. They are given by:

\[
\Phi(I_t, K_t, t) \equiv f_Y(t)\frac{Y}{2} \left( \frac{I_t}{K_t} - \delta \right)^2 K_t, \quad \text{where} \quad f_Y(t) = 1 - \frac{b_y}{1 + t}. \tag{1.4}
\]

The parameter \( \gamma \) is the curvature of the adjustment cost function. It is scaled by the factor \( f_Y(t) \), which increases over time and converges to one. The parameter \( b_y \) determines by how much adjustment costs increase over time.

The firm maximizes the sum of cash flows, which are discounted at a constant rate \( \beta \). Cash flows are operating income minus capital expenditures, where operating income is sales minus adjustment costs. Thus cash flows are given by:

\[
C_t = A_tK_t^{\alpha} - \Phi(I_t, K_t, t) - I_t. \tag{1.5}
\]

### 1.3.2 Initialization

The model starts at \( t = 0 \), which corresponds in the empirical setting to the time of IPO. At \( t = 0 \), the firm draws its initial and permanent productivity, forms beliefs about it’s type and chooses its initial capital stock. It’s permanent productivity \( \mu \) is drawn from a normal distribution with mean 0 and variance \( \sigma^2_\mu \). It’s initial transitory productivity \( z_0 \) is also drawn from a normal distribution but with mean \( \mu_{z0} \) and variance \( (1 + b_z)m_z^{-1} \), where \( m_z = \frac{1 - \rho_z^2}{\sigma^2_z} \). Thus if \( \mu_{z0} > 0 \), then the firm starts with an on average higher productivity than in the long-run. The variance of \( z_0 \) is just the long-run variance of \( z_t \) adjusted for the fact that earlier it is higher.

---

6 I focus on physical capital, not other production factors. One can thus think of \( \alpha \) as a combination of the firms market power and the relative importance of physical capital compared to other production factors (under the assumption that they are frictionlessly adjustable). It is easy to show this analytically in a setting with constant returns to scale, capital and labor as production factors and monopolistic competition (see e.g., Catherine et al. (2018)).
Following Alti (2003), the firm chooses its initial capital stock $K_0$ to maximize the discounted sum of future cash flows. To capture the fact that small firms grow faster than larger firms, it faces an additional deadweight cost $C_0 \geq 0$ for purchasing capital at $t = 0$ (over and above the rental rate of capital). It’s initial capital stock will thus naturally be smaller than it’s expected long-run efficient capital stock.\footnote{The parameter $C_0$ does not have a clear interpretation, it could mean physical installation costs, higher costs of external finance pre-IPO, or how large the initial growth option of the firm is. Loosely speaking, it is just a measure of how far the firm is from its expected long-run efficient capital stock.}

### 1.3.3 Beliefs

I assume that the firm does not separately observe its permanent and transitory productivity, but only the sum of the two. At $t = 0$ it forms beliefs about $\mu$ (and $z_0$) upon observing productivity $a_0$. The firm’s initial belief $\hat{\mu}_0$ about its permanent productivity is:

$$\hat{\mu}_0 = a_0(1 + b_z)^{-1}m_zP_0, \text{ where } P_0 = \frac{1}{\sigma_{\hat{\mu}}^2 + \frac{m_z}{1+b_z}}, \quad (1.6)$$

which is a product of its initial productivity $a_0$, the precision of the initial productivity signal $(1 + b_z)^{-1}m_z$ and a factor $P_0$. The latter is the remaining uncertainty the firm faces after observing the productivity signal.

The firm gradually learns about $\mu$ over time. At the beginning of each period, when its productivity changes, it updates its beliefs about $\mu$. When $a$ is unexpectedly high, then it revises its beliefs upward. When $a$ is unexpectedly low, then it revises its beliefs downward. How aggressively it does so depends firstly on the signal precision $(1 + f_z(t))^{-1}m_z$, which depends positively on the volatility and persistence of the transitory shock. A higher $b_z$ means that the signal is noisier early on, which slows down learning. Secondly, it also depends on how much uncertainty $P_t$ the firm still faces. Early on when $P$ high it reacts a lot to news. Over time $P$ declines as the firm learns about $\mu$.

I also assume that the firm observes a private signal $l_t$ about $\mu$ in each period (except at birth). This signal is orthogonal to productivity and captures all other sources the firm is learning from, for example soft information. It is given by:

$$l_t = \mu + \varepsilon_{l,t}, \text{ where } \varepsilon_{l,t} \sim N(0, \sigma_l^2), \quad (1.7)$$

where $\sigma_l$ reflects the noisiness of the signal.

Summarizing, The value of the firm and it’s capital investment choice thus depends on four state variables. First, it’s capital stock $K$, second, it’s (log)productivity $a$, third, the belief about it’s permanent productivity $\hat{\mu}$, and fourth, time $t$. I solve the firm’s problem with value function iteration. Appendix A.1 contains details about the procedure, including the recursive formulation of the firm’s maximization problem and it’s choice of initial capital stock.

### 1.3.4 Discussion

In what follows, I first provide intuition on how learning and volatility can generate a declining conditional investment pattern. Then I discuss some of the functional forms I used in the model and which mechanisms I chose not to include.
How learning and volatility generate net investment

As firms learn, some revise their beliefs about $\mu$ upward and some downward. How does this result in net investment? Since productivity is log-normally distributed, a positive shift in beliefs of $\mu$ coincides with a bigger increase in (perceived long-term) productivity than the decrease in productivity resulting from a negative shift in beliefs, ceteris paribus.\(^8\) Since productivity is linked to size, a firm with a positive belief shock invests more than a firm with a negative belief shock divests, ceteris paribus. Furthermore, for the same reason a firm that received a positive belief shock in the past also responds stronger to a positive belief shock in the future, being further to the right in the productivity distribution. The more firms are learning, the stronger this mechanism. Since learning decreases over time, this results in a declining investment pattern. A similar logic applies to how volatility produces net investment. Those firms with a positive transitory shock invest more than those with a negative shock disinvest, ceteris paribus. Since volatility also decreases over time, this also results in a declining investment pattern.

The question remains how these two mechanisms can generate a decline in conditional investment. Regarding learning, since private signals are unobservable to the econometrician, controlling for profitability will not capture that. Second, as previously argued, the higher the volatility of productivity, the stronger the investment asymmetry. Essentially the omitted variable in the conditional investment regression is how strongly firms update their beliefs about $\mu$ in the case of learning and how volatile productivity is in the case of the volatility mechanism. Both these variables are correlated with time, which is what produces the variation in conditional investment.

Functional forms for rigidity and volatility

It is plausible that firms become more rigid and their volatility declines as they become larger, rather than over time as I assumed in the model. But parameterizing firms’ rigidity or volatility as a function of size makes it impossible for either mechanism to match the decline in investment conditional on size and profitability, the main stylized fact.\(^9\)

Other possible mechanisms

In the firm dynamics literature (which studies mostly private firms) a popular way to rationalize the declining growth as firms age (conditional on size) is selection through exit. There, when a firm’s productivity is too low for it to operate profitably (e.g., due to fixed costs) it will exit (Jovanovic, 1982). Public firms however mostly exit the Compustat sample not due to liquidations, but rather due to acquisitions, mergers or other types of delistings (Grullon et al., 2017, Figure 5). Also, for private firms the likelihood of exiting is higher for younger firms (Decker et al., 2014; Arkolakis et al., 2017).

---

\(^8\) This is illustrated in Figure A.42 in the appendix.

\(^9\) Using only one parameter to capture the increase in adjustment costs ($b_1$) or decrease in shock volatility ($b_2$) is also a rather rigid parametrization, putting a lot of structure. Having a more flexible form with more parameters could provide a better model fit to the data. Section 1.4.3 however shows that the model does quite well as is. I also experimented with a different parametrization than the reciprocal of one plus firm age, using the log of one plus firm age. This gave very similar results in the estimation.
which is consistent with models with fixed costs where firms may exit if they learn they are unprofitable (Jovanovic, 1982). For public firms however there is no declining pattern, if anything firms that more recently went public have a lower chance of exit.\textsuperscript{10} For these reasons I implicitly assume that firms are large enough compared to their fixed costs to operate profitably. This is intuitive for public firms.

Financing frictions could also produce declining investment as firms age (Cooley and Quadrini, 2001). I omit them for multiple reasons. First, I find that the decline in conditional investment, my primary object of interest, is not explained by measures of financing constraints such as cash flows, leverage or cash holdings. Second, public firms have widespread access to capital markets. The literature on the existence and effects of financing frictions on investment for public firms is inconclusive at best (see e.g., Farre-Mensa and Ljungqvist (2016)). Furthermore, existing structural models only find modest effects of financing frictions on investment (Hennessy and Whited, 2007; Warusawitharana and Whited, 2015).

Frictions in product markets could also play a role. In Gourio and Rudanko (2014) for example, it takes time for firms to build a customer base, which translate into sluggish sales expansion. This friction slows down capital growth and reduces the sensitivity of capital investment to productivity shocks. The amount of customers a firm has could be an omitted variable, which is correlated with the time since IPO. Firms which recently went public however grow faster (conditional on size) and react more to shocks than firms which have been public for longer. The friction therefore produces exactly the opposite of what is required to match the declining sensitivity of investment to profitability I find in my sample. More generally, this argument applies to any friction that dampens the sensitivity of investment to profitability more for firms that recently went public.

Next, firms may continuously become less innovative from the moment on that they are founded, implying they get less new ideas over time. If a new idea warrants capital investment then this mechanism could produce a decline in investment. I show in section 1.6.1 however that the post-IPO dynamics in investment and conditional investment are related to the number years since the IPO, not the number of years since founding.

A more nuanced theory that is in line with this fact is the one of Ferreira et al. (2012). There firms go public precisely to exploit existing ideas, which on the other hand reduces their innovative capacity. One can think of an extension of the theory where this tradeoff manifests itself gradually during the first few years after the IPO. Similarly, firms may still have some ideas left over from the time when they used to be private and may implement them gradually when they go public until they run out. If implementing a new idea leads to capital investment (i.e., an increase in size), then this mechanism could produce the conditional investment decline. However, the implementation of an idea should also increase the productivity of a firm if it warrants an increase in firm size. It turns out however that productivity declines after firms go public (Chemmanur et al., 2009, Figure 1).

Theories of the going-public decision revolving around competition could also affect post-IPO dynamics (Bhattacharya and Ritter, 1983; Maksimovic and Pichler, 2001). Firms’ market share is flat in the years after they go public however, making it unlikely (Chemmanur et al., 2009, Figure 6).

\textsuperscript{10}See Figure A.43 in the appendix.
1.4 Estimation and identification

In this section I discuss the estimation of the model. This involves calibrating two parameters and estimating the rest using the simulated method of moments (SSM). I will also discuss in detail how my choice of moments pins down the parameters in the model. Lastly, I discuss the parameter estimates and how well the model fits the data.

1.4.1 Estimation

I estimate most of the structural parameters of the model using SMM. This involves simulating the model and calculating interesting moments from the simulated data and actual data. SMM then finds the model parameters that make the actual and simulated moments as close as possible. Appendix A.2 provides technical details on the estimation procedure.

I calibrate two parameters. First, following Warusawitharana and Whited (2015) I estimate the risk-free interest rate, \( r \), as the average real Baa interest rate over the (observation-weighted) sample period.\(^{11}\) This translates into a discount factor \( \beta \) of 0.95. Second, as previously mentioned firms sometimes exit the sample. Without any adjustments this could introduce bias towards firms with a long time since IPO. I therefore assume that firms face an exogenous probability \( \pi \) of exiting the simulated sample. Since most firms exit Compustat due to acquisitions or delistings, I assume that the chance of exiting does not distort firms’ decisions, i.e., it does not affect firms’ discount factor. I calibrate \( \pi = 0.12 \) to match the exit rate in the data.

I then estimate the following 11 parameters using SMM: the capital depreciation rate, \( \delta \); the capital initialization cost, \( C_0 \); the baseline volatility and autocorrelation of the productivity process, \( \sigma \) and \( \rho \); the returns to scale parameter, \( \alpha \); the quadratic adjustment cost parameter, \( \gamma \); the dispersion in firm quality, \( \sigma_\mu \); the volatility of the private signal, \( \sigma_l \); the mean initial transitory productivity, \( \mu_{z0} \); the volatility scaling parameter, \( b_z \) and the rigidity scaling parameter, \( b_\gamma \).

1.4.2 Model identification

In this section I discuss my choice of moments and how they help pin down the model parameters. How well the estimation works depends on whether the moments change a lot depending on the parameters and that the model is identified in a statistical sense. That is, all I require for the model to be identified is that the Jacobian matrix (how the moments change with the parameters) is invertible. But for the procedure to be successful and the estimates credible, exactly how individual moments contribute to pinning down the parameters must be as transparent as possible. The entire analysis is about local identification, in the sense that I operate around the main SMM estimate for \((\delta, C_0, \sigma_z, \rho_z, \alpha, \gamma, \sigma_\mu, \sigma_\mu, \mu_{z0}, b_z, b_\gamma)\) – which I discuss in detail in what follows.

Standard moments

The average investment rate of firms with more than 10 years since IPO is highly informative about the depreciation rate of capital \( \delta \). The higher \( \delta \), the larger the required investment rate to maintain the capital stock.

\(^{11}\)I obtained the data from the Federal Reserve Bank of St. Louis FRED database.
The average scaled operating income of firms with more than 10 years since IPO helps pin down the returns to scale parameter $\alpha$. In a hypothetical environment with constant returns to scale and monopolistic competition, higher competition translates into a higher $\alpha$ and intuitively also into lower scaled operating income. Thus they are inversely related.

The dynamics of the log sales-to-capital ratio are informative about the parameters driving the TFP process. Specifically, the autocorrelation thereof is informative about the autocorrelation of productivity $\rho_z$. The variance of log sales-to-capital growth of firms with long time since IPO pin down the baseline volatility of productivity $\sigma_z$. The same moment but for firms with five or less years since IPO helps pin down the volatility scaling parameter $b_z$.\textsuperscript{12}

Capturing firm dynamics

The moments I discuss next are related to the dynamics of variables such as investment, profitability and Q after the IPO. Here, a delicate issue arises whether to take a parametric or non-parametric approach to describe the data in terms of moments, and how to implement it. Figure 1.1 for example which showed the stylized facts plots 21 years-since-IPO dummies, which could all be used as moments. Such a granular, non-parametric approach is problematic. The SMM procedure will put more weight on the first few years because there are more observations. This results in a great fit in the first few years but a terrible fit later on. I experimented with forming age groups that have roughly the same number of observations, which works better. But a problem that remains with providing detailed information about slopes at different points in time is that the dynamics of some variables such as Q will be matched (too) well, and the dynamics of other variables such as profitability will be matched poorly.

I also experimented with parametric approaches. For example, I attempted to fit the decline in the variables simply using the reciprocal of one plus firm age.\textsuperscript{13} This approach worked relatively well, due to its simplicity and because empirically the decline in the variables of interest is close to proportional to the reciprocal of one plus firm age.

Summarizing, there is a delicate tradeoff between providing a lot of information to the SMM procedure and not matching the total decline of some variables and providing little information, matching poorly the speed of decline. I settle for the the parametric approach, using the reciprocal of one plus firm age for all variables. The only deviation of this concerns the decline in conditional Q and the sensitivity of investment to profitability where I use a more granular approach, described later in detail. What provides piece of mind is that when I granularly compare in section 1.4.3 the dynamics of the simulated model to the data, the fit is pretty good.

\textsuperscript{12}Note that both the sales-to-capital ratio and scaled operating income could be classified as measures of profitability. The latter also includes costs of goods sold and SG&A. In Compustat, SG&A is a combined measure for fixed overhead costs, the wage bill, marketing costs and training costs. The log sales-to-capital ratio is my preferred measure of profitability to capture the dynamics of productivity, since it is least contaminated by the firms decisions. When mentioning profitability, from now on I am referring to scaled operating income when discussing the level of profitability, and in all other cases I am referring to the log of the sales-to-capital ratio.

\textsuperscript{13}Using the natural log of one plus firm age gave similar results.
Novel moments

Next, I regress the log of the sales-to-capital ratio on a constant and the reciprocal of one plus firm age. The age coefficient captures the decline in profitability as firms age and is informative about the average initial transitory productivity $\mu_0$. Due to mean-reversion, intuitively productivity and thus profitability declines over time.

I obtain additional moments from an empirical policy function regression (EPF), which estimates an approximation the firms policy function, i.e., investment as a function of the state variables. Note that not all state variables are observable to the econometrician, so the EPF will be incomplete. This is only a problem to the extent that it may be imprecise, as any bias will be reflected equally in the estimates of the EPF based on the empirical and simulated sample. Specifically, I regress investment growth on profitability growth, log capital stock growth, and interactions with years-since-IPO group dummies.\textsuperscript{14} In the EPF regression, the (un-interacted) coefficient on profitability is highly informative about the adjustment cost parameter $\gamma$. The higher $\gamma$, the less investment reacts to productivity shocks, which implies a lower regression coefficient.

Which moments are informative about $C_0$, $\sigma_\mu$, $b_\gamma$ and $\sigma_l$ remains to be discussed. I normalize $C_0$ to isolate GTES from the other sources, which facilitates the identification and counterfactual experiments later on. Details are in Appendix A.2.1.

How the parameters affect the informative moments is shown in Figure 1.2. The decline in the sensitivity of investment to profitability as firms age is highly informative about the increasing adjustment cost parameter $b_\gamma$. This is intuitive as firms with lower adjustment costs respond more to shocks. Note that also $C_0$ affects the decline in the investment-profitability sensitivity because early on firms have a high marginal product of capital (because $K$ is low), which makes them react more to changes in profitability. This is obvious if one takes the partial derivative of $AK^\alpha/K$ with respect to $K$ and productivity. The smaller $K$, the larger is the resulting term. Apart from $C_0$, also $\sigma_\mu$ affects that moment positively. When firms are learning, then current profitability also has an informational component. They react more to profitability because it provides a signal about their efficient scale, as opposed to merely reacting to transitory shocks. Importantly for what follows, the other moments in Figure 1.2 are not affected by $b_\gamma$.

Next, I regress the log of $Q$ on equally-sized year-since-IPO groups, the log capital stock, the log of the sales-to-capital ratio and squared terms thereof. I also use firm fixed effects to account for persistent heterogeneity in firms’ profitability and size. I target different years-since-IPO group dummies in the estimation to capture the speed of decline in conditional $Q$, which is informative about the precision of the private signal. The total decline in conditional $Q$ is almost flat in $C_0$, which helps the SMM procedure to separate $C_0$ from ($\sigma_\mu$, $\sigma_l$). The flatness comes from the fact that $C_0$, representing GTES, operates through profitability and size which I control for.

Next, I regress the log of $Q$ on a constant and the reciprocal of one plus the number of years since IPO. The coefficient on the latter captures the decline in unconditional $Q$ over time and is informative about $C_0$. If firms start with a lower than long-run efficient capital stock, then future cash flows are relatively high compared to their current size, so early on $Q$ is high. Over time, as they grow, the denominator of $Q$ increases and decreases.

\textsuperscript{14}I sort all observations across years since IPO and form five groups that all have (roughly) the same number of observations. The resulting groups are 0 and 1; 2 and 3; 4 to 6; 7 to 11; 12 to 20. Table A.33 in the appendix shows this regression for the data.
and $\gamma$ is the adjustment cost scaling factor.

Years since IPO refer to 0 and 1 and 4 to 6 dummy variables, the log capital stock, the log sales-to-capital ratio and squared terms thereof while using firm fixed effects. $\sigma$ is the (normalized) initial deadweight cost of capital, $\mu$ is the dispersion in quality, $\sigma$ is the log capital stock, the log sales-to-capital ratio and squared terms thereof while using firm fixed effects, and $\gamma$ is the adjustment cost scaling factor.

In these figures only one parameter is changed at a time, while the others are held constant at the SMM estimates.
it shrinks. The decline in unconditional Q is also affected by $\sigma_\mu$, but as previously mentioned the decline in conditional Q helps separate them.

Finally, comparing the total decline in conditional Q and the decline in conditional Q from years 4 to 6 provides information on the speed of decline in conditional Q. The latter is highly informative about the noisiness of the private signal $\sigma_t$. The lower $\sigma_t$, the faster firms learn. The total decline in conditional Q is informative about the total amount of learning/uncertainty, $\sigma_\mu$.

I target two additional moments, the decline in investment and the decline in conditional investment. I use a parametric approach for both.

**Limitations of the model**

Naturally there are features of the data that the model is not designed to explain. If I force the model to match them nevertheless, it could do poorly in matching the features of the data I am actually interested in. In what follows I discuss this.

First, in the data the autocorrelation of investment is relatively low. It is well known that non-convex adjustment costs are necessary to match this fact (Cooper and Haltiwanger, 2006). Experimenting with the inclusion of non-convex adjustment costs revealed however that they don’t play a first-order effect in the mechanisms that I am studying. Intuitively, non-convex adjustment costs have more of a bite in models with financing frictions for example, where firms may have difficulty financing lumpy investment outlays out of profits (see e.g., Riddick and Whited (2009)). I am already estimating quite a lot of parameters. Including more would increase complexity without adding any insights. Therefore I don’t target the autocorrelation of investment and the coefficient on capital stock growth in the EPF regression (but I do control for it).

Second, in the data the correlation of investment with other observables such as profitability is relatively low. The model can not match this because there are only productivity shocks. Since the correlation can be decomposed into the variance of investment, variance of profitability and covariance of investment and profitability, I therefore can only match two out of the three. I must target the variance of profitability to pin down the TFP parameters. If I choose to match the entire variation of investment, then in the model it will come mostly from variation in profitability, whereas in reality there must be other unobservable sources (or measurement error). By instead matching the covariance of investment with profitability, I can at least capture that relationship, while admitting that I can not match the entire variation of investment.

Third, I do not attempt to match the level of Q. In the model, the firm is risk-neutral so stock prices and Q don’t contain any risk premia. This is clearly at odds with reality.

**1.4.3 Goodness of fit**

Figure 1.3 plots all variables of interest against years since IPO, comparing the data to the simulated sample obtained from the SMM estimates.\(^{15}\) The model fits the data well. While it matches the total decline in investment, it declines slightly too fast. The

\(^{15}\)Table A.34 in the appendix reports the fit of the moments targeted in the estimation. Table A.35 in the appendix contains the Jacobian matrix, i.e., the derivatives of the moments with respect to the parameters.
This Table plots the variables of interest for the data and simulated sample at the SMM estimates. The scale on the y-axis of the conditional investment rate starts with zero because that specification uses firm fixed effects, which removes the mean. The decline in log Q, conditional log Q and log sales/K are normalized (start at zero) because I do not attempt to match the means of those variables. I also do not attempt to match the decline in scaled operating income. The investment to profitability sensitivity is obtained by regressing investment growth on the growth of the log sales to capital ratio and log capital growth for each year since IPO.
area between the orange and blue curve represents 31 percent of the total area under the blue curve.

Although my primary interest is explaining the decline in investment, it is surprising how well the model fits the dynamics of other variables too. It has a bit of difficulty matching the decline in the sensitivity of investment profitability from year four on. Also, conditional Q declines too slow compared to the data. The model also has no chance matching the different decline in the sales to capital ratio and scaled operating income. The reason is that they are constructed almost the same in the model, but in the data scaled operating income also contains sales, general and administrative costs (SG&A).

1.4.4 Results

Table 1.2: Parameters estimated with SMM.

<table>
<thead>
<tr>
<th>Par</th>
<th>Estimate</th>
<th>Std. Err.</th>
</tr>
</thead>
<tbody>
<tr>
<td>depreciation rate</td>
<td>δ</td>
<td>0.138</td>
</tr>
<tr>
<td>(normalized) initial C.o.C.</td>
<td>C₀</td>
<td>0.296</td>
</tr>
<tr>
<td>volatility of productivity</td>
<td>σ₂</td>
<td>0.337</td>
</tr>
<tr>
<td>autocorrelation of productivity</td>
<td>ρ₂</td>
<td>0.800</td>
</tr>
<tr>
<td>returns to scale</td>
<td>α</td>
<td>0.506</td>
</tr>
<tr>
<td>adjustment costs</td>
<td>γ</td>
<td>3.267</td>
</tr>
<tr>
<td>dispersion in quality</td>
<td>σₚ</td>
<td>0.460</td>
</tr>
<tr>
<td>private signal noisiness</td>
<td>σ₁</td>
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</tr>
<tr>
<td>initial mean log productivity</td>
<td>µₓ₀</td>
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<tr>
<td>volatility scaling parameter</td>
<td>b₂</td>
<td>1.702</td>
</tr>
<tr>
<td>adjustment cost scaling parameter</td>
<td>bγ</td>
<td>0.740</td>
</tr>
</tbody>
</table>

Table 1.2 reports the estimated parameters and their respective standard errors. All parameters are significantly different from zero.

The estimated volatility and autocorrelation of TFP, as well as the depreciation rate of capital are values in line with the literature. The returns to scale parameter $\alpha = 0.51$ is lower than is typically calibrated, which is usually in the range of 0.6 to 0.7 (see e.g., Gomes (2001)). In a robustness exercise in section 1.6.3, I show however that my results are not that sensitive to the estimate of $\alpha$.

The estimated adjustment costs are $\gamma = 3.3$, which is higher than what what people typically find in the firm dynamics literature (Cooper and Helpiwanger, 2006) and structural corporate finance literature (DeAngelo et al., 2011). The reason is that in these studies, people target the variance of investment, which is relatively high, whereas I target the covariance of investment and profitability, which is relatively low. Altı (2003) for example calibrates $\gamma$ to match regression coefficients as I do and gets a similar value as I do. Interestingly, I estimate that adjustment costs increase quite a

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\[16\] In the structural corporate finance literature, people sometimes obtain estimates of close to 0.8 (see e.g., DeAngelo et al. (2011)). The reason is that in their sample average profitability is lower, which translates into a higher $\alpha$. In Compustat, depending on the sample selection and winsorization, estimates of average scaled operating income can be sensitive to outliers.
lot over time. The adjustment cost scaling parameter $b_\gamma = 0.74$ together with $\gamma = 3.3$ implies that firms that just went public have roughly 3.5 times lower adjustment costs compared to 10 years later. This is in line with the reduced-form evidence of Asker et al. (2014), who compare private and public firms. The average estimated adjustment cost averaged over all observations in the sample is 2.5.

The parameter $C_0 = 0.3$ capturing GTES does not have a direct interpretation. It is informative however to translate it into how much firms are growing towards their efficient capital stock after their IPO (assuming they know their efficient scale). This turns out to be 0.67 times an order of a magnitude.

The estimate $b_x = 1.7$ implies that the volatility of productivity significantly decreases over time. The standard deviation of the shocks decreases from 0.56 at $t = 0$ to 0.36 10 years later, a 35 percent reduction.

Furthermore, the estimates imply that when firms go public, uncertainty about their efficient scale is quite high. This on the one hand has to do with $\sigma_\mu = 0.46$ being quite high and on the other hand firms having quite volatile productivity at the IPO, which makes it a rather uninformative signal. The private signal $\sigma_l = 0.22$ is estimated to be quite precise, because the fast decline in conditional $Q$ implies that uncertainty about $\mu$ must be resolving quickly compared to the noisiness of productivity. The weight put on the private signal is high at $m_L = 18.4$, whereas the weight put on the profitability signal $m_x = 0.2$ is low. Taylor (2010) also finds that non-earnings information is much more informative in the context of boards learning about their CEOs skill.

It is informative to compare the uncertainty related to learning from the long-run variation in transitory productivity, which depends on $\sigma_z$ and $\rho_x$. For a firm trying to forecast its transitory productivity $z$ many years from now, the 95% confidence interval lies in $[-1.77, 1.77]$. If the firm at $t=0$ estimates what its true $\mu$ is, then the 95% confidence interval lies in $[-1.32, 1.32]$. The intervals look similar but imply quite different variations in size. The standard deviation in the long-run log-capital stock coming from uncertainty about $\mu$ is 0.80, much larger than the variation coming from transitory shocks, which is 0.30. The reason for this is that $\mu$ represents permanent productivity compared to $z$ which is transitory, so firms react much less to changes in $z$ compared to changes in beliefs about $\mu$.

The abnormal initial productivity $\mu_{z0}$ is estimated at 0.4. To put this into perspective, it is 71% of the long-run variation (standard deviation) of transitory shocks. Thus at IPO, on average firms transitory productivity $z$ is at the 76th percentile of their long-run transitory productivity (as opposed to the 50th percentile for $\mu_{z0} = 0$).

### 1.5 What explains firm’s post-IPO dynamics?

Previously, I established that my model fits the data well. Now I use the estimated model to investigate which mechanisms are quantitatively important in explaining firms’ post-IPO dynamics. Of particular interest are the sources of the decline in conditional investment. To do this, I run different counterfactual experiments where each source is either activated (set to the SMM estimate) or deactivated. I then compare the dynamics of these counterfactuals with the dynamics of the baseline estimation. All five mechanisms are directly related to five specific model parameters, described as follows. If $C_0 = 0$, then firms are not growing towards their efficient scale. Because of the normalization of $C_0$ discussed in Appendix A.2.1, setting $C_0 = 0$ only affects
GTES. If the firm receives a perfect signal about $\mu$ when it is born then there is no learning. If $\beta = 0$, then adjustment costs are constant. If $\gamma = 0$, then the volatility of productivity is constant. If $\mu = 0$, then firms on average don’t have an abnormal productivity at IPO. Due to interactions there are many possible combinations possible, so in what follows I only discuss those that illustrate the main mechanisms at work. This is the outcome of an iterative procedure where I started with examining all combinations and removing one at a time to get to the drivers of the dynamics.\(^{17}\)

First I analyze which mechanisms explain the decline in conditional investment. Figure 1.4 shows that no source alone comes close to matching it, so it must come from combinations of sources and interactions between them. Eyeballing the Figure, it looks like learning and volatility together could account for the slow and steady the decline from year four on. This is indeed the case, as is shown in Figure 1.5. During the first four years, learning explains 31 percent and volatility 21 percent of investment. Of the total conditional investment, learning contributes 37 percent, and volatility 32 percent.\(^{18}\)

![Figure 1.4: Conditional investment - individual sources.](image)

The circle line plots the simulated conditional investment rate at the SMM estimates, i.e., when all sources are activated. The other lines are simulations from the model when only one source at a time is activated.

Figure 1.5 shows that the interaction of GTES and rigidity explains the remaining 32 percent of conditional investment. The intuition is as follows. GTES creates a strong motive for firms to invest, but it is entirely explained by profitability (and size). In combination with asymmetric adjustment costs over time however, early on firms respond more to fundamentals than firms long since their IPO. Therefore two firms with the same profitability and size can have very different investment rates. When they want to grow, the firm that recently went public will invest more aggressively.

\(^{17}\)Table A.36 in the appendix shows the results of all combinations of counterfactual experiments.

\(^{18}\)These percentages are calculated as the integral of the respective curves divided by the integral of the curve of the baseline simulation at the SMM estimates.
The effect of GTES in combination with rigidity is most prominent in the first four years after IPO, where it explains 48 percent of investment. Apart from the interaction between GTES and rigidity, I find that other interaction effects between the mechanisms are quite small.

*No productivity* means that all sources are activated except high abnormal initial productivity, which is set to zero.

Next, Figure 1.6 illustrates that GTES is the dominant mechanism responsible for the decline in unconditional investment. Rigidity interacts with GTES only by changing the timing of investment, i.e., how fast firms grow towards their efficient scale. However, alone it does not generate a declining investment pattern because for firms that recently went public there is no particular investment motive compared to
that it could accelerate. The effects of learning and volatility are small, and there is little interaction between them and GTES.

Interestingly, Figure 1.6 also shows that without an abnormally high productivity at IPO, the investment decline would actually be more pronounced. The reason is that if firms (in the model) start with an abnormally high productivity, then they choose a larger capital stock to take advantage of it. This means they have to grow less towards their efficient scale. Put differently, if firms have abnormally high (transitory) productivity at IPO, then optimally they must have grown before the IPO and ceteris paribus they will shrink after the IPO when productivity mean-reverts. In the data of course there are other mechanisms in play that overall incentivize them to grow.

Next, Figure 1.7 shows that GTES, learning and volatility produce a declining pattern in $Q$, whereas abnormal initial productivity increases it. GTES contributes 40 percent towards the decrease in log $Q$, the reason being that size in the denominator increases. Learning and volatility explain 39 percent and 21 percent, respectively, by creating an implicit option value which decreases over time (see section 1.3.4). Abnormal initial productivity dampens the decline in log $Q$ by 16%. The intuition is the same as previously discussed. Firms choose a larger capital stock at $t=0$, which means that their current size in the denominator is high compared to future profitability.

Next I turn towards the decline in conditional $Q$, shown in Figure 1.8. Only learning and volatility create a meaningful decline in conditional $Q$, learning (66%) being more important than volatility (26%). The combination of GTES and rigidity plays a very small role (8%). Pástor and Veronesi (2003) interpret the decline in conditional $Q$ as evidence of learning. For the most part, my model confirms this.

The main sources behind the decline in profitability are shown in Figure 1.9. GTES contributes 55 percent and abnormal initial productivity 45 percent, the other mechanisms are unimportant. Evaluating the two competing theories of Clementi (2002) and Pástor et al. (2008), both seem to be roughly equally important in generating the
Figure 1.8: Conditional Q.

Figure 1.9: Profitability.

decline in profitability after firms’ IPO. Profitability thus declines both because firms grow in size and because productivity mean-reverts.

Finally, I also discuss the causes of the decline in the sensitivity of investment to profitability, shown in Figure 1.10. It almost all comes from increasing rigidity (63%), a bit from learning (20%) and GTES (17%). In the learning literature, it is common to interpret a declining investment-to-profitability sensitivity as evidence of learning from cash flows (e.g., Moyen and Platikanov (2013)). My estimates paint a different picture. First, I find that firms learn mostly from other signals than profitability, so learning can not be responsible for the decline. The bulk of the decline rather comes from from increasing rigidity. This is in line with Asker et al. (2014), who show that public firms respond less to fundamentals than private firms. My analysis underlines that this is a change which happens within firm, and at least part of it occurs gradually during the
The investment to profitability sensitivity is obtained by regressing investment growth on the growth of the log sales to capital ratio and log capital growth for each firm age.

first few years after the IPO.

1.6 Robustness

In this section I perform three robustness exercises. First, I show that the investment decline is not just an artifact of firms’ life-cycle since founding but is directly related to the IPO. The second is aimed at better understanding where the identification is coming from and the third gauges how sensitive my results are to the returns to scale parameter $\alpha$.

1.6.1 Founding age vs years since IPO

My model explains firms’ dynamics after their IPO. A natural question to ask is whether these dynamics simply are a manifestation of firms’ life-cycle dynamics from when they are founded to when they dissolve, sometime in between being the IPO. It is well known from the firm dynamics literature that private firms receive large productivity shocks (Catherine, 2018) and grow in spikes (Cooper and Haltiwanger, 2006). Permanent productivity shocks basically are changes in the efficient scale of operations (GTES). Chemmanur et al. (2009) show that firms’ sales growth, the investment rate, and profitability and productivity increase before and then decrease after the IPO, i.e., they spike around the IPO.

In the backdrop of these previous findings, the interpretation of my approach is as follows. I study the process of firms converging to their efficient scale after having received a particularly large permanent shock. For the firms in my sample, that shock was large enough to incentivize them to go public, for example to access a broader capital market. I decompose the subsequent dynamics of investment and other variables.

---

19 Another reason for firms to go public is for diversification purposes.
into different mechanisms.

Unfortunately, Compustat does not have reliable pre-IPO data (see the discussion in Pástor et al. (2008)) to confirm the aforementioned intuition in my sample. However, I merge it with Jay Ritter’s dataset on firm founding dates. With the merged dataset, which has roughly a third of the number of observations, I run a horserace between years since founding and years since IPO. Table A.37 in the Appendix confirms that indeed years since IPO explains the decline in investment and conditional investment after the IPO much better than years since founding.

1.6.2 Identification

To better understand the model and the identification of key parameters, I estimate it under the assumptions that (i) there is no growing towards the efficient scale \((C_0 = 0)\), (ii) there is no learning (firms get a perfect signal at \(t = 0\)), (iii) adjustment costs are constant \((b_{\gamma} = 0)\), (iv) the volatility of productivity is constant \((b_{\sigma} = 0)\), and (v) have no abnormal initial productivity \((\mu_{\sigma_0} = 0)\). Table A.38 in the Appendix shows the parameter estimates of this exercise and Table A.39 the fitted moments.

When there is no GTES, \(\alpha\) is estimated much higher than in the baseline. The model can not match average profitability and the decline in conditional \(Q\) is too strong. This is surprising, as a priori the model is expected to do badly in matching the decline of unconditional \(Q\) since this moment is important in pinning down \(C_0\), but this is not the case. If however I fix \(\alpha\) at the baseline value and rerun the estimation, then the dispersion in firm quality \(\sigma_\mu\) and adjustment costs are estimated to be quite high. Learning is doing all the heavy lifting in matching the the dynamics of \(Q\). The model also can not match the decline in the sensitivity of investment to profitability. This shows that not including GTES into the estimation would strongly bias the results towards the other mechanisms, in particular learning.

If there is no learning, then \(\alpha\) and \(C_0\) are estimated much higher than in the baseline. Due to the high \(\alpha\), profitability is too low in the simulated sample, while the other moments fit rather well. However, one would expect that without learning the model would have difficulty matching the decline in conditional \(Q\) rather than average profitability. The reason is that the SMM procedure by increasing \(\alpha\) is choosing to match the decline in conditional \(Q\) rather than profitability. To double-check I rerun the estimation without learning and fix \(\alpha\) at the baseline SMM estimate (and do not target average profitability). The estimate for \(C_0\) then is closer to the baseline estimate and as suspected the model can not match the decline in conditional \(Q\). This exercise confirms that indeed the decline in conditional \(Q\) plays an important role in pinning down how much firms learn.

When adjustment costs are constant, then as expected the SMM procedure has difficulty matching the declining sensitivity of investment to profitability. The estimated parameters are close to the benchmark, except that adjustment costs \(\gamma\) are lower to make firms that recently went public more flexible. But then firms far from IPO react too much to profitability. This exercise confirms that indeed the decline in the investment-to-profitability sensitivity plays an important role in pinning down by how much adjustment costs increase over time.

If volatility is kept constant, then unsurprisingly the model can not match the decreasing shock volatility as firms age. As a consequence, the SMM procedure estimates
a higher shock volatility $\sigma_z$ than in the baseline, doing the splits between matching the volatility of profitability of firms that recently versus long since went public. This shows that $b_z$ is important in matching the decline the volatility of profitability as firms age.

When there is no high abnormal initial productivity, then the estimated returns to scale parameter $\alpha$ is lower than in the baseline and $C_0$ higher, because they need to do the heavy lifting to match the decline in profitability. Nevertheless the model still has difficulties matching the pronounced decline in profitability. This shows that $\mu_{z0}$ is important to be able to match that moment, and omitting it can bias the results towards GTES.

1.6.3 Returns to scale parameter

The previous robustness section raises the question whether my results are sensitive to the estimate of the returns to scale parameter $\alpha$. As a robustness check, I estimate the model for different fixed levels of $\alpha$. The parameter estimates for this exercise are reported in Table A.310 in the Appendix. They are quite stable across specifications. Only the dispersion in quality $\sigma_{\mu}$, which determines how much firms have to learn, is different. Table A.311 in the Appendix however shows that the conclusion - that each mechanism contributes roughly one third to the conditional investment decline (section 1.5) - does not change much, apart from when $\alpha$ is as high as 0.8.

1.7 Conclusion

This paper studies why firms gradually cut investment in the years after they go public, conditional on their profitability and size. There are three different causes, each explaining roughly one third of the decline. First, the combination of firms growing towards their efficient scale and increasing rigidity. Second, firms are learning about their efficient scale. Third, their shock volatility is decreasing over time. As a byproduct of the structural estimation, I also examine the causes of the underperformance of firms after they go public. I find that both mean-reversion in productivity and increase in size are important, validating the theories of Pástor et al. (2008) and Clementi (2002), respectively. I find that learning is an important determinant of Q conditional on size and profitability, confirming the interpretation of Pástor and Veronesi (2003). Previous researchers also interpret a declining sensitivity of investment to profitability as evidence of learning. My analysis cautions against this, as I find it is mostly driven by increasing rigidity.

In line with Asker et al. (2014), I find that firms become more rigid over time after they go public. There can be different reasons for this, for example short-termism (Holmström, 1999) or a restructuring into a more hierarchical and formal organization to exploit existing ideas (Ferreira et al., 2012). Future research could answer this question by taking parts of the current model and expanding it across those dimensions.
Appendix A

Appendix to chapter 1

A.1 Model

A.1.1 Dynamic problem

Under full information about $\mu$, the dynamic problem is as follows:

$$V(K, z, \mu, t) = \max_i [C(K, a, t, I) + \mathbb{E}\beta V(K', z', \mu', t + 1)]$$

where $C(K, a, t, I) = e^{z+\mu}K^\alpha_i - I - f_y(t)\Phi(I, K)$

$$f_y(t) = 1 - \frac{b_y}{1 + t}$$

s.t. $K' = (1 - \delta)K + I$

$$z_{t+1} = z_t + \epsilon_t, \text{ where } \epsilon_t \sim N(0, f_z(t)\sigma_z^2)$$

$$f_z(t) = 1 + \frac{b_z}{1 + t}$$

$\mu' = \mu$

Taking into account that the firm is learning about $\mu$, the dynamic problem is as follows:

$$V(K, \hat{z}, \hat{\mu}, t) = \max_i [C(K, a, t, I) + \mathbb{E}\beta V(K', \hat{z}', \hat{\mu}', t + 1)]$$

where $C(K, a, t, I) = e^{a}K^\alpha_i - I - f_y(t)\Phi(I, K)$

$$a = \hat{\mu} + \hat{z}$$

$$f_y(t) = 1 - \frac{b_y}{1 + t}$$

s.t. $K' = (1 - \delta)K + I$

$$\hat{z}' = \rho_z\hat{z} - \frac{m_z/f(t)}{p^{-1} + m_z/f(t)}v'_a(t) - \frac{m_l}{p^{-1} + m_z/f(t) + m_l}v'_l(t) + (1 - \rho_z)v'_a(t)$$

$$\hat{\mu}' = \hat{\mu} + \frac{m_z/f(t)}{p^{-1} + m_z/f(t) + m_l}v'_a(t) + \frac{m_l}{p^{-1} + m_z/f(t) + m_l}v'_l(t)$$

$$P' = \frac{1}{p^{-1} + m_z/f(t) + m_l}$$
where \( \nu_a(t) = \frac{a' - \rho z a}{1 - \rho z} \) is the forecast error of \( a \), and \( \nu_l(t) \) is the forecast error of the private signal \( l \). The joint distribution of \( \nu_a(t) \) and \( \nu_l(t) \) is

\[
\begin{pmatrix} \nu_a(t) \\ \nu_l(t) \end{pmatrix} \sim \mathcal{N} \left( \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} P(t) + \frac{f_z(t)}{m_z} & P(t) \\ P(t) & P(t) + \frac{1}{m_l} \end{pmatrix} \right)
\]

where \( m_z = \frac{1 - \rho^2 z}{\sigma_z} \) and \( m_l = \frac{\sigma^2 l}{\sigma^2 l} \). Uncertainty \( P \) is essentially pinned down by the firms age \( t \).

### A.1.2 Choice of initial capital

To choose it’s initial capital stock, the firm solves the following problem:

\[
\max_{K_0} V(K_0, a_0, \hat{\mu}_0, t = 0) - (1 + r + C_0)K_0,
\]

where \( r = (1 - \beta)/\beta \) is the rental rate of capital.

### A.1.3 Numerical solution

I discretize the state space as follows. The lower bound for the capital stock is set to

\[
\left( \frac{ae^x}{1 - \beta \gamma (1 + \gamma \delta) + \delta} \right)^{\frac{1}{\alpha}} \text{ where } \begin{cases} x = 1.5 \sqrt{m_z^{-1} + 2\sigma_{\mu}} & \text{for upper bound} \\ x = -1.5 \sqrt{m_z^{-1} - 2\sigma_{\mu}} & \text{for lower bound} \end{cases}
\]

I use 200 log-spaced nodes for \( K \). The bounds for \( \hat{z} \) are \([-3\sigma_{z,\text{init}}, 3\sigma_{z,\text{init}}]\) where \( \sigma_{z,\text{init}} \) is the standard deviation of \( z_0 \). I use 16 equally-spaced nodes for \( \hat{z} \). The bounds for \( \hat{\mu} \) are \([-3\mu, 3\mu]\). I use \( \max(2, \sigma_{\mu} * 12) \) number of nodes for \( \hat{\mu} \), depending on the value of \( \sigma_{\mu} \). The bounds for \( t \) are \([0, 21]\) and are log-spaced. I use 4 nodes for \( t \), plus I add another node for \( t = 200 \) to do the normalization of \( C_0 \), described in section A.2.1. I chose the bounds for each variable such that at least 99% of the simulated values are inbetween. To choose the number of nodes I started at a low number and then increased them until the moments from the simulated data did not change anymore at the 1% level. I interpolate linearly between nodes. This procedure ensures that the model is solved accurately but still as fast as possible.

To solve the linear initial capital choice problem I simply check which for which \( K \) the slope of the value function \( V(a_0, \hat{\mu}_0, t = 0) \) is closest to the cost of capital \( 1 + r + C_0 \).

### A.2 SMM procedure

#### A.2.1 Normalisation of initial cost of capital

I estimate a version of the model where \( C_0 \) is normalised to facilitate the identification of the parameters and the subsequent comparative statics. In the model, firms have incentives to start with a high capital stock to smooth future adjustment costs in case
they learn they are productive over time or get a positive transitory productivity shock. The initial deadweight cost of capital $C_0$ thus not only affects how much a firm will grow towards its efficient scale, but also how much on average it will grow due to due to other sources. To isolate GTES from the other sources, I assume that firms choose their initial capital stock believing that $t = \infty$, i.e., shock volatility and adjustment costs are that of a mature firm and that its current belief about $\mu$ is correct, i.e., $P = 0$. This allows me to shut down GTES when performing comparative statics by setting $C_0 = 0$, without affecting the other mechanisms. Essentially, if investment declines when $C_0 = 0$ in the model, then it must come from a mechanism other than GTES. Note that this is just a normalisation that facilitates the interpretation. Estimating the model this way will provide exactly the same fit to the data.

A.2.2 Global optimization routine

The SMM estimation proceeds as follows. First, I generate simulated data using the numerical solution to the model. Specifically, I take a random draw from the distribution of $(\mu, v_u, v_l)$ and then compute simulated time series for 10'000 firms. To be clear, each firm draws from the same distribution, but not the same value of $\mu$. Since I truncated the the empirical data by including only firm-year observations where years since IPO is 20 or less, I do exactly the same with the simulated sample. For consistency I also winsorize all ratios at the 1% level, as I did for the data. The variables in the model map into the the data as described in Table A.31. Then I calculate the moments for the simulated sample and calculate a loss function together with the weight matrix. I use a differential evolution optimizer to sweep over different parameter values and minimize the distance between the empirical and simulated moments, implemented in the Julia Package BlackBoxOptim.jl (Feldt, 2018). This algorithm is specialized to find global minima when the objective function is not differentiable. Importantly, I feed the same draw of shocks in the simulator for each set of parameter values that the algorithm tries.

A.2.3 Weight matrix and standard errors

In the estimation I am using more moments than parameters, so the question of how to construct the weight matrix. I use influence functions to calculate the optimal weight matrix, which has been shown to yield good finite sample performance (Bazdresch et al., 2017). I calculate clustered standard errors for the moments and parameter estimates using usual GMM formulas, see section A.4 in Warusawitharana and Whited (2015) for more details.
### Additional tables

Table A.31: Mapping the model to the data

<table>
<thead>
<tr>
<th>data</th>
<th>model</th>
</tr>
</thead>
<tbody>
<tr>
<td>time</td>
<td>years since IPO</td>
</tr>
<tr>
<td>capital stock</td>
<td>ppegt</td>
</tr>
<tr>
<td>investment</td>
<td>capx/ppegt</td>
</tr>
<tr>
<td>sales</td>
<td>sale</td>
</tr>
<tr>
<td>sales-to-capital ratio</td>
<td>sale/ppegt</td>
</tr>
<tr>
<td>scaled operating income</td>
<td>oibdp/ppegt</td>
</tr>
<tr>
<td>Q</td>
<td>$(\text{mkteq} + \text{dltt} + \text{dlc}) / \text{ppegt}$</td>
</tr>
</tbody>
</table>

This table is the bridge between the variables in the model and in Compustat data. Note that in the main text I use two different measures for profitability, scaled operating income and the sales-to-capital ratio. I use scaled operating income for the level of profitability, and the sales-to-capital ratio for the dynamics of profitability.
Table A.32: Investment regressions

<table>
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<td></td>
<td>(1)</td>
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<tr>
<td>logK</td>
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<tr>
<td>logK2</td>
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<tr>
<td>logsaleK</td>
<td>0.105***</td>
</tr>
<tr>
<td>logsaleK2</td>
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<tr>
<td>oibdpK</td>
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<tr>
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<tr>
<td>AgeIPOFE</td>
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<tr>
<td>FirmFE</td>
<td>Yes</td>
</tr>
<tr>
<td>N</td>
<td>57,351</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.133</td>
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<tr>
<td>Within-$R^2$</td>
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Calculations are based on a sample of nonfinancial firms from the annual COMPUSTAT database. The sample period is from 1960 to 2018. The construction of variables is described in Table A.31. *AgeIPOFE* are number-of-years-since-IPO fixed effects. Standard errors are clustered at the firm level.
This table shows the estimates of the empirical policy function regression used for the SMM estimation. The Standard errors are clustered at the firm level. The construction of variables is described in Table A.31. A variable starting with $\Delta$ means first difference of that variable. year$_{i,j}$ is a dummy for all $i$ to $j$ years since IPO. AgeIPOFE are number-of-years-since-IPO fixed effects. Standard errors are clustered at the firm level.

<table>
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<tr>
<td>$\Delta$logsaleK \times year$_{0,1}$</td>
<td>0.223***</td>
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<td>$\Delta$logsaleK \times year$_{2,3}$</td>
<td>0.090***</td>
<td>(0.019)</td>
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<td>$\Delta$logsaleK \times year$_{4,6}$</td>
<td>0.074***</td>
<td>(0.016)</td>
<td></td>
</tr>
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<td>$\Delta$logsaleK \times year$_{7,11}$</td>
<td>0.010</td>
<td>(0.018)</td>
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<tr>
<td>$\Delta$logK \times year$_{0,1}$</td>
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<td>(0.033)</td>
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<td>(0.023)</td>
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<td>$\Delta$logK</td>
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<table>
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<td>$N$</td>
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<td>$R^2$</td>
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Table A.34: Fitted moments

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<td>average investment years 10 to 20</td>
<td>0.128</td>
<td>0.127</td>
<td>0.379</td>
</tr>
<tr>
<td>average profitability years 10 to 20</td>
<td>0.296</td>
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<td>volatility of profitability years 10 to 20</td>
<td>0.132</td>
<td>0.146</td>
<td>-1.686</td>
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<tr>
<td>volatility of profitability years 0 to 5</td>
<td>0.216</td>
<td>0.214</td>
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<tr>
<td>autocorrelation of profitability</td>
<td>0.604</td>
<td>0.587</td>
<td>1.877</td>
</tr>
<tr>
<td>sens. of invest. to prof. at years 0 + 1</td>
<td>0.313</td>
<td>0.283</td>
<td>1.459</td>
</tr>
<tr>
<td>sens. of invest. to prof. at years 2 + 3</td>
<td>0.180</td>
<td>0.183</td>
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<td>sens. of invest. to prof. at years 4 to 6</td>
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<td>0.131</td>
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<td>sens. of invest. to prof. at years 7 to 11</td>
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<td>0.128</td>
<td>-2.223</td>
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<td>sens. of invest. to prof. at years 12 to 20</td>
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<td>0.122</td>
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<td>decline in investment</td>
<td>0.358</td>
<td>0.357</td>
<td>0.118</td>
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<td>decline in conditional investment</td>
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<td>decline in profitability</td>
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<td>0.604</td>
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<td>decl. in cond. Q from years 2 + 3 on</td>
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<td>decl. in cond. Q from years 4 to 6 on</td>
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<td>-1.839</td>
</tr>
<tr>
<td>decl. in cond. Q from years 7 to 11 on</td>
<td>0.047</td>
<td>0.064</td>
<td>-1.165</td>
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</table>

Calculations are based on a sample of nonfinancial firms from the annual COMPU-STAT database. The sample period is from 1960 to 2018. The Figure reports the simulated and actual moments and the clustered t-statistics for the differences between the corresponding moments.
This Table contains the derivatives of the moments with respect to the estimated parameters at the SMM estimates. Table 1.2 contains these estimates and describes the parameters.

<table>
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<tr>
<th>Parameter</th>
<th>Average Investment Years 10 to 20</th>
<th>Decl. in Conditional Profitability Years 0 to 5</th>
<th>Volatility of Profitability Years 0 to 5</th>
<th>Average Investment Years 10 to 20</th>
</tr>
</thead>
<tbody>
<tr>
<td>Decline in Investment</td>
<td>0.130 0.730 0.520 -0.350 0.430 -0.070 -2.710 -0.010 -0.050 -0.000 0.590</td>
<td>0.660 0.070 0.140 -0.040 0.100 0.030</td>
<td>0.030 0.010 0.090 0.160 0.240</td>
<td>0.970 0.010 0.010 0.020 -0.030 0.000 -0.100 -0.000 -0.030 0.000 -0.010</td>
</tr>
<tr>
<td>Decline in Conditional Investment</td>
<td>0.490 0.220 0.500 -0.410 0.440 -0.020 -1.140 0.110 0.010 0.530</td>
<td>0.310 -0.040 0.340 0.250 0.850 -0.000 1.150 -0.090 0.510</td>
<td>0.030 0.020 0.190 0.330 0.430 -0.000 -0.480 0.200 -0.060 0.030 -0.010</td>
<td>0.030 0.000 0.090 0.160 0.240</td>
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Table A.36: Counterfactuals

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<th>$C_0$</th>
<th>lrn</th>
<th>$b_y$</th>
<th>$b_z$</th>
<th>$\mu_{z0}$</th>
<th>(i)</th>
<th>(ii)</th>
<th>(iii)</th>
<th>(iv)</th>
<th>(v)</th>
<th>(vi)</th>
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</table>

Each row in this Table represents one counterfactual exercise. Row 32 coincides with the baseline estimates. (i) and (ii) calculate the integral of the investment and conditional investment curves, respectively. (iii) and (iv) calculate the decline in log $Q$ and conditional log $Q$, (v) the decline in the sensitivity of investment to profitability and (vi) the decline in profitability. For example, from row 2 it is apparent that if one simulates the model when only GTES is activated, then $Q$ at year 0 higher than at year 20 by 0.473.
Table A.37: Time since IPO vs. founding

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<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
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<td>-0.000</td>
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<td></td>
</tr>
<tr>
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<td>0.028***</td>
<td>0.034***</td>
<td>0.034***</td>
<td></td>
<td></td>
<td></td>
</tr>
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<td>logsaleK2</td>
<td>0.008***</td>
<td>0.009***</td>
<td>0.007***</td>
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<td>0.012***</td>
<td>0.013***</td>
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<table>
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<th>Yes</th>
<th>Yes</th>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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<td>19,960</td>
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</tr>
<tr>
<td>R²</td>
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<td>0.000</td>
<td>0.000</td>
<td>0.143</td>
<td>0.171</td>
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</table>

These regressions are based on a subsample of firms with available founding dates from Jay Ritters website. I only include firms that went public within 25 years of founding, which are the only firms for which conditional investment declines in the first place. The construction of variables is described in Table A.31. Variables ending with "2" are squared terms of that variable. AgeIPOFE are number-of-years-since-IPO fixed effects and AgeFoundFE are number-of-years-since-founding fixed effects. Standard errors are clustered at the firm level.
Table A.38: Robustness of identification - parameter estimates.

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<th>$C_0 = 0$, $\sigma_l = 0$</th>
<th>$\sigma_l = 0$, $\sigma_z = 0$</th>
<th>$b_\gamma = 0$</th>
<th>$b_z = 0$</th>
<th>$\mu_{z0} = 0$</th>
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<td>$\delta$</td>
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<td>0.152</td>
<td>0.133</td>
<td>0.146</td>
<td>0.130</td>
<td>0.138</td>
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<td>0.000</td>
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<td>0.332</td>
<td>0.339</td>
<td>0.337</td>
<td>0.301</td>
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<td>0.795</td>
<td>0.755</td>
<td>0.766</td>
<td>0.723</td>
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<td>0.783</td>
<td>0.506</td>
<td>0.880</td>
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<td>0.560</td>
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</tbody>
</table>

This Table contains the parameter estimates for SMM estimations under different parameter restrictions. The descriptions of the parameters are in Table 1.2. The first column is the baseline estimation, $C_0 = 0$ means no growing towards the efficient scale, $\sigma_l = 0$ means there is no learning, $b_\gamma = 0$ means no rigidity, $b_z = 0$ means no decreasing volatility and $\mu_{z0} = 0$ means no abnormal initial productivity.
Table A.39: Robustness of identification - moments

<table>
<thead>
<tr>
<th>Baseline</th>
<th>0 = 0</th>
<th>0 = 0</th>
<th>0 = 0</th>
<th>0 = 0</th>
<th>0 = 0</th>
<th>0 = 0</th>
<th>0 = 0</th>
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<td></td>
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<td>0.14</td>
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<td>0.14</td>
<td>0.15</td>
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</tr>
</tbody>
</table>

Table A.39: Robustness of identification - moments

This Table contains the fitted moments for SMM estimations under different parameter restrictions. The descriptions of the parameters are in Table 1.2. The first column is the baseline estimation, C = 0 means no growing towards the efficient scale, σ_l,0 = 0 means no learning, bγ = 0 means no rigidity, b_z = 0 means no decreasing volatility and µ_z,0 = 0 means no abnormal initial productivity.
Table A.310: Robustness of $\alpha$ - parameter estimates

<table>
<thead>
<tr>
<th>$\alpha$</th>
<th>baseline</th>
<th>0.4</th>
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<th>0.6</th>
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<td>$\delta$</td>
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<td>0.137</td>
<td>0.139</td>
<td>0.141</td>
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<tr>
<td>$C_0$</td>
<td>0.296</td>
<td>0.350</td>
<td>0.326</td>
<td>0.384</td>
<td>0.394</td>
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</tr>
<tr>
<td>$\sigma_z$</td>
<td>0.337</td>
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<td>0.339</td>
<td>0.351</td>
<td>0.355</td>
<td>0.347</td>
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<tr>
<td>$\rho_z$</td>
<td>0.800</td>
<td>0.811</td>
<td>0.794</td>
<td>0.785</td>
<td>0.799</td>
<td>0.753</td>
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<tr>
<td>$\alpha$</td>
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<td>0.600</td>
<td>0.700</td>
<td>0.800</td>
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<tr>
<td>$\gamma$</td>
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<td>3.385</td>
<td>3.337</td>
<td>3.552</td>
<td>4.088</td>
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<tr>
<td>$\sigma_u$</td>
<td>0.460</td>
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<td>0.459</td>
<td>0.348</td>
<td>0.293</td>
<td>0.293</td>
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<tr>
<td>$\sigma_l$</td>
<td>0.224</td>
<td>0.137</td>
<td>0.224</td>
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<td>$\mu_0$</td>
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<tr>
<td>$b_z$</td>
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<td>$b_y$</td>
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</table>

This Table contains the parameter estimates for SMM estimations under different restrictions of the returns to scale parameter $\alpha$. The descriptions of the parameters are in Table 1.2. The first column is the baseline estimation, and the following corresponds to the value I set $\alpha$ to.

Table A.311: Robustness of $\alpha$ - percentage contribution to conditional investment

<table>
<thead>
<tr>
<th>$\alpha$</th>
<th>baseline</th>
<th>0.4</th>
<th>0.5</th>
<th>0.6</th>
<th>0.7</th>
<th>0.8</th>
</tr>
</thead>
<tbody>
<tr>
<td>GTES + rigidity</td>
<td>31</td>
<td>40</td>
<td>32</td>
<td>35</td>
<td>34</td>
<td>12</td>
</tr>
<tr>
<td>learning + rigidity</td>
<td>37</td>
<td>29</td>
<td>37</td>
<td>35</td>
<td>38</td>
<td>58</td>
</tr>
<tr>
<td>volatility + rigidity</td>
<td>32</td>
<td>31</td>
<td>31</td>
<td>30</td>
<td>28</td>
<td>30</td>
</tr>
<tr>
<td>Age 0 to 4: GTES + rigidity</td>
<td>48</td>
<td>57</td>
<td>48</td>
<td>52</td>
<td>53</td>
<td>25</td>
</tr>
<tr>
<td>Age 0 to 4: learning + rigidity</td>
<td>31</td>
<td>24</td>
<td>31</td>
<td>32</td>
<td>32</td>
<td>55</td>
</tr>
<tr>
<td>Age 0 to 4: volatility + rigidity</td>
<td>21</td>
<td>19</td>
<td>21</td>
<td>16</td>
<td>15</td>
<td>20</td>
</tr>
</tbody>
</table>

This Table contains the percentage contribution of the relevant mechanisms to the conditional investment for SMM estimations under different restrictions of the returns to scale parameter $\alpha$. The bottom three rows contain the percentage contribution for ages 0 to 4.
A.4 Additional figures

Figure A.41: Observations across fiscal year.

Figure A.42: How skewness produces positive average net investment.

The curve plots the distribution of productivity. The three vertical lines mark the mean (1.00) and two standard deviations below (0.37) and above (2.70) the mean. Starting at the same point of the productivity distribution, a firm that receives a positive productivity shock will grow more than a firm with a negative productivity shrinks. On average, this implies a positive net investment rate.
A firm is defined as exiting the sample if Compustat contains no observation the following year and the year is not 2018, which is when my sample stops. The Figure plots the conditional exit rate, i.e., the exit rate is calculated as the number of exiting firms divided by all firm-year observations available for that year since IPO.
Chapter 2

Inefficient securitization booms

2.1 Introduction

The recent financial crisis came as a surprise. The riskiness of securitized tranches and the underlying mortgages only came to light when U.S. house prices declined nationwide and foreclosures rapidly increased. A highly leveraged and interconnected financial sector propagated the mortgage losses which eventually resulted in a large recession. In hindsight, there arguably was a capital misallocation into securitized mortgages due to a lack of knowledge about their true risks.

To not repeat events, policy makers called for more transparency in securitization and money markets (which used securitized tranches as collateral) more generally. For example, the Dodd-Frank Act (2010) requires the disclosure of loan-level data as opposed to merely summary statistics. Some influential researchers however argue that it is the main purpose of money markets to be opaque so that they can provide liquidity by limiting informational asymmetries (Holmstrom, 2015). Indeed, also mortgage-backed securities themselves are designed to limit information production, which enhances their liquidity (Dang et al., 2015).

What is missing in the academic debate is the role of capital allocation. Even if their main purpose is to provide liquidity, a long history of banking crises shows that there is potential for massive capital misallocation in money markets. It is well known that capital allocation and liquidity provision do not go hand in hand, as information (asymmetries) or the lack thereof benefits the first and harms the latter. One would thus expect that markets produce an optimal amount of information, trading off the two. My contribution is to show that this is generally not the case when assets are correlated. Under laissez-faire, there is too much liquidity and too little information acquisition compared to what is socially optimal. This deteriorates capital allocation. At the heart of the inefficiency is a novel information externality originating from firms’ securitization decisions. The implication for policy is that money markets may be too opaque, i.e., excessive in limiting information production.

To analyze the tension between liquidity and capital allocation, I consider a model where firms learn from security prices. As I mentioned, the effect of information production (by traders in the secondary market) is a double-edged sword: on the one hand it hinders liquidity provision due to adverse selection, and on the other hand some of it gets reflected in prices through the process of trading. The first effect harms the
firms issuing the securities because the anticipated illiquidity in the secondary market raises investors’ required rate of return in the primary market. The second effect benefits them because new information contained in prices improves firms’ real investment decisions, an idea which goes back to Hayek (1945). For example, following a drop in the price of a firm’s traded security, it may learn that its growth opportunity has a negative net present value, thus preventing inefficient investment. Here, the underlying assumption is that prices may reflect information that is new firms, for example because the market aggregates information by speculators which collectively may be better informed (Grossman (1976), Hellwig, 1980).1

Firms trade off the benefits and costs of information by actively managing their information environment. For example, by issuing securities which are more sensitive to fundamentals, firms increase outsiders’ return to becoming informed by levering up their informational advantage (Dang et al., 2015). Or, when firms disclose more, for example by providing outsiders with detailed financial reports, then this decreases outsiders costs of estimating the value of the firm. In the model, firms choose their capital structure, but the results would also carry over to different contexts, such as choice of disclosure. What is important is that firms can fine-tune the informational tradeoff between liquidity and capital efficiency. Indeed, this way they can achieve an interior optimum.

I show that this tradeoff is distorted in a decentralized setting with multiple firms that face firm-specific as well as common risk. Firms may provide too little incentives for information production, which deteriorates capital allocation efficiency. There can also be too much information acquisition, excessively increasing firms’ cost of capital.2

The mechanism works as follows. When firms make their securitization decision, their action has a direct and indirect effect. The direct effect is that issuing a more information-sensitive security increases their cost of capital, keeping constant the amount of information production (Myers and Majluf, 1984). The indirect effect is that this also increases information production, which further increases the cost of capital but also improves the informational content of prices, which benefits investment decisions.

The issue is that when it comes to information about common risks, firms do not internalize the indirect effect because they perceive information production as exogenous. When speculators become informed about the common risk factor, they trade on all firms’ securities to take full advantage of their information. Thus their incentives to become informed depend on firms’ joint decisions.3 But this implies that each firm’s decision only has a marginal effect on information production about common risk factors.

When information production about the common risk factor has social value, meaning that the social benefits are larger than the social costs, then firms have incentives to

---

1 This does not necessarily imply that firms are less informed about their investment opportunities than outsiders, but rather that outsiders can gather additional (or entirely different) signals.
2 A concern with models of endogenous information acquisition is typically that noise traders do not have well-defined utility functions, precluding welfare analysis (Grossman and Stiglitz, 1980). Here, I endow them with utility functions and although they pay a passive role, they do have participation constraints. This allows me to do a full-blown welfare analysis.
3 This does not necessarily imply that information about the common risk factor is cheap, since these risks are typically more difficult to analyze due to complexity (Coval et al., 2009a, 2009b).
excessively limit information production. The reason is that issuing risky securities to stimulate information production is privately costly due to their illiquidity. But more information production means more signals about the common risk factor, which increases indirectly also the option value of other firms’ investment opportunities. Here, information about the common risk factor is a public good, the provision of which entails a private cost.

Firms thus free-ride by issuing too information-insensitive securities. This leads to ignorance about the common risk factor, related to when agents neglect risks due to their behavioral traits (Gennaioli et al., 2012a). There is an ignorance-fueled boom, which features over-investment relative to the social optimum where more information were produced. Information about the true risks only surfaces when they materialize.

Surprisingly, it is also possible that firms induce too much information production. When there is a lot of uncertainty about firm-specific risk (which is also learned through market prices), then firms have high-powered incentives to issue information-sensitive securities to learn from prices. This is because in contrast to the common factor, they fully internalize the costs and benefits of that information, since information production about their firm-specific risk only depends by their own action. However, when uncertainty about the common risk factor is low such that from a social perspective it is not worth learning about it, then firms may push it too far. By triggering information production about the common risk factor, this causes market illiquidity which also increases other firms’ cost of capital. Here the externality is operating in the opposite direction. Where before the problem was that firms did not internalize the benefits of information about common risks accruing to others, here it is that they do not internalize the costs. Put differently, information is a public "bad". If firms could coordinate, they would issue information-sensitive securities so as to learn about firm-specific risk, but only up to the point where they do not induce wasteful information production about the common risk factor.

At the core of my paper is an information externality. Positive information externalities occur in different literatures due to the ease of duplication and common value. In Veldkamp (2006) and Veldkamp and Wolfers (2007), there is an efficient market for information due to certification and intellectual property rights protection. In contrast, I make the implicit assumption that information acquisition can not be certified and thus information can not be credibly sold. It must be revealed through privately optimal actions of the informed such as financial market trading. In the model of Veldkamp and Wolfers (2007), it is firms and not outsiders that produce information. They show that firms’ labor market decisions may reveal this information, leading to free-riding by other firms. In these models there can not be an overproduction of information, because it only has a positive externality on other firms, not negative.

The herding literature uses information externalities to explain waves of financial innovations (Persons and Warther, 1997) and IPO’s (e.g. Lowry and Schwert (2002), Benveniste et al., 2003). Going public reveals investors’ information, which can trigger further IPO’s. To the best of my knowledge, the positive information externality stemming from firms’ capital structure decisions, with financial market trading as an information aggregation mechanism, has not been previously studied.

The implication of the information externality is that too little information is produced in booms, which has real consequences. In the model of Gorton and Ordonez
(2014), ignorance is optimal in a boom because there are no externalities. In related models, agents produce too little information in good times at the cost of inefficient market breakdowns in bad times when the scope for adverse selection increases (e.g. Pagano and Volpin (2012), Hanson and Sunderam, 2013). These models predict that that over time, market liquidity and thus investment should rebound as information asymmetries decrease. My theory implies that sudden halts to investments such as mortgages may be caused by more than financial frictions. Rather, under a state of large uncertainty, even moderate news can change expectations drastically. The release of adverse news is even ex post efficient, as then finally the veil of ignorance is lifted and further capital misallocation can be prevented. My theory implies that investment breakdowns should thus be very persistent, a testable empirical distinction. Also in terms of policy implications the theories differ. If investment breakdowns are only due to financial frictions, then ex post liquidity provision can alleviate the inefficiency. But limiting ignorance and overinvestment in booms requires ex ante policies.

On the methodological side, my model is related to a growing literature studying the feedback of information contained in asset prices on firms’ real decisions. There are only few papers featuring coordination failures on the firm side. In Subrahmanyam and Titman (1999) for example, there is a positive externality of having a large stock market due to more serendipitous information. Therefore in the good (bad) equilibrium, firms decide (not) to go public and the stock market is large (small). My model is closely related to a recent branch which incorporates multiple types of information (Goldstein Yang, 2014, 2015) and cross-learning via other firms’ asset prices (Foucault and Frésard, 2018). Most related to the present approach are Huang and Zeng (2015), who also consider a model with multiple firms and a common risk factor. In their model, traders put too much weight on their information of the common risk factor relative to firm-specific risk factors when trading because real investment conforms more to the common shock due to informational spillovers, a reinforcing cycle. Other papers in the comovement literature share the idea that information about common risks crowds out information about idiosyncratic risk (e.g. Veldkamp and Wolfers (2007), Hoberg and Phillips, 2010). In my theory however it is the quality of information about common risks that is too low. While these two effects may even reinforce each other, there are also testable differences. According to comovement literature, in booms too many unproductive firms invest because of the lack of firm-specific information. Thus we should observe that real and financial busts should be concentrated among only a subset of firms in the industry. If during booms however it is the quality of information about industry risk factors that is poor, then in busts losses should be observed across the entire industry.

The rest of the paper is structured as follows. In section 2.2, I describe the model. In section 2.3, I solve for the equilibrium and study welfare. In section 2.4, I describe the private market inefficiency. Finally, I conclude in section 2.5.

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4 See Bond et al. (2012) for a survey.
2.2 The model

In this section I describe the model. There is a unit mass of firms indexed \( i \), a large mass of investors, a large mass of speculators and a large mass of market makers. All are risk neutral and the discount rate is normalized to one. There are three dates \( t=0,1,2 \). At \( t=0 \), firms issue securities to raise cash for the purpose of making an investment. At \( t=1 \), before the firms invest, the securities are traded in the secondary market. This process aggregates the information endogenously acquired by speculators into prices. Then, upon inferring the signals contained in the prices of the securities, the firms decide whether to invest. At \( t=2 \), payoffs are distributed. This order of events allows firms to learn from market prices to guide their investment decisions. Importantly, the security design decision of firms influences how much information is acquired, which determines how much they can learn.

2.2.1 Investment

Firms are endowed with a project that can be undertaken at \( t=1 \) at cost \( K \) and generates cash flow \( A_a A_i (x_H - x_L) + x_L \) at \( t=2 \). There is a safe return \( x_L \) and an excess return \( x_H - x_L \). The factors \( A_a \) and \( A_i \) are two stochastic productivity shocks which determine whether the excess return will be realized. Specifically, shock \( A_a \) captures an industry-wide, common productivity shock and shock \( A_i \) captures a firm-specific, idiosyncratic productivity shock. The shocks are independently and binomially distributed. With probability \( q_a \) respectively \( q_I \) they are 1, otherwise they are 0.

I make two assumptions on firms’ cash flows. First, investment is risky:

A.1: \( x_L < K \).

Otherwise information would have no value, as investment is always NPV > 0. I also assume that the NPV of a project is positive under the prior:

A.2: \( q_a q_I (x_H - x_L) + x_L \geq K \).

This is not a trivial assumption. Due to learning it is possible that even a negative NPV project becomes positive when there is good news at \( t=1 \), as in Dow et al. (2017). Rather, it restricts the amount of possible equilibria by ensuring that firms’ default option is to invest.

2.2.2 Securities

Firms are penniless. At \( t=0 \), firm \( i \) raises capital \( K \) by issuing a security to investors by making them a take-or-leave offer. The security promises return \( R_{H,i} \leq x_H \) at \( t=2 \) if the excess return is realized and \( R_{L,i} \leq x_L \) if not, both conditional on investment being undertaken at \( t=1 \). In case the firm does not invest, the security pays out an amount \( R_i \) of the undeployed capital \( K \).

To be clear, I use simple binomial distributions to solve the model in closed form and to make a point about the information-sensitivity of the claims firms issue. The

\[ R_{L,i} \leq R_{H,i} \]

\[ R_i \]

\[ R_{H,i} - R_{L,i} \]

\[ q_a q_I (x_H - x_L) + x_L \geq K \]

As in the securitization literature, I assume that \( R_{L,i} \leq R_{H,i} \). Also, here it is not important that \( R_{L,i} \) is different from \( R_i \). In fact, we will see later that they are not uniquely pinned down in equilibrium as all that matters will be \( R_{H,i} - R_{L,i} \).
aim of this paper is not to derive a general security design in a continuous state-space. We will see that the binomial structure nevertheless can capture the notion of information-sensitivity.

2.2.3 Information acquisition and trading

At $t=1$, a large measure of speculators are born who can acquire information about the two productivity shocks. The cost of becoming fully informed about the realization of the idiosyncratic risk factor of a unit measure of firms is $c_I$. Becoming fully informed about the common risk factor costs $c_a$. The informed trade on their superior information by submitting market orders to deep-pocketed, competitive and uninformed market makers in the spirit of Kyle (1985).

As in Foucault and Frésard (2018), I assume that there is "cross-asset learning". That is, market makers observe the order flow in each security before setting their price. This assumption is natural because firms make their decisions at low frequency. Thus, by the time firms make their decisions, security prices are likely to reflect all order flow information. This implies that the price of firm $i$ is a sufficient statistic for all information contained in order flow about the prospects of firm $i$. Therefore, firm $i$’s investment decision will only depend on its own security price in equilibrium. I could assume that market makers can condition their price only on the order flow they receive themselves (no cross-asset learning). In this case, firm $i$ optimally conditions its investment decision on all security prices. This does not change the implications of the model. The reason, intuitively, is that cross-asset learning is then performed by the firms rather than market makers.

For the speculators’ information not to be fully revealed, the investors which funded the firms at $t=0$ experience unobservable liquidity shocks and are forced to sell their security. Their noisy supply of security $i$ is $l_i = \frac{1}{2} + \Theta_a + \Theta_i$, where $\Theta_a \sim U[-\theta_a, \theta_a]$ and $\Theta_i \sim U[-\theta_i, \theta_i]$ are independently distributed. The factor $\Theta_a$ is an aggregate liquidity shock which masks the speculators’ trades who are informed about the common productivity shock $A_a$. $\Theta_i$ is an idiosyncratic liquidity shock which masks the speculators’ trades who about the idiosyncratic productivity shock $A_i$.

For completeness, next I specify a utility function for investors that is consistent with the noisy supply of securities just specified. It is a linear Diamond and Dybvig (1983) type utility function. I assume that each investor $j$ holds only a small amount of securities issued by only one firm $i$. Then her utility is as follows:

$$U_{j,i} = l_{j,i}c_1^j + c_2^j,$$

where $l_{j,i} = \frac{1}{2} + \Theta_a + \Theta_i$ (2.1)

where $c_1$ and $c_2$ is consumption at $t=1$ resp. $t=2$ and $l_{j,i}$ is the probability that she must consume early by selling the security in the market. $l_{j,i}$ depends on the realizations of $\Theta_a$ and $\Theta_i$. If we add up the mass of securities of firm $i$ at $t=1$, as required we get exactly $l_i$. The underlying assumption here is that liquidity risk is not diversifiable in the cross-section. Without this assumption, each investor would hold a diversified portfolio and there would be no trades in individual securities, and thus no informed

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7 I assume that $\theta_a + \theta_i \leq \frac{1}{2}$ to ensure that the noisy supply doesn’t exceed the total supply of securities.

8 Bernhardt and Taub (2008) elaborate further why this is required.
trades about individual firms. This is clearly at odds with reality.

Finally, placing unbounded orders would reveal the speculators’ information even in the presence of noise trades, so I restrict them to buy or (short-) sell only up to one unit measure of each security.  

Recapping the sequence of events:

0.1 Each firm $i$ raises cash $K$ by selling a security $(R_{H,i}, R_{L,i}, R_i)$ to investors.
1.1 Investors are forced to sell an unobservable fraction $\ell_i$ of each firms security.
1.2 Speculators choose to become informed about $A_a$ and/or $A_i$.
1.3 Investors and speculators submit their orders and market makers set prices.
   Trades are executed.
1.4 Firms choose whether to invest.
2.1 Funded projects mature and payoffs are distributed.

2.2.4 Discussion
By assuming that all agents apart from firms are competitive, firms capture the entire social surplus. This allows me to isolate the inefficiency stemming from firms’ decisions.

For simplicity I also assume that speculators don’t participate in primary market. This has two reasons. First, if some informed speculators were forced to sell the securities they acquired in the primary market then they can not make use of their private information. The amount of informed capital would then be a random variable, and I would lose tractibility. Second, if they could also acquire information before they participate in the primary market, then this would lead to a complicated game in the primary market. What is important is that there is some way for information acquired by speculators to flow back to firms and that this information is aggregated and visible to all participants. Plus the fact that firms bear the costs of adverse selection, which is natural given that all other agents have participation constraints.

2.3 Equilibrium and social optimum
In this section, I solve for the competitive equilibrium of the model and the social planner’s solution.

2.3.1 Trading strategies and investment decisions
Due to risk neutrality and perfect competition, each informed speculator trades the maximum size possible. Speculators thus go long one unit of security $i$ when they receive a positive signal and short otherwise.

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9 As discussed in the survey by Brunnermeier and Oehmke (2013a), the specific size of this position limit is not essential for the results, as long as speculators can not take unlimited positions.

10 Other papers show that monopolistic speculators would also spread their trades across multiple securities to camouflage their information (e.g. Bernhardt and Taub (2008)), so this is consistent. Moreover, competitive speculators would only trade the most information sensitive security when informed about $A_a$ if they for example had a dollar constraint instead.
I assume that a single speculator can only acquire information about either firm-specific risk or common risk. Note that the two types of information are (partial) substitutes for learning the fundamental value of securities, because if either $A_a$ or $A_i$ are zero, then the realization of the other factor is irrelevant. Combined with the fact that signal costs are additive separable, this assumption is natural.

Total order flow $X_i$ for security $i$ is $\frac{1}{2} + \Theta_a + \Theta_i + (2A_a - 1)\phi_a + (2A_i - 1)\phi_i$, the sum of the liquidation shocks and speculators informed trades. Upon observing order flow, market makers update their beliefs. Due to cross-learning, all market makers have the same information set. Therefore there is a representative market maker who prices all securities.

Market makers infer speculators’ information about the common shock $A_a$ by calculating the average order flow over all the securities, $\bar{X} \equiv \int X_i di$. Define $q_a \equiv \Pr(A_a = 1|X, \phi_a, \{\phi_i\})$ as their updated belief that the common productivity shock is positive conditional on observed total order flow $\bar{X}$ and the equilibrium measure of informed speculators $\phi_a$ and $\phi_i$ for all $i$. By Bayes’ rule,

\[
\hat{q}_a = \frac{q_a \varphi(a)(\bar{X} - \int \frac{1}{2} + \phi_a + (2A_i - 1)\phi(d_i))}{q_a \varphi(a)(\bar{X} - \int \frac{1}{2} + \phi_a + (2A_i - 1)\phi(d_i)) + (1 - q_a) \varphi(a)(\bar{X} - \int \frac{1}{2} - \phi_a + (2A_i - 1)\phi(d_i))},
\]

where $\varphi(a)(\Theta_a)$ is the density function of the uniform distribution of $\Theta_a$. This yields

\[
\hat{q}_a = \begin{cases} 1 & \text{if } \bar{X} \in [-\phi_a + \theta_a, \phi_a + \theta_a] \\ q_a & \text{if } \bar{X} \in [\phi_a - \theta_a, -\phi_a + \theta_a] \\ 0 & \text{if } \bar{X} \in [-\phi_a - \theta_a, \phi_a - \theta_a]. \end{cases}
\]

where $\bar{X} \equiv \bar{X} - \int \frac{1}{2} - (2A_i - 1)\phi_i di$ is the normalized total order flow market makers use to infer $A_a$. Thus there are three possible contingencies. When aggregate order flow $\bar{X}$ (resp. $\bar{X}$) is very large (small), then speculators’ positive (negative) signal about the common risk factor is fully revealed. When $\bar{X}$ is intermediate, their private information remains unknown and market makers’ updated belief that $\Pr(A_a = 1)$ is equal to the prior $q_a$.$^{11}$

To infer speculators’ signal about the idiosyncratic factor $A_i$ of firm $i$, market makers subtract total order flow $\bar{X}$ and a constant term from the order flow of security $i$. Define $\hat{q}_i \equiv \Pr(A_i = 1|X_i, \bar{X}, \phi_a, \{\phi_i\})$ as their updated belief that the productivity shock of firm $i$ is positive. Then by Bayes’ rule,

\[
\hat{q}_i = \frac{q_i \varphi_i(X_i - \bar{X} + \int (2A_i - 1)\phi_i di - \phi_i)}{q_i \varphi_i(X_i - \bar{X} + \int (2A_i - 1)\phi_i di - \phi_i) + (1 - q_i) \varphi_i(X_i - \bar{X} + \int (2A_i - 1)\phi_i di + \phi_i)},
\]

where $\varphi_i(\Theta_i)$ is the density function of the uniform distribution of $\Theta_i$. This gives

\[
\hat{q}_i = \begin{cases} 1 & \text{if } \bar{X}_i \in [-\phi_i + \theta_i, \phi_i + \theta_i] \\ q_i & \text{if } \bar{X}_i \in [\phi_i - \theta_i, -\phi_i + \theta_i] \\ 0 & \text{if } \bar{X}_i \in [-\phi_i - \theta_i, \phi_i - \theta_i]. \end{cases}
\]

$^{11}$The reason that their signal is either fully revealed or masked is due to the simplicity of the uniform distribution of liquidity shocks.
where $\tilde{X}_i \equiv X_i - \bar{X} + \int (2A_i - 1)\phi_i di$ is the normalized order flow market makers use to infer $A_i$. The intuition is the same as for the inference about $A_a$. Firms’ idiosyncratic productivity shock $A_i$ is revealed to be 1 (0) if their securities order flow is large (small) compared to the aggregate. If it is intermediate, no information is revealed and the updated belief remains equal to the prior $q_I$.

To price the securities, market makers must also anticipate firms’ investment decisions conditional on the information that will be contained in prices. The project is worth undertaking for firm $i$ if the updated probabilities $\hat{q}_i$ and $\hat{q}_a$ are high enough. Since by assumption investment is NPV > 0 under the prior, firms’ default option is to invest. Thus they forgo investment if prices signal that either $A_a$ or $A_i$ are 0, in which case the securities’ payoff is just $R_i$. The pricing rule of security $(R_{H,i}, R_{L,i}, R_i)$ thus is

$$P(X_i, \bar{X}) = \begin{cases} \hat{q}_i \hat{q}_a (R_{H,i} - R_{L,i}) + R_{L,i} & \text{if } \tilde{X} > \phi_a - \theta_a \\
 & \text{and } \tilde{X}_i > \phi_i - \theta_I. \\
R_i & \text{otherwise.} \end{cases}$$

### 2.3.2 Trading profits

To analyze the equilibrium amount of speculators becoming informed about each firms’ idiosyncratic risk factor $\phi_i$ and the common risk factor $\phi_a$ we first must know speculators’ expected profit if they become informed.

**Lemma 1.** The expected trading profit to becoming informed about $A_i$ resp. $A_a$ is

$$\pi_i(\phi_i) = \left(1 - \frac{\phi_i}{\theta_I}\right) q_i (1 - q_i) q_a (R_{H,i} - R_{L,i}) \quad \forall i$$

$$\pi_a(\phi_a) = \left(1 - \frac{\phi_a}{\theta_a}\right) q_a (1 - q_a) q_I \int R_{H,i} - R_{L,i} di.$$  

**Proof:** Appendix B.1.1.

Expected profits are made up of three terms. The first, $1 - \frac{\phi_i}{\theta_I}$ resp. $1 - \frac{\phi_a}{\theta_a}$ is the probability that speculators’ information remains hidden. It depends inversely on how many speculators become informed relative to the noisiness of liquidity-driven trades. We can interpret $\frac{\phi_i}{\theta_I}$ resp. $\frac{\phi_a}{\theta_a}$ as a signal to noise ratio. The higher it is, the likelier the chance that the true state of nature will be revealed through trading and thus the lower speculators’ profits.

In the second term, the cross-product $q_i (1 - q_i)$ is the difference in beliefs about $\hat{q}_i$ between the informed and uninformed (when no information is revealed). With probability $q_i$, $A_i = 1$ and thus the difference is in beliefs between knowing and not knowing is $1 - q_i$. Similarly, with probability $1 - q_i$, $A_i = 0$ and thus the difference is $q_i - 0$. $q_a$ turns up because it affects the expected fundamental value of a security. Given that speculators can trade one security of each firm, this de facto allows them to make larger trades. For the profits from information about $A_a$ the same logic applies.

---

Footnote: As discussed in Dow et al. (2017), there can also exist equilibria where market makers do not guide firms to make the right investment decision in expectation. Apart from being uninteresting, they do not survive a slight perturbation of the model where firms can observe order flow directly, so I rule them out.
The third term $R_{H,i} - R_{L,i}$ in the first equation is the excess return of the security. The larger it is, the more useful knowing what state will occur is. Note that the profits to becoming informed about firm-specific risk and the common risk factor are near mirror images except for the signal to noise ratio and the last term. For the latter, what matters is the excess return of all securities combined, because information about the common factor can be used to trade on all securities. Furthermore, this implies that the excess return $R_{H,i} - R_{L,i}$ of firm $i$’s security on the margin has no effect on speculators’ incentives to become informed about the common risk factor because it is atomistic. This is the source of the inefficiency in the competitive equilibrium described in section 2.3.6.

Note that profits are independent of the payout $R_i$ when firms do not invest. The reason simply is that the informed lose their advantage when firms choose to retain the cash that they raised.

One should also note the surprising fact that expected trading profits are independent of how many speculators become informed about the other productivity shock. That is, $\pi_i(\phi_i)$ is independent of $\phi_a$ and vice-versa. The intuition for this is as follows. Take for example an increase in the mass of speculators becoming informed about the common risk factor. This increases the probability that there is bad news about $A_a$, which decreases profits of being informed about the idiosyncratic risk factor because then the firm does not invest. But there is also a higher chance that there is good news about $A_a$, which increases the expected value of the security. This effect increases the profits of becoming informed about $A_i$ because information can be "levered up more", as explained earlier. In this setup these two forces cancel each other out, which keeps things tractable.

### 2.3.3 Information acquisition in equilibrium

Speculators decide whether to acquire information by comparing the cost $c_a$ and $c_I$ to the profit $\pi_a(\phi_a)$ and $\pi_i(\phi_i)$, respectively. Denoting the equilibrium level of $\phi_a$ and $\phi_i$ by $\phi_a^*$ and $\phi_i^*$, respectively, an equilibrium with interim level of information production $\phi_a^* \in [0, \theta_a)$ and $\phi_i^* \in [0, \theta_I)$ is obtained when, given that a measure $\phi_a^*$ resp. $\phi_i^*$ of speculators choose to produce information, a speculator who acquires information breaks even in expectation:

$$\pi_a(\phi_a^*) = c_a$$

Alternatively, there may be a corner solution for $\phi_a$. An equilibrium with no information production $\phi^* = 0$ is obtained when, given that none of the speculators produce information, the cost of producing information is greater than the expected trading profit:

$$\pi_a(0) < c_a$$

The equilibrium amount of information production $\phi_a^*$ and $\phi_i^*$ can not exceed $\theta_a$ and $\theta_I$, respectively, otherwise there is a Grossman and Stiglitz (1980) type of paradox. Information would be perfectly revealed, preventing the informed of recuperating their information costs. Solving the two conditions above for both aggregate and idiosyncratic information directly leads to Lemma 2:
LEMMA 2. The equilibrium amount of speculators $\phi^*_a$ and $\phi^*_i$ becoming informed about the common shock $A_a$ and firm-specific shocks $A_i$ are

$$
\phi^*_a = \max \left[ \theta_a \left( 1 - \frac{c_a}{q_a(q_a(1 - q_a) \int R_{H,i} - R_{L,i})} \right), 0 \right] \\
\phi^*_i = \max \left[ \theta_i \left( 1 - \frac{c_i}{q_i q_i(1 - q_i)(R_{H,i} - R_{L,i})} \right), 0 \right] \forall i
$$

To shorten notation, I define the excess return $\Delta R_i = R_{H,i} - R_{L,i}$ each firm issues and the total excess return $\Delta R = \int \Delta R_i \, di$. For the analysis later it is also useful to define the thresholds $\overline{\Delta R}_i = \overline{\Delta R}_a = \frac{q_i}{q_i(1 - q_i)}$ and $\overline{\Delta R}_a = \frac{c_i}{q_i(1 - q_i)}$ for which speculators are just indifferent in acquiring information about that factor. In the knife-edge case where $\Delta R = \overline{\Delta R}_a$ resp. $\Delta R_i = \overline{\Delta R}_i$, the signal to noise ratios $\phi^*_a \overline{\Delta R}_a$ and $\phi^*_i \overline{\Delta R}_i$ are just a function of $\overline{\Delta R}_a$ and $\overline{\Delta R}_i$, respectively. If $\Delta R > \overline{\Delta R}_a$ resp. $\Delta R_i > \overline{\Delta R}_i$, then speculators acquire information about the common factor resp. idiosyncratic risk factor, otherwise not. These thresholds are important when I characterize the social planners problem problem and the competitive equilibrium.

2.3.4 Primary market underpricing

Investors are only willing to buy securities in the primary market if they are sufficiently underpriced because they anticipate liquidation losses in the secondary market due to the informed. The value investors attach to security $(R_{H,i}, R_{L,i}, R_i)$ at t=0 must be at least K for them to be willing to finance:

$$
\text{Fundamental value under the prior} - \text{Probability that firm does not invest} \geq K
$$

$$
\begin{align*}
&\overline{q_a} q_i (R_{H,i} - R_{L,i}) + R_{L,i} \quad \text{+} \quad \left[ (1 - q_i) \frac{\phi^*_a}{\theta_a} + (1 - q_i) \frac{\phi^*_i}{\theta_i} \left( 1 - \frac{\phi^*_a}{\theta_a} \right) \right] (R_i - R_{L,i}) \\
&- \frac{\phi^*_a}{\theta_a} \left( 1 - \frac{\phi^*_a}{\theta_a} \right) q_a (1 - q_a) q_i (R_{H,i} - R_{L,i}) \quad - \quad \frac{\phi^*_i}{\theta_i} \left( 1 - \frac{\phi^*_i}{\theta_i} \right) q_i (1 - q_i) q_a (R_{H,i} - R_{L,i}) \geq K
\end{align*}
$$

Their valuation can simply be written as the fundamental value of the security adjusted by a few terms. First, if there is bad news because the project will fail, firms forgo investment and investors receive $R_i$ instead of $R_{L,i}$. Second, since trading is a zero-sum game and market makers break even, investors’ losses are equal to speculators’ gains from trade. Intuitively, with probability $1 - \phi^*_a \overline{\Delta R}_a$ resp. $1 - \phi^*_i \overline{\Delta R}_i$, market makers remain uninformed and there is over- or underpricing. The investors’ curse is that many (few) of them must liquidate precisely when the firms’ fundamentals are strong (weak), conditional on market makers not learning speculators’ information. The difference between how many must liquidate when information remains hidden versus unconditionally is exactly $\phi^*_i$, the first term in the liquidation losses in equation 2.4.

Now we have all the ingredients to set up the maximization problem at t=0. I will first characterize the constrained planner’s problem as a benchmark before analyzing the competitive equilibrium.
2.3.5 The constrained planner’s problem

The planner is constrained, i.e. he can neither acquire information himself nor have speculators report to him directly. He can only regulate firms capital structure. I focus on policies where all firms must issue the same security. This is a natural assumption given that firms are ex ante identical in this setup. It also implies that the same amount of firm-specific information is gathered for each firm, so I define $\phi_i \equiv \phi_I$ for all $i$.

The welfare criterion can simply be written as the ex ante surplus of firms, because investors, speculators and market makers all break even. The planner’s objective function therefore is

$$\max_{R_H, R_L, R} W = \left( q_a q_I (x_H - x_L) + x_L - K \right) - \phi^*_I c_I - \phi^*_a c_a$$

$$+ \left[ \frac{\phi^*_a}{\theta_a} (1 - q_a) + \frac{\phi^*_I}{\theta_I} (1 - q_I) - \frac{\phi^*_a}{\theta_a} (1 - q_a) \frac{\phi^*_I}{\theta_I} (1 - q_I) \right] (K - x_L),$$

subject to the break even constraint (2.4) of the investors for all firms and the equilibrium amount of speculators becoming informed about the common (2.2) and idiosyncratic factors (2.3).

The first term is simply the expected value of the project under the prior. The second term is the real cost of information acquisition born by the speculators, which is passed on to firms in the form of underpricing in the primary market. The third term reflects the gains of information. If there is bad news, this prevents firms from investing in a negative NPV project, which would produce a sure loss of $K - x_L$. The decision whether to invest can be interpreted as a call option, where $K$ corresponds to the strike price and the signal-to-noise ratios $\frac{\phi^*_a}{\theta_a}$ and $\frac{\phi^*_I}{\theta_I}$ to the volatility.\(^{13}\)

Note that the third term is decreasing in the signal-to-noise ratios. This is because there is a chance that bad information about both risk factors is revealed for a given firm, but only one of them is sufficient to deter investment. In other words, the two types of signals are (imperfect) substitutes for investment decisions.

It turns out that welfare only depends on the securities’ excess return $\Delta R$ because information acquisition only depends on $\Delta R$. The investor’s breakeven condition pins down $R_L$ and $R$.\(^{14}\) $\Delta R$ thus is a sufficient statistic to characterize the optimal security. However, this also implies that the planner only has one choice variable and can not fine-tune the signal-to-noise ratios of the two risk factors independently from each other. We get the planner’s first order condition (FOC) by plugging in the equilibrium mass of speculators becoming informed into the objective and taking the derivative.

---

\(^{13}\)In this simple model where firms’ investment decisions are binary, in good states information has no value because by assumption A.2. firms’ default option is to invest. This assumption is not crucial however.

\(^{14}\)In fact, $R_L$ and $R$ are only pinned down jointly, thus they are indeterminate.
Take for example the marginal change in the signal-to-noise ratio of the common risk factor, i.e. if \( \frac{\partial \phi_a}{\partial \Delta R} / \theta_a \). For the fraction \( q_I \) of firms with good firm-specific realizations, bad news about the common risk factor can prevent them from making a NPV < 0 investment. Thus, for them a higher signal-to-noise ratio of the common risk factor has proportional efficiency gains, so the marginal value of information is constant. On the other hand, for the fraction \( 1 - q_I \) of firms with bad firm-specific outcomes, more information about the common risk factor is only useful for those that do not learn about their firm-specific shock. The others that do learn forgo investment regardless. Thus, the marginal value of increasing \( \phi_a^* \) is smaller the larger the firm-specific signal to noise ratio \( \frac{\theta}{q_I} \) is for \( 1 - q_I \) of firms.

The feasible range of \( \Delta R \) is bounded from above and below. Define as \( \Delta R_{\text{min}} \) resp. \( \Delta R_{\text{max}} \) the safest possible security that firms can issue. Since investment is risky, also securities must be risky, so \( \Delta R_{\text{min}} < 0 \). Due to limited liability, there is also an upper bound on \( \Delta R \), defined as \( \Delta R_{\text{max}} \) resp. \( \Delta R_{\text{max}} - R_{L_{\text{max}}} \). Thus for \( \Delta R \) to be feasible, we need that \( \Delta R \in [\Delta R_{\text{min}}, \Delta R_{\text{max}}] \). To make the problem interesting, I assume that \( \Delta R_{\text{max}} \) is sufficiently large to incentivize information production, i.e. \( \Delta R_{\text{max}} > \max[\Delta R_{I_f}, \Delta R_{a}] \).

**PROPOSITION 1.** (planner’s solution) If \( \left( \frac{c_a}{q_a} + \frac{c_I}{q_I} \right)(K-x_L) > c_I \frac{\theta}{q_a q_I (1-q_I)} + c_a \frac{\theta_c}{q_a (1-q_a)} \), then it is optimal to set \( \Delta R \) maximal. Otherwise, an interior solution \( \Delta R_{\text{Int}}^{SP} \) is optimal if it exists, where

\[
\Delta R_{\text{Int}}^{SP} = \frac{2 \Delta R_a (1-q_a) \Delta R_I (1-q_I) (K-x_L)}{\theta_I \Delta R_c c_I + \theta_a \Delta R_a c_a - \left( \frac{\Delta R_I (1-q_I) q_a + \Delta R_a (1-q_a) q_I}{\theta_I} \right)(K-x_L)}. 
\]

It exists as long as it profitable for speculators to acquire information about both risk factors, i.e. if \( \Delta R_{\text{Int}}^{SP} > \max[\Delta R_I, \Delta R_a] \). If not, then there are two possibilities. (i) If \( \Delta R_I > \Delta R_a \), then \( \Delta R_I \) is optimal whenever \( \frac{1}{q_a} (1-q_a) (K-x_L) > c_a \), otherwise \( \Delta R_{\text{min}} \). (ii) If \( \Delta R_I < \Delta R_a \), then \( \Delta R_a \) is optimal whenever \( \frac{1}{q_I} (1-q_I) (K-x_L) > c_I \), otherwise \( \Delta R_{\text{min}} \).

Proof: appendix B.1.2

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\(^{15}\)I normalize the FOC by multiplying it with \( \Delta R^2 \) for the entire analysis. Then the marginal cost as well as part of the marginal value of information is a constant function of \( \Delta R \).

\(^{16}\)There are three different configurations of \( R_H, R_L \) and \( R \) which maximize \( R_H - R_L \), depending on the parameter values.
This Figure shows the socially optimal security depending on the costs of information $c_I$ and $c_a$ about the firm-specific factor and common risk factor, respectively. $\Delta R$ is the difference in payoffs between the high and low state. Accordingly, $\Delta R_{\max}$ and $\Delta R_{\min}$ are the most and least information-sensitive securities, respectively. $\Delta R_{a}$ and $\Delta R_{I}$ are the most information-sensitive securities without triggering information production about the common and firm-specific factor, respectively. $\Delta R_{SP}^{Int}$ is the interior solution to the planner’s problem.

Figure 2.31 illustrates the proposition. Speculators’ cost of becoming informed about the idiosyncratic risk factor is measured on the horizontal axis, and for the common risk factor on the vertical axis. If the costs of information are sufficiently low, then maximizing information acquisition is optimal. The planner thus has firms issue $\Delta R_{\max}$ to learn as much as possible. If on the other hand the costs of information are sufficiently large, then $\Delta R_{\min}$ is optimal so as to limit information acquisition as much as possible. If the costs are intermediate, then there is an interior solution $\Delta R_{SP}^{Int}$ which trades off the value and cost of information.

In the off-diagonal regions, the costs of information are asymmetric, and information production about only one risk factor can be socially optimal. In the upper left region for example, from a social perspective the cost of inducing information about the idiosyncratic risk factor is sufficiently low compared to the value. Speculators also have more incentives to become informed about the idiosyncratic risk factor ($\Delta R_{a} > $ $\Delta R_{I}$). Thus the planner can cherry-pick to some extent. He maximizes $\Delta R$ up to $\Delta R_{a}$ to get as much firm-specific information as possible. Exceeding $\Delta R_{a}$ however would induce wasteful information acquisition about the common risk factor.\footnote{The parametrization in the figure assumes that $\theta_{a} = \theta_{I}$ for simplicity. If $\theta_{a} \neq \theta_{I}$, then there is also a region where the planner can not cherry-pick and minimizes $\Delta R$ instead.}

A figure with $q_I$ instead of $c_I$ and $q_a$ instead of $c_a$ as the axes would look very similar to figure 2.31. The higher the probability of success, the lower the value of knowing whether the bad state will occur, which is similar to increasing the costs. What matters is the value of information compared to the costs.

\footnote{The parametrization in the figure assumes that $\theta_{a} = \theta_{I}$ for simplicity. If $\theta_{a} \neq \theta_{I}$, then there is also a region where the planner can not cherry-pick and minimizes $\Delta R$ instead.}
2.3.6 Competitive equilibrium

Now I characterize the competitive equilibrium. Each firm optimally chooses a security to issue in the primary market, taking the securities others issue as given. The objective function of firm \( i \) at \( t=0 \) is

\[
\max_{R_{H,i}, R_{L,i}, \Pi_i} \Pi_i = q_a q_i (x_H - x_L) + x_L - K \int \left[ (1 - q_a) \frac{\phi_a^*}{\theta_a} + (1 - q_i) \frac{\phi_i^*}{\theta_i} \left( 1 - (1 - q_a) \frac{\phi_a^*}{\theta_a} \right) \right] (K - R_i - (x_L - R_{L,i})) (K - x_L).
\]

subject to the break even constraint (2.4) of the investors and the equilibrium amount of speculators becoming informed about the common (2.2) and idiosyncratic factors (2.3). By plugging in investors breakeven condition, we can rewrite it as

\[
\max_{\Delta R_i} \Pi_i = q_a q_i (x_H - x_L) + x_L - K - \phi_a^* c_i - \phi_a^* \left( 1 - \frac{\phi_a^*}{\theta_a} \right) q_a (1 - q_a) q_i (R_{H,i} - R_{L,i}) \int \left[ (1 - q_a) \frac{\phi_a^*}{\theta_a} + (1 - q_i) \frac{\phi_i^*}{\theta_i} \left( 1 - (1 - q_a) \frac{\phi_a^*}{\theta_a} \right) \right] (K - x_L).
\]

The problem is almost identical to the planner’s except for the fact that the firm does not internalize it’s effect on information acquired about the common risk factor, \( \phi_a^* \). Same in the planner’s problem, the excess return \( \Delta R_i \equiv R_{H,i} - R_{L,i} \) also is a sufficient statistic to characterize each firm’s optimal security. \( R_{L,i} \) resp. \( R_i \) are pinned down by investors’ breakeven condition. The first order condition of \( \Pi_i \) with respect to \( \Delta R_i \) is

\[
\frac{\partial \Pi_i}{\partial \Delta R_i} = \frac{\partial \phi_i}{\partial \Delta R_i} \left[ (1 - (1 - q_a) \frac{\phi_a^*}{\theta_a} \right) \frac{1 - q_i (K - x_L) - c_i}{\theta_i} - \phi_a^* \left( 1 - \frac{\phi_a^*}{\theta_a} \right) q_i q_a (1 - q_a). \quad (2.6)
\]

The first term is the difference between marginal value and costs of increasing information acquired about the firm’s idiosyncratic risk factor. In that respect firms face the same tradeoff as the planner. The second term however differs from the planners FOC, because firms do not internalize their impact on how many speculators acquire signals about the common risk factor. The implication is that they treat as exogenous the informativeness of prices and thus their impact on capital allocation and the premium demanded by investors (market illiquidity) per unit of excess return \( \Delta R \). What the second term reflects is that increasing the excess return of a security nevertheless depresses it’s price in the primary market, keeping constant it’s fundamental value.

**PROPOSITION 2. (competitive equilibrium)** If \( \frac{1}{\theta_i} (1 - q_i)(K - x_L) < c_i \), then firm-specific information is not sufficiently valuable relative to the costs and in equilibrium firms issue \( \Delta R_{min} \). Otherwise there is a unique equilibrium with \( \Delta R > \Delta R_a \). If \( \frac{\Delta R_{CE}}{\Delta R_a} - 1 \geq 73 \).
\begin{align*}
1 - \frac{\Delta R_{\text{min}}}{\Delta R_{\text{CE Int}}} & , \text{ then each firm issues } \Delta R_{\text{CE Int}}^{\text{CE}}, \text{ where } \\
\Delta R_{\text{CE Int}}^{\text{CE}} &= \frac{1}{2\theta_a c_a} \left\{ \frac{\Delta R_d + \Delta R_I(1 - q_I)q_a(K - x_L) - \theta_I c_I}{\sqrt{\left( \Delta R_d + \Delta R_I(1 - q_I)q_a(K - x_L) - \theta_I c_I \right)^2 + 4(1 - q_I)\Delta R_I(1 - q_a)\Delta R_d(K - x_L)}} \right\}.
\end{align*}

Otherwise, a fraction \( f^* \) of firms issues \( \Delta R \equiv \Delta R_I \left( 1 + \sqrt{1 - \frac{\Delta R_{\text{min}}}{\Delta R_I}} \right) \) and a fraction \( 1 - f^* \) issues \( \Delta R_{\text{min}} \). The aggregate \( \Delta R_{\text{CE Mix}}^{\text{CE}} \equiv f^* \Delta R + (1 - f^*)\Delta R_{\text{min}} \) is given by

\begin{align*}
\Delta R_{\text{CE Mix}}^{\text{CE}} &= \frac{1}{2\Delta R_I(1 - q_I)q_a(K - x_L) - \theta_I c_I} \\
& \quad \times \left\{ \theta_a c_a \Delta R^2 - \Delta R_d(1 - q_a)\Delta R_I(1 - q_I)(K - x_L) \right. \\
& \quad \left. - \sqrt{\left[ \theta_a c_a \Delta R^2 - \Delta R_d(1 - q_a)\Delta R_I(1 - q_I)(K - x_L) \right]^2 - 4\Delta R_I(1 - q_I)q_a(K - x_L) - \theta_I c_I} \theta_a c_a \Delta R_d \Delta R^2} \right\}.
\end{align*}

Proof: appendix B.1.3

Figure 2.32: Security issued in the competitive equilibrium.

This Figure shows the type of security firms issue in the competitive equilibrium, depending on the costs of information \( c_I \) and \( c_a \) about the firm-specific factor and common risk factor, respectively. \( \Delta R \) is the difference in payoffs between the high and low state. \( \Delta R_{\text{min}} \) is the least information-sensitive security. \( \Delta R_{\text{CE Int}}^{\text{CE}} \) and \( \Delta R_{\text{CE Mix}}^{\text{CE}} \) are the securities where firms trade off the benefits and costs of information about their firm-specific risk factors.

Figure 2.32 illustrates the proposition. In the region to the right, the value of information about the idiosyncratic risk factor is smaller than the costs. There, firms
issue $\Delta R_{\text{min}}$ to minimize their cost of capital. In the other two regions the value of information about the idiosyncratic risk factor is larger than the cost, and firms have incentives to issue information-sensitive securities to learn about it. In the region to the left, firms are at an interior optimum where they trade off the gains from receiving firm-specific information against illiquidity coming from speculators being informed about $A_i$ and $A_a$. In this region the information-sensitivity of the securities that firms issue is highest. In the middle region, the net benefit from learning about $A_i$ is moderate. Here, some firms issue an information-sensitive security to learn about $A_i$ and some issue an information-insensitive security to maximize the liquidity of their securities.

2.4 The inefficiency

Next I analyze under which conditions the equilibrium is inefficient compared to the constrained planner’s solution.

**PROPOSITION 3.** For $\frac{1}{\theta I}(1 - q_I)(K - x_L) < c_I$, there are two possibilities. If $\frac{1}{\theta a}(1 - q_a)(K - x_L) < c_a$ or $\Delta R_a > \Delta R_I$, then there is no intervention (region 1). Otherwise the planner can increase total surplus by forcing firms to issue riskier securities (region 2). For $\frac{1}{\theta I}(1 - q_I)(K - x_L) \geq c_I$, there are also two possibilities. If $c_a$ is small enough such that $c_a < \bar{c}_a$, then the planner can increase total surplus by forcing firms to issue riskier securities (region 3). If $c_a$ is large enough such that $c_a > \bar{c}_a$, then the planner can increase total surplus by forcing firms to issue safer securities (region 4).

Figure 2.41 illustrates the planner’s intervention, depending on the costs of information production. In regions 1 and 2, firms have no desire to induce information acquisition (about the firm-specific risk factor) and thus issue $\Delta R_{\text{min}}$. In region 1 on the top right, also the planner would like to limit information production, because learning about the common risk factor is not worthwhile either. Minimizing information production is optimal, both socially and privately, so there is no intervention. In region 2 on the bottom right, the planner however would like to induce information production about the common risk factor since it is cheap. This is in contrast to the competitive equilibrium, where firms issue information-insensitive securities because learning about $A_i$ is expensive. He would therefore have them issue the most information-sensitive security up to the point where information production about $A_i$ is triggered, $\Delta R_I$.

In region 3, also firms would like to trigger information production, but they do so less than the planner because they only internalize the value of information about firm-specific, not common risk. The planner therefore makes them issue more information-sensitive securities. In region 4, we get the surprising result that firms induce too much information production. They like to learn about the idiosyncratic risk factor, but doing so triggers excessive information production about the common risk factor. The planner would make them be more conservative so that speculators do not waste resources learning about $A_a$.
This Figure illustrates how the planner intervenes, depending on the costs of information $c_I$ and $c_a$ about the firm-specific factor and common risk factor, respectively. $\Delta R$ is the difference in payoffs between the high and low state, and is positively related with the information-sensitivity of the issued securities.

### 2.5 Conclusion

I provide a model of capital misallocation due to an informational externality. Firms have incentives to limit information production to decrease their cost of capital. This comes at the cost of uninformative prices, which deteriorates capital allocation. The inefficiency arises because valuable information about risk factors common across firms is a public good from their perspective. Providing this public good entails a private cost in the form of issuing securities that will become illiquid in the secondary market, which increases firms’ individual cost of capital.

This externality has implications not just for money markets, but also for non-financial industries during periods where there is large aggregate uncertainty, for example when there is an innovation that is broadly adopted or uncertainty about product demand. These industries may experience inefficient booms due to insufficient knowledge about the risks of the innovation. A social planner would incentivize more information production in such periods, for example by forcing firms to retain a certain amount of information-insensitive securities. This would force them to finance themselves with more information-sensitive securities, which would promote information production.
Appendix B

Appendix to chapter 2

B.1 Proofs

B.1.1 Proof of Lemma 1

The expected trading profit of a speculator becoming informed about the idiosyncratic risk factor of firm $i$ is

$$
\left(1 - \frac{\phi_i}{\theta_i}\right) \left[(1 - q_a) \frac{\phi_a}{\theta_a} \cdot 0 + \left(1 - \frac{\phi_a}{\theta_a}\right) \left(q_a q_I \left(R_{H,i} - R_{L,i}\right) + R_{L,i} - R_{L,i}\right)\right]
\quad + q_a \frac{\phi_a}{\theta_a} \left[q_I \left(R_{H,i} - R_{L,i}\right) + R_{L,i} - R_{L,i}\right]
$$

if $A_i = 0$ and

$$
\left(1 - \frac{\phi_i}{\theta_i}\right) \left[(1 - q_a) \frac{\phi_a}{\theta_a} \cdot 0 + \left(1 - \frac{\phi_a}{\theta_a}\right) \left(-q_a q_I \left(R_{H,i} - R_{L,i}\right) - R_{L,i} + q_a \left(R_{H,i} - R_{L,i}\right) + R_{L,i}\right)\right]
\quad + q_a \frac{\phi_a}{\theta_a} \left[-q_I \left(R_{H,i} - R_{L,i}\right) - R_{L,i} + R_{H,i}\right]
$$

if $A_i = 1$. Simplifying these terms and taking the unconditional expectation yields the term in Lemma 1. The analogue holds for the incentives to become informed about the common risk factor $A_a$, except that the summation is over all securities.

B.1.2 Proof of Proposition 1

For the proof, note that welfare is a smooth function of $\Delta R$. There are four cases to distinguish depending on whether the information acquisition equations (2.2) and (2.3) are binding:

$(\phi_a > 0, \phi_I > 0)$: solve the FOC (equation 2.5) to get the interior solution $\Delta R^{SP}_{\text{int}}$. It goes to infinite as $\left(\frac{c_a}{q_a} + \frac{c_I}{q_I}\right) (K - x_L) \rightarrow c_I \frac{\theta_{ac_I}}{q_a q_I (1 - q_I)} + c_a \frac{\theta_{ac_a}}{q_I q_a (1 - q_a)}$. Thus, if $\left(\frac{c_a}{q_a} + \frac{c_I}{q_I}\right) (K - x_L) > c_I \frac{\theta_{ac_I}}{q_a q_I (1 - q_I)} + c_a \frac{\theta_{ac_a}}{q_I q_a (1 - q_a)}$, the optimal solution is $\Delta R_{\text{max}}$ maximal. By assumption $\Delta R_{\text{max}} >$
max[ΔR_t, ΔR_a], so this is possible. If \((\frac{c_a}{q_a} + \frac{c_l}{q_l})(K - x_L) \leq c_l \frac{\theta_l c_l}{q_l(1 - q_l)} + c_a \frac{\theta_a c_a}{q_a q_a(1 - q_a)}\), then it is ΔR^{SP}_{Int}. For existence we need that ΔR^{SP}_{Int} > max[ΔR_t, ΔR_a].

(φ_a = 0, φ_l = 0): no information is acquired. Welfare is just \(q_a q_l (x_H - x_L) + x_L - K\). Any ΔR < min[ΔR_t, ΔR_a] is optimal.

(φ_a > 0, φ_l = 0): Setting \(\frac{\partial \phi_l}{\partial \Delta R} = φ_l = 0\), the FOC reduces to

\[
\frac{\partial \phi_a}{\partial \Delta R} (1 - q_a) (K - x_L) - c_a \frac{\partial \phi_a}{\partial \Delta R}.
\]

\(\frac{\partial \phi_a}{\partial \Delta R}\) cancels out and we get \(\frac{1}{\theta_a} (1 - q_a)(K - x_L) - c_a\). Therefore, if \(K - x_L > \frac{\theta_a c_a}{1 - q_a}\), then the FOC is positive for all ΔR. Setting ΔR maximally without violating \(φ_a > 0\), \(φ_l = 0\) gives ΔR = ΔR_t. If on the other hand \(K - x_L < \frac{\theta_a c_a}{1 - q_a}\), then the FOC is negative for all ΔR. We would like to minimize ΔR. But this violates \(φ_a > 0\), so it is not possible that \(K - x_L < \frac{\theta_a c_a}{1 - q_a}\).

(φ_a = 0, φ_l > 0): Setting \(\frac{\partial \phi_a}{\partial \Delta R} = φ_a = 0\), the FOC reduces to

\[
\frac{\partial \phi_l}{\partial \Delta R} (1 - q_l) (K - x_L) - c_l \frac{\partial \phi_l}{\partial \Delta R}.
\]

\(\frac{\partial \phi_l}{\partial \Delta R}\) cancels out and we get \(\frac{1}{\theta_l} (1 - q_l)(K - x_L) - c_l\). If \(K - x_L > \frac{\theta_l c_l}{1 - q_l}\), then the FOC (2.5) is positive for all ΔR. Setting ΔR maximally without violating \(φ_a = 0\), \(φ_l > 0\) gives ΔR = ΔR_a. If on the other hand \(K - x_L < \frac{\theta_l c_l}{1 - q_l}\), then the FOC is negative for ΔR. But minimizing ΔR violates \(φ_l > 0\), so it is not possible that \(K - x_L < \frac{\theta_l c_l}{1 - q_l}\).

Next, I show that the interior solution is in fact a local maximum. If ΔR^{SP}_{Int} > max[ΔR_t, ΔR_a], then welfare is concave in ΔR around ΔR^{SP}_{Int} because the second derivative is negative as I will show:

\[
\frac{\partial^2 W}{\partial \Delta R^2} = \frac{\partial^2 \phi_a}{\partial \Delta R^2} \left[ \frac{1 - q_a}{\theta_a} \left(1 - \frac{1 - q_l}{\theta_l}\phi_l\right) (K - x_L) - c_a \right] + \frac{\partial^2 \phi_l}{\partial \Delta R^2} \left[ \frac{1 - q_l}{\theta_l} \left(1 - \frac{1 - q_a}{\theta_a}\phi_a\right) (K - x_L) - c_l \right]
\]

\[
- 2(K - x_L) \frac{1 - q_l}{\theta_l} \frac{1 - q_a}{\theta_a} \frac{\partial \phi_l}{\partial \Delta R} \frac{\partial \phi_a}{\partial \Delta R}.
\]
Using $\frac{\partial^2 W}{\partial \Delta R^2} = -\frac{\partial W}{\partial \Delta R} \frac{2}{\Delta R}$, this yields

$$\frac{\partial^2 W}{\partial \Delta R^2} = -\frac{2}{\Delta R} \left\{ \frac{\partial^2 \phi_a}{\partial \Delta R^2} \left[ 1 - q_a \left( 1 - \frac{1 - q_l}{\theta_a} \phi_l \right) (K - x_L) - c_a \right] \right. \\
\quad \left. \quad + \frac{\partial^2 \phi_I}{\partial \Delta R^2} \left[ 1 - q_I \left( 1 - \frac{1 - q_a}{\theta_a} \phi_a \right) (K - x_L) - c_I \right] \right\} \\
\quad - 2(K - x_L) \frac{1 - q_l}{\theta_I} \frac{1 - q_a}{\theta_a} \frac{\partial \phi_I}{\partial \Delta R} \frac{\partial \phi_a}{\partial \Delta R} > 0 > 0.$$

The term in curly brackets is equal to the FOC (2.5) and therefore 0, so welfare is concave around the interior solution.

Let us compare the interior solution to the other three possible corner solutions. The claim is that the interior solution is optimal if it exists. Note that in the cases where $(\phi_a > 0, \phi_l = 0)$ or $(\phi_a = 0, \phi_I > 0)$, welfare is increasing in $\Delta R$. But then then the interior solution must be better because $\Delta R_I < \Delta R_{\text{Interior}}$ resp. $\Delta R_a < \Delta R_{\text{Interior}}$ and the fact that welfare is smooth in $\Delta R$. Is it possible that choosing $\Delta R$ minimal such that $(\phi_a = 0, \phi_I = 0)$ is better? No, as the difference between welfare under the interior solution and under no information only depends on linear terms containing $\phi_I^*$ and $\phi_a^*$, without a constant (thus not affine).

If $0 < \Delta R^{SP}_{\text{Int}} < \max\{\Delta R_I, \Delta R_a\}$, then the interior solution does not exist. If $\Delta R_I > \Delta R_a$, then only cases $(\phi_a > 0, \phi_I = 0)$ or $(\phi_a = 0, \phi_I = 0)$ can exist, which means the optimal solution must either be $\Delta R_I$ or $\Delta R_{\min}$. If $K - x_L > \frac{\theta_a c_a}{1 - q_a}$, then the optimal solution is therefore $\Delta R_I$, otherwise $\Delta R_{\min}$. The reasoning is the same when $\Delta R_I > \Delta R_a$.

If the optimal solution is not within the corner solutions, then naturally it must be the corner solution closest since the objective function is smooth.

### B.1.3 Proof of Proposition 2

If $K - x_L < \frac{\theta_a c_a}{1 - q_a}$, then the FOC (equation 2.6) is negative regardless of $\phi_a$ (the equilibrium $\Delta R$). So in that case the unique equilibrium must be $\Delta R = \Delta R_{\min}$.

**Simple Equilibrium** If however $K - x_L \geq \frac{\theta_a c_a}{1 - q_a}$, then potentially firms would like have some information. FOC 2.6 is a quadratic equation,

$$\Delta R^{CE}_{\text{Int}} \theta_a c_a - \Delta R^{CE}_{\text{Int}} [\Delta R_l ((1 - q_l)q_a(K - x_L) - \theta_l c_l) + \theta_a c_a \Delta R_a] \\
\quad - (1 - q_l) \Delta R_l (1 - q_a) \Delta R_a (K - x_L) = 0 \quad (B.1)$$

Solving for $\Delta R$ yields the term in the proposition. The determinant is always positive therefore a solution always exists. It is also easy to verify that the first term of $\Delta R^{CE}_{\text{Int}}$ is smaller than the second, thus the sign in front of the second term can not be negative.

For the interior solution to be an equilibrium, we need that $\Delta R^{CE}_{\text{Int}} > \max\{\Delta R_I, \Delta R_a\}$ such that $\phi_I^* > 0$ and $\phi_a^* > 0$ and that it is not profitable for a firm to deviate. At the
interior solution, it is easy to show that firms are always at a local maximum so any (marginal) deviation $\Delta R'_j > \Delta R_j$ from $\Delta R_{CE \text{Int}}$ is not profitable. For a firm not to deviate to $\Delta R'_j < \Delta R_j$, we need that

$$
\Pi_{\Delta R_{CE \text{Int}}} - \Pi_{\Delta R_j} = \phi^j \int \left[ 1 - \frac{q_j}{\theta_j} \left( 1 - \frac{1 - q\phi^j}{\theta_a} \right) (K - x_L) - c_j \right] - \phi^j \int c_a \left( 1 - \frac{\Delta R'_j}{\Delta R_{CE \text{Int}}} \right) \geq 0 \quad (B.2)
$$

where $\phi^j$ and $\phi^a$ are the amount of speculators becoming informed in equilibrium under no deviation. Rearranging terms and simplifying yields

$$
\phi^j \int c_a \left[ \frac{\Delta R_{CE \text{Int}}}{\Delta R_j} - 1 - \left( 1 - \frac{\Delta R'_j}{\Delta R_{CE \text{Int}}} \right) \right] \geq 0.
$$

The condition is least likely to hold when $\Delta R'_j$ is chosen minimally, $\Delta R_{\text{min}}$. The term in square brackets then is exactly the condition in the proposition.

We also need that $\Delta R_{CE \text{Int}} > \Delta R_j$ and $\Delta R_{CE \text{Int}} > \Delta R_a$. Rewriting condition $\Delta R_{CE \text{Int}} > \Delta R_a$, it turns out that it is equivalent to $(1 - q_j)(K - x_L) \geq \theta_j c_j$, so it always holds. Condition $\Delta R_{CE \text{Int}} > \Delta R_j$ always holds if the no-deviation condition $\frac{\Delta R_{CE \text{Int}}}{\Delta R_j} - 1 \geq 1 - \frac{\Delta R_{\text{min}}}{\Delta R_{CE \text{Int}}}$. To see this, note that if $\Delta R_{\text{min}} > \Delta R_j$, then together with the no-deviation condition this directly implies that $\Delta R_{CE \text{Int}} > \Delta R_j$. If on the other hand $\Delta R_{\text{min}} < \Delta R_j$, then condition $\frac{\Delta R_{CE \text{Int}}}{\Delta R_j} - 1 \geq 1 - \frac{\Delta R_{\text{min}}}{\Delta R_{CE \text{Int}}}$ is equivalent to $\Delta R_{CE \text{Int}} \geq \Delta R_j \left( 1 + \sqrt{1 - \frac{\Delta R_{\text{min}}}{\Delta R_j}} \right)$. From that condition it automatically follows that $\Delta R_{CE \text{Int}} > \Delta R_j$.

**Mixed Equilibrium** When $(1 - q_j)(K - x_L) \geq \theta_j c_j$ and $\frac{\Delta R_{CE \text{Int}}}{\Delta R_j} - 1 < 1 - \frac{\Delta R_{\text{min}}}{\Delta R_{CE \text{Int}}}$ we will show that the mixed equilibrium described in the proposition is indeed an equilibrium and that it is unique. For it to be an equilibrium, we need that firms issuing $\Delta R_j$ with $\Delta R_{CE \text{Int}} > \Delta R_j$ and firms issuing $\Delta R_{\text{min}}$ do not deviate at the margin and that both types earn the same profits. Note that the equilibrium can only exist if $\Delta R_{\text{min}} < \Delta R_j$. Then condition $\frac{\Delta R_{CE \text{Int}}}{\Delta R_j} - 1 < 1 - \frac{\Delta R_{\text{min}}}{\Delta R_{CE \text{Int}}}$ becomes $\Delta R_{CE \text{Mix}} = \Delta R \equiv \Delta R_j \left( 1 + \sqrt{1 - \frac{\Delta R_{\text{min}}}{\Delta R_j}} \right)$.

Firms issuing $\Delta R_{\text{min}}$ do not deviate at the margin because for them $\phi^j = 0$ (due to $\Delta R_{\text{min}} < \Delta R_j$), thus they only care about the adverse selection costs stemming from information about the common risk factor induced by the other firms.

The condition for all firms to earn the same profits is:

$$
c_a \phi^j |_{\Delta R = \Delta R_{CE \text{Mix}}} \left[ \frac{\Delta R}{\Delta R_j} - 1 \left( 1 - \frac{\Delta R_{\text{min}}}{\Delta R_j} \right) \right] = 0.
$$

Solving this quadratic equation for $\Delta R$ yields $\Delta R = \Delta R_j \left( 1 + \sqrt{1 - \frac{\Delta R_{\text{min}}}{\Delta R_j}} \right)$.

$\Delta R_{CE \text{Mix}}$ is pinned down by the local optimality condition of the firms issuing $\Delta R$. We can rewrite FOC (equation 2.6) with $\frac{\theta_j c_j}{q_j (1 - q_j) \Delta R^2}$ in place of $\frac{\partial \Pi_j}{\partial \Delta R_j}$ and $\theta_a (1 - \theta_a (1 - q_j) \Delta R^2)}$ in place of $\frac{\partial \Pi_a}{\partial \Delta R_a}$.
\[
\frac{c_a}{q_a(1-q_a)\Delta R^{CE}_{\text{Mix}}} \text{ in place of } \phi'_a,
\]

\[
\Delta R^{CE}_{\text{Mix}} 2 \Delta R_l[(1-q_l)q_a(K-x_L) - \theta_Ic_I] \\
- \Delta R^{CE}_{\text{Mix}} \left[ \theta_a c_a \Delta R^2 - \Delta R_a(1-q_a)\Delta R_l(1-q_l)(K-x_L) \right] + \theta_a c_a \Delta R_a \Delta R^2 = 0.
\]

Solving this equation yields

\[
\Delta R^{CE}_{\text{Mix}} = \frac{1}{2\Delta R_l[(1-q_l)q_a(K-x_L) - \theta_Ic_I]} \left\{ \left[ \theta_a c_a \Delta R^2 - \Delta R_a(1-q_a)\Delta R_l(1-q_l)(K-x_L) \right] \right. \\
\left. \pm \sqrt{\left[ \theta_a c_a \Delta R^2 - \Delta R_a(1-q_a)\Delta R_l(1-q_l)(K-x_L) \right]^2 - 4\Delta R_l[(1-q_l)q_a(K-x_L) - \theta_Ic_I] \theta_a c_a \Delta R_a \Delta R^2} \right\}.
\]

I will prove that the discriminant is always positive. Thus we require that

\[
\left[ \theta_a c_a \Delta R^2 - \Delta R_a(1-q_a)\Delta R_l(1-q_l)(K-x_L) \right]^2 > 4\Delta R_l[(1-q_l)q_a(K-x_L) - \theta_Ic_I] \theta_a c_a \Delta R_a \Delta R^2.
\]

Using equation B.1 together with \( \Delta R^{CE}_{\text{Mix}} < \Delta R \), we also know that

\[
\Delta R^2 \theta_a c_a - (1-q_l)\Delta R_l(1-q_a)\Delta R_a(K-x_L) > \\
\Delta R[\Delta R_l((1-q_l)q_a(K-x_L) - \theta_Ic_I) + \theta_a c_a \Delta R_a]. \quad (B.3)
\]

Thus we can underestimate the LHS of the determinant condition,

\[
\Delta R^2 [\Delta R_l((1-q_l)q_a(K-x_L) - \theta_Ic_I) + \theta_a c_a \Delta R_a]^2 > \\
4\Delta R_l[(1-q_l)q_a(K-x_L) - \theta_Ic_I] \theta_a c_a \Delta R_a \Delta R^2.
\]

Reformulating this condition yields

\[
[\Delta R_l((1-q_l)q_a(K-x_L) - \theta_Ic_I) - \theta_a c_a \Delta R_a]^2 > 0,
\]

which always holds.

One can also show that the sign in front of the square root must be negative.

The fraction \( f^* \) of firms issuing \( \Delta R \) is then pinned down by

\[
\Delta R^{CE}_{\text{Mix}} = f^* \Delta R + (1-f^*)\Delta R_{\text{min}} \\
\leftrightarrow f^* = \frac{\Delta R^{CE}_{\text{Mix}} - \Delta R_{\text{min}}}{\Delta R - \Delta R_{\text{min}}}
\]

Next I show that \( f \in [0,1] \) if and only if \( \frac{\Delta R^{CE}_{\text{int}}}{\Delta R_l} - 1 < 1 - \frac{\Delta R_{\text{min}}}{\Delta R^{CE}_{\text{int}}} \). This implies that a mixed equilibrium only exists in that region. For \( f < 1 \) to hold, we require that \( \Delta R^{CE}_{\text{Mix}} < \Delta R \). Solving this inequality yields condition B.3, the condition that holds if and only if \( \frac{\Delta R^{CE}_{\text{int}}}{\Delta R_l} - 1 < 1 - \frac{\Delta R_{\text{min}}}{\Delta R^{CE}_{\text{int}}} \) (the inequality sign flips twice when \((1-q_l)q_a(K-x_L) < \theta_Ic_I\)). Condition \( f > 0 \) is equivalent to \( \Delta R^{CE}_{\text{Mix}} > \Delta R_{\text{min}} \). But firms can not issue a safer security than \( \Delta R_{\text{min}} \), so it is impossible that \( f < 0 \). A mixed equilibrium with three or more different strategies can not exist because there are only two local maxima (one for \( \Delta R < \Delta R_l \) and one for \( \Delta R > \Delta R_l \)). This implies that the mixed equilibrium in the proposition is unique.
B.1.4 Proof of Proposition 3

If $\frac{1}{\theta_I}(1 - q_I)(K - x_L) < c_I$, then from proposition 2 it follows that firms issue that $\Delta R_{\text{min}}$ in the private market equilibrium. Region 1 is defined exactly as the parameter values where $\Delta R_{\text{min}}$ is also socially optimal (proposition 1), thus no intervention by the planner is necessary. Since region 2 is just the difference between the region defined by $\frac{1}{\theta_I}(1 - q_I)(K - x_L) < c_I$ and region 1, the socially optimal security has $\Delta R > \Delta R_{\text{min}}$. Thus the planner would like to increase information production.

Next take the case when $\frac{1}{\theta_I}(1 - q_I)(K - x_L) \geq c_I$. We need to show that the socially optimal security is riskier than in equilibrium when $c_a$ small and safer when $c_a$ large. Since both the socially optimal and equilibrium security are smooth in $c_a$, then we can conclude that there must be a cutoff $c_a^*$ which defines the regions 3 and 4 together with $\frac{1}{\theta_I}(1 - q_I)(K - x_L) \geq c_I$. First I show that the socially optimal security is riskier than in equilibrium when $c_a$ small. If $\frac{1}{\theta_I}(1 - q_I)(K - x_L)q_a < c_I$, then the socially optimal security is $\bar{R}_I$ whereas in equilibrium firms issue $\Delta R_{\text{min}}$ (follows from their FOC (2.6)). If on the other hand $\frac{1}{\theta_I}(1 - q_I)(K - x_L)q_a \geq c_I$, then the socially optimal security is $\Delta R_{\text{max}}$ for a $c_a$ >> 0, whereas in equilibrium firms only issue $\Delta R_{\text{max}}$ if $c_a \rightarrow 0$. To see this, note that From the first part of proposition 1, $\Delta R_{\text{max}}$ is socially optimal whenever $\theta_I\bar{R}_I c_I + \theta_a \Delta R_a c_a \leq \left(\bar{R}_I(1 - q_I)q_a + \Delta R_a(1 - q_a)q_I\right)(K - x_L)$. The condition can be rewritten as

$$c_a \left(\frac{\theta_a c_a}{q_I q_a(1 - q_a)} - \frac{K - x_L}{q_a}\right) \leq \bar{R}_I \left[ (1 - q_I)q_a(K - x_L) - \theta_I c_I \right].$$

The right hand side is positive. Thus the condition always holds for $\frac{1}{\theta_a q_I(1 - q_a)(K - x_L)} > c_a > 0$.

Now I show that the socially optimal security is safer than in the private equilibrium when $c_a$ is large. Note that when $c_a$ is large, then $\Delta R_a > \bar{R}_I$. We can also show that $\Delta R_{\text{Int}}^{\text{CE}} < \bar{R}_a$. Rewriting that inequality yields

$$\bar{R}_I \left[ 2(1 - q_a)(1 - q_I)(K - x_L) + (1 - q_I)q_a(K - x_L) - \theta_I c_I \right] \leq \Delta R_a \left[ \theta_a c_a - (1 - q_a)q_I(K - x_L) \right],$$

which holds if $c_a$ large enough. Thus we have that $\Delta R_{\text{SP}} = \bar{R}_a$. In the private market equilibrium the solution is interior if $\frac{1}{\theta_I}(1 - q_I)(K - x_L) \geq c_I$. Rewriting the inequality yields exactly $\Delta R_{\text{Int}}^{\text{CE}} > \bar{R}_a$ yields $\frac{1}{\theta_I}(1 - q_I)(K - x_L) > c_I$, thus it holds.

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Chapter 3
Safe assets: a review

3.1 Introduction

The recent banking crisis was largely unanticipated, and has forced a major reassessment of views on risk creation during credit cycles. The macro finance research agenda is seeking a more integrated framework to describe the evolution of aggregate endogenous risk. There appears to be a clear division of tasks. New macro models study the dynamics of economic propagation of financial shocks under financial constraints. Financial research looks at how risk incentives shape the distribution of shocks and how contracts redistribute their impact. Novel concepts such as maturity races, volatility spirals, information sensitivity, induced runs and correlated risk strategies have come to enrich our understanding of excess risk creation over the financial cycle. These new insights complement the established notion of the liquidity risk externality associated with banking.

A novel insight comes from the recognition of a fundamental demand for safety, distinct from liquidity and money demand, with a major role in shaping contracting and the structure of financial intermediation. This survey focuses on the nature and consequences of safe asset demand, in particular how it shapes the behavior of financial intermediaries, and encourages the private supply of (quasi) safe assets. This enables to understand financial innovation during the credit boom, when novel forms of tranching, funding and hedging were developed to satisfy a strong demand for safety. Ultimately, a critical issue is whether pressure for safety contributes to aggregate risk.

Considerable evidence has emerged on a strong demand for financial safety. Krishnamurthy and Vissing-Jorgensen (2012) find long-term evidence of a safety premium on Treasury debt distinct from its liquidity premium. Whereas the liquidity premium reflects the ease of converting Treasuries into money, one can think of the safety premium as their implicit value of offering absolute security of nominal repayment.

The safety premium is especially elevated at times of scarcity of U.S. public debt, the primary safe asset. This is consistent with the evidence of a historically very stable demand for safe assets in U.S. household portfolios (Gorton et al., 2012). These results indicate a structural demand for safety rather than a new phenomenon. This implies a sharp market segmentation between safe and speculative asset markets.¹

¹ A discontinuity at the zero risk boundary may explain low empirical estimates of CAPM market
A consequence of a stable demand for safe assets is that a period of low supply of government debt tends to boost (in fact, crowds in) the creation of private safe assets in the form of short-term liabilities issued by the financial sector, such as repo and commercial paper (Krishnamurthy and Vissing-Jorgensen, 2015). On the asset side, this appears to be associated with credit expansion and an increase in net long-term investment by intermediaries, increasing maturity transformation.

This insight has major implications for the macro and banking literature, where the volume of credit is assumed to be demand driven. The existence of shocks to credit supply suggests an independent component of credit cycles next to real shocks driving the business cycle. Their impact on aggregate credit volume and liquidity risk needs to be understood by macro finance research, so as to inform preventive prudential policy.

3.1.1 A global demand for safety

The earliest recognition of a strong demand for safety came with research on the large capital inflows into the US during the credit boom in 2002-2007, associated with the recycling of global imbalances (Bernanke (2005), Caballero et al., 2008). Historically, capital flowed from rich to developing countries. However, since 1998 net capital flows have reversed (Prasad et al., 2007), as emerging country investors have invested their rising trade surpluses abroad (Gourinchas and Rey, 2007), especially in safe dollar assets (Bernanke et al., 2011). Foreign holdings now represent more than 20 per cent of US debt securities, and over half of the Treasury market. US public debt is mostly held by central banks as reserves against sudden capital outflows. As foreign demand for safety has grown faster than US public debt, US intermediaries have issued more "safe" claims to foreign private investors, who by some measures account for 80 per cent of total foreign inflows (Forbes, 2010).

A common explanation is that safe asset markets are less developed in emerging markets (Caballero et al., 2008), and are more exposed to enforcement risk (Quadrini et al., 2009) or face expropriation risk (Ahnert and Perotti, 2015). At the same time, the dollar also acts as the reserve currency for the international monetary system. This makes dollar assets a prime target for safety seeking flows. Indeed, the dollar is a safe haven in times of crisis, when a global flight to quality takes place (Maggiori, 2013).

The direct effect of safety seeking inflows is a higher risk concentration for US residents and intermediaries (Caballero and Krishnamurthy, 2009). As these safety seeking foreign flows appear to be stable, they do not contribute to exchange rate risk, and indeed the 2007-2008 financial crisis did not lead to sharp outflows from dollar assets. However, huge inflows are bound to reshape the scale and risk profile of credit, and can lead to runs on individual assets or intermediaries. A better understanding of the demand and supply for safe assets is needed to clarify whether pressure to create

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2 There is a large literature on the international monetary system, see Farhi et al. (2011) and references therein. He et al. (2016) model the endogenous emergence of a dominant safe asset. Strikingly, they show how relative market size plays a significant role next to fundamentals, favoring large country currencies such as the dollar versus the Swiss Franc.

3 Govillot et al. (2010) show that the US provides insurance to the rest of the world, in the form of a lower yield during normal times, and a transfer of wealth to foreign investors in crises.
safe assets ultimately contributes to aggregate instability.

The remainder of the survey is structured as follows. Section 3.2 defines various concepts and introduces an asset classification used in the review. Section 3.3 reviews the empirical evidence on demand and supply of safe assets. Section 3.4 discusses possible fundamental causes of safety demand by investors. Section 3.5 looks at theoretical models of private (quasi) safe asset creation, identifies the main contractual forms and their effect on risk creation. Section 3.6 discusses the policy implications. Section 3.7 concludes.

### 3.2 What are safe assets?

We introduce some definitions to distinguish safety, liquidity and money demand. Naturally, no asset is absolutely safe. We will use the term *safe assets* to describe unconditional financial promises with no credit risk, so that nominal repayment is certain. This defines as safe any debt issued or guaranteed by a "safe" government, implying a country with an own central bank, stable currency and good protection of property rights.\(^4\) Although the safe asset literature has so far ignored inflation risk, a low inflation environment presumably is a prerequisite for a safe asset.

We define the safest privately issued claims as *quasi-safe*, implying that they have no credit risk outside of major crises. Most private quasi-safe assets arise in the process of inside money creation by private intermediaries, such as short term and secured debt. While generally safe, at time of systemic distress, these private assets lose their perceived safety and become rapidly illiquid.

Two conventional definitions also belong to a general classification. *Outside money* is the stock of liabilities of the central bank, the statutory legal tender at face value for any obligation. *Inside money* is the stock of liabilities issued by the financial sector that can be used for immediate payment by households and firms.

Traditional money demand seeks claims that serve as immediate form of payment, such as cash, reserves or demandable bank debt. It is the ultimate liquid and nominally safe asset, which also has zero interest-rate risk. While it can serve as a low return store of value, for purely safety purposes it is dominated by other safe assets, since it also enjoys a convenience yield due to its immediate use as payment (Stein, 2012). This transactional view of money demand formalized in the "money in the utility function" approach (Sidrauski, 1967) is still at the core of many money demand models.

Liquidity demand seeks assets easily converted into money quickly, such as government debt and short term debt issued by borrowers with access to liquidity. Asset liquidity is valued as it can satisfy sudden needs for consumption or investment, either for consumption (Diamond and Dybvig (1983), Gorton and Pennacchi, 1990) or productive purposes (Holmström and Tirole, 1998, 2001). Holding liquid or unencumbered pledgeable assets serves as a precaution to avoid costly access to external finance caused by asymmetric information or moral hazard. When illiquid assets trade at fire-sale prices, hoarding liquidity is particularly profitable (Allen and Gale (2004),

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\(^4\) A central bank can always honor any nominal debt in domestic currency by expanding outside money.
Diamond and Rajan (2011), Gale and Yorulmazer (2013), Malherbe, 2014). Thus both a hedging or speculative demand for liquidity can justify a lower yield for liquid assets (Vayanos and Vila, 1999). In contrast, safety demand does not seek access to means of payment, but is aimed at wealth preservation in all states, resulting in extreme risk avoiding behavior. It therefore targets public debt or the safest private assets.

The distinction between safety and liquidity is conceptually sharp but has long been neglected, for good reasons. First, safe assets are typically very liquid, provided they have an active secondary market. However, empirically the distinction is possible. Some safe assets are illiquid by construction (e.g. insured savings deposits, or term repo on safe collateral). In contrast, some very risky assets such as listed shares can be more liquid during a crisis than much safer assets such as corporate bonds or rated ABS. A second reason is that banking theory has long explained demandable debt exclusively as a response to contingent liquidity demand. However, a distinct safety premium suggests a demand for an absolutely safe store of value distinct from demand for liquidity. We consider the emerging literature on the nature and implications of this demand.

![Asset safety and liquidity under our definition.](image)

We offer in Figure 3.21 a classification of low-risk assets in terms of their safety, liquidity or moneyness. There is a clear positive correlation between safety and liquidity though the two concepts remain distinct. On the bottom are money assets, mostly safe and (almost) always liquid, whose issuers benefit from a convenience yield. While money claims with a government guarantee (including insured deposits) are safe and liquid, uninsured deposits are quasi-safe forms of immediate payment, and are accepted until banks become insolvent.

Private quasi-safe assets are safe and liquid only outside of systemic crises. The

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5 For non-marketable claims, liquidity here equals maturity.
safest among non monetary private claims are repos,\(^6\) ranked by the quality of their collateral, followed by short term financial debt and money market fund shares. In the upper right quadrant are senior tranches of AAA asset backed securities, which were designed to be extremely safe but proved otherwise.\(^7\) This graph implicitly defines which assets enjoy a (measure of) safety, convenience or liquidity premium. While these yields are usually fairly stable, in a crisis, the liquidity and perceived safety of private quasi safe assets drops sharply. The rapid adjustment of safety and liquidity premia leads to sharp changes in relative yields. As we will see in the theoretical review in section 3.5, a strong safety demand may then lead to (or reinforce) a market breakdown, with no rollover at any price, all the more when the supply of quasi safe assets has been excessive.

### 3.3 Demand and supply for safe assets

#### 3.3.1 Evidence on safety and liquidity premia in safe assets

Krishnamurthy and Vissing-Jorgensen (2012) provide historical evidence of a strong price sensitivity of safe assets to demand and supply shocks. The yield spread between corporate and Treasury bonds, controlling for default risk, is strongly negatively correlated with the ratio of privately held government debt to GDP from 1926 to 2008. Whenever the supply of public debt is low, investors are willing to pay a higher premium for Treasuries. The magnitude of the effect is large, with an average spread of 73 bp between Baa-rated corporate bonds and Treasuries explained by Treasury supply. A similar relationship exists for the yield spread of commercial paper over Treasury bills. This evidence is inconsistent with the classical portfolio theory, where asset prices are determined exclusively by the discount factor (pricing kernel), and are independent of their supply.\(^8\) It strongly suggests that the Treasury rate is determined on a segmented market, and its size is presumably linked with aggregate income and wealth. The relationship is stronger for lower rated corporate bonds (Baa vs Aaa) and commercial paper (A2/P2 vs A1/P1), suggesting that also the highest rated private debt claims offer some safety and liquidity that investors value. This insight allows to decompose the premium on Treasuries into a liquidity (at most 46 bp) and safety premium (at least 27 bp). To identify the liquidity premium, they regress public debt on the yield spread between 6 months insured certificates of deposits (CDs) and Treasury Bills, finding a negative relationship. This spread captures the liquidity premium, as both assets are equally safe but CDs are illiquid until maturity. Their measure of the short-term safety premium is the spread of lower (A2/P2) and higher (A1/P1) rated commercial paper with 3 months maturity, both illiquid claims. Finally, a measure of the long-term safety premium is the yield spread of Baa and Aaa rated corporate bonds, whose liquidity is quite similar (Chen et al., 2007). Also the safety spreads have a significant negative relation with the stock of public debt.

\(^6\) Overnight repo are private claims, but so safe and liquid that they are often added to an enlarged definition of monetary aggregates such as M3.

\(^7\) They were never very liquid even during the credit boom, as they were mostly held for their extra yield, and were at the epicenter of the 2007-2008 crisis.

\(^8\) If changes in Treasury supply reflects more fiscal expenditures and a structural change in future output, in principle the pricing kernel will change, though the effect is hard to predict.
Nagel (2014) questions whether the liquidity premium on Treasuries is determined by supply and demand effects. He argues that money (reserves, deposits) and near-money assets (Treasuries) are substitutes in providing liquidity, so liquidity premia and convenience yield must be linked. Thus it is necessary to control for the opportunity cost of holding money (such as the federal funds rate) when estimating the impact of Treasury supply on the price of liquidity. Indeed, the federal funds rate is strongly correlated with the liquidity premium, and has a better fit than the highly persistent Treasury supply. The interpretation is that the Fed effectively neutralizes liquidity shocks by adjusting the amount of reserves (money) to keep the federal funds rate on target. However, Nagel finds some transitory effects of liquidity shocks. Changes in t-bill supply affect liquidity premia in the same month even controlling for changes in interest rates, but the effect reverts during the next month. Vissing-Jorgensen (2015) reports that the effect of Treasury supply on the safety premium remains significant, just as its impact on the Aaa-Treasury yield spread, a combined measure for safety and liquidity. The part of the Baa-Treasury spread explained by low-frequency variation in Treasury supply (73 bp) thus presumably consists mainly of a safety premium.

Other research documents a segmentation between short-term and longer-term Treasuries. The yields on short-term Treasuries are affected by changes in the supply of Treasury bills (at high frequency), but not of notes and bonds. A priori it is unclear whether this segmentation reflects the superior liquidity or a lower interest rate risk of T-bills. They may also contain a convenience yield because of their close conversion into cash. Combined, these characteristics are by some authors referred to as "moneyness". Another view is that the segmentation reflects investors preferred habitat, i.e. that there are investor clienteles with a preference for specific maturities (Greenwood and Vayanos, 2010).

Duffee (1996) provides some early evidence of a segmentation at the short end of the yield curve. He finds a unique common component in Treasury bill yields not shared by Treasury notes and bonds, nor private claims of equal maturity in monthly data from 1975 to 1994. Also, when changes in yields of bills close to maturity are regressed on changes in yields of bills further from maturity to filter out time-varying common components, the residuals are correlated with the supply of short-term bills. Interestingly, his results are stronger since the 1980s.

Greenwood et al. (2015) seek to explain the spread over 1983-2009 of actual T-bill yields over fitted Treasury yields. Bill yields closer to maturity (with less than 3 months to maturity) are significantly lower than the extrapolation of a yield curve estimated using only notes and bonds with remaining maturities greater than three months. A reduction in the supply of T-bills further decreases the spread, which in contrast is unaffected by the supply of Treasuries with longer maturities.

Carlson et al. (2014) observe how the average excess one-month holding return to buying Treasury bills from 1988 to 2007 increases sharply at the short end of the

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9 As a measure of liquidity premium he uses the general collateral (GC) repo - t-bill yield spread. As GC repo is collateralized by government debt it is fully safe, but the investment is locked in until maturity.

10 They exploit time variation in short-term government financing patterns associated with seasonal tax receipts to address endogeneity concerns.
maturity spectrum. An decrease in Treasury bill supply increases the average excess return, more so for short maturities.

Greenwood and Vayanos (2014) get similar results in their sample from 1952 to 2007. They find that the returns to short-term on short-term bills decrease compared to those on longer-term Treasuries when the supply of Treasury bills increases.

Interestingly, safe asset demand can explain a puzzling behavior of monetary aggregates ("missing money") since the 1980s. Money balances (M1) rose only slightly as interest rates dramatically fell. Krishnamurthy and Vissing-Jorgensen argue that massive foreign demand for safe dollar assets reduced net supply of Treasury in this period. The effect was an increase in the convenience yield, as Treasuries are needed to back demand deposits. Households thus shifted to savings deposits, counteracting the effect of lower interest rates on demand deposits.

Summarizing, the evidence suggests a segmented and inelastic demand for Treasuries due to their safety and liquidity. While the safety premium is subject to supply and demand shocks, the liquidity premium is correlated with the federal funds rate (and thus by the convenience yield on money assets) at the business-cycle and long-run frequency. There also is evidence for a a segmented and inelastic demand for Treasury bills with less than 3 months to maturity, reflecting "moneyness".

### 3.3.2 Supply of (quasi-) safe assets

The evidence points to a private supply response by financial intermediaries of (quasi-) safe assets as a substitute to scarce government debt. Krishnamurthy and Vissing-Jorgensen (2015) find a strong negative correlation of privately held government debt/GDP with the net supply of financial short-term debt in a long time-series from 1875 to 2014. The magnitude is quite large, a one dollar increase in Treasury debt decreases financial short-term debt by 50 cent. Interestingly, intermediaries appear to expand long-term lending one for one with short-term debt issuance. Thus a scarcity of privately held government debt increases not just credit supply but also the degree of maturity mismatch. Krishnamurthy and Vissing-Jorgensen argue for a causal relationship, as shocks to government debt supply are in part driven by war financing and the business cycle. As a robustness check they rule out a standard crowding out of investment via higher rates. They also use gold inflows in the 1930s and increased foreign official holdings of Treasuries from the 1970s as exogenous supply shocks.

Short-term debt issued by the financial sector may provide a closer substitute for short-term Treasuries than long-term Treasuries due to their "moneyness". Under that premise short-term Treasury supply should have a stronger crowding out effect than long-term Treasuries. Greenwood et al. (2015) indeed find some evidence that T-bill supply is more strongly correlated with highly rated, unsecured financial commercial paper than the non-bill Treasury supply at high frequency (weekly, monthly & quarterly).

A common measure for liquidity and money demand is the spread between T-bill yields and the overnight indexed swap rate (OIS) (Sunderam, 2014).\textsuperscript{11} Sunderam shows

\textsuperscript{11} The OIS rate represents the expected average of the federal funds rate over a given term. OIS
how asset-backed commercial paper (ABCP) issuance positively responds to weekly variation in the T-bill-OIS yield spread and is crowded out by T-bill supply from 2001 to 2007.

Xie (2012) finds that even private claims whose issuance is less flexible also respond to high-frequency variation in liquidity premia. Using daily data from 1978-2011, he finds that ABS/MBS issuance positively responds to seasonal variation in liquidity premia, proxied by the GC repo - Treasury bill spread.

Krishnamurthy and Vissing-Jorgensen (2015) however do not find a stronger crowding out effect of short-term financial debt in their historical yearly sample.

There is also evidence of a gap-filling behavior by highly rated non-financial firms at the long end of the maturity spectrum. Greenwood et al. (2010) find that corporate debt maturity is negatively correlated with government debt maturity from 1963 to 2005, more strongly for firms with stronger balance sheets. Using more granular data on debt maturity, Badoer and James (2015) show that corporate gap-filling behavior is more pronounced at the long end of the maturity spectrum (20+ years) and for firms with higher credit ratings. This evidence is supported by Graham et al. (2014), who additionally find that corporate long-term debt issuance responds more strongly to changes in the supply of government debt after the 1970's when foreign holdings of Treasuries increased. There is no significant evidence however that changes long-term Treasury supply also affect highly-rated firms propensity to invest. Also, the magnitude of long-term corporate debt issuance is dwarfed by short-term debt issued by the financial sector.

Summarizing, the evidence suggests a strong crowding out effect of Treasury supply on financial sector short-term debt at low and business-cycle frequency. The effect appears to be driven by changes in the safety premium, which affects the spread financial intermediaries earn by issuing short-term debt. At high frequencies, it is short-term government debt that crowds out financial sector debt. The channel is likely via changes in the money or liquidity premium. There is also some evidence of a crowding out effect on high quality long-term debt issued by non-financials. The secular increase in foreign Treasury holdings from the 1970s on strengthens the crowding-out effect, as it amounts to a reduction in net safe debt supply.

3.4 Origins of safe asset demand

A traditional approach explains demand for (safe) money in terms of transaction costs or "money in the utility function" (Tobin (1965), Sidrauski, 1967). This view justifies a convenience yield on demandable debt because of its payment services (see Stein (2012) for a modern formulation).

Other views on why intermediaries provide short term debt involve agency costs or a liquidity rationale. Calomiris and Kahn (1990) and Diamond and Rajan (1998) view contracts carry little credit risk because initially no principal is exchanged and they are relatively liquid, thus serving as a good proxy for risk-free rates.

12There is a large literature on the role of money for transactions purposes in place of barter, which provides micro-foundations for this (Williamson and Wright (2010)).
short-term debt as a commitment device for bankers to maximize bank value. Finally, Diamond and Dybvig (1983), Gorton and Pennacchi (1990) and Dang, Gorton and Holmstrom (2010) focused on the ability of banks to create liquidity. These approaches argue that claims providing convenience or liquidity or commitment should be safer than other claims, but they do not identify absolute safety as the main benefit of short term debt.

3.4.1 Models of demand for absolute safety

The introduction of a segmented demand for absolute safety requires some discontinuity in the classic utility maximization framework. For example, infinite risk aversion arise episodically in response to shocks to beliefs. In some extreme contingencies, agents may no longer be able to assess the risk return tradeoff of assets or the allocation of losses across counterparties, a form of Knightian uncertainty (Caballero and Krishnamurthy, 2008). As a result they only consider worst-case scenarios, as if they had infinite risk aversion.

A different framing presumes that all investors have a structural demand for safety in the context of their portfolio choice. Ahnert and Perotti (2015) model directly a structural safety demand by assuming a version of the Stone-Geary utility function, which is often used in the context of development economics. Under such preferences, individuals need to attain a minimum subsistence (survival) level of wealth in all states to avoid a huge loss in utility. Thus a safe storage of value needs to be secured before agents absorb any risk in their residual portfolio. The subsistence level may be subjective and depend on wealth. A dynamic version of these preferences (habit formation) have become standard in recent asset pricing models, where a strong reluctance to adjust consumption downward appears necessary to explain the time series behavior of stock prices (Campbell and Cochrane, 1999).

Intuitively, when investors choose some assets to ensure this subsistence level, they may act very risk intolerant at the zero risk boundary. Thus behavior in (quasi) safe asset markets may be subject to sudden runs, even when new information suggests even a minimal chance of loss (Gennaioli et al. (2013), Ahnert and Perotti, 2015).

When agents face different access to safe assets, this can lead to large safety-seeking flows (Caballero and Krishnamurthy, 2009). Investors from emerging markets have a particularly strong demand for safety, as domestic assets suffer from weaker property or contractual rights (Mendoza, 2000). Under a demand for subsistence wealth, the distinction is important. Poor contractual enforcement reduces the value of local investment and asset price. However, unsafe property rights cuts deeper, as it exposes risk intolerant savers to full expropriation. This creates an acute need to find safety in developed markets, often in anonymous form. The massive role of off shore centers in transferring wealth across borders is explained by their essential role to anonymize holdings.\(^\text{13}\)

Next to individual demand for safety, there are institutional reasons for safety demand. A leading example is the reserve accumulation by central banks from emerging

\(^{13}\)Anonymity may be essential to avoid prosecution or taxation.
countries for liquidity self-insurance, especially pronounced since the Asian crisis in 1997 (Prasad, 2014). Such public institutions have a strict mandate to avoid risk, with the effect of reducing the available supply of public debt for private investors. At present public foreign institutions hold over half of the entire US Treasury bond supply. As a result, private demand for safety is crowded out and induced to turn to (quasi) safe private claims (Bernanke et al., 2011).

3.4.2 Demand for safe assets driven by liquidity needs

In recent models based on endogenous adverse selection, a demand for safe assets may also originate from a demand for liquidity (Dang et al. (2012), Farhi and Tirole, 2014). When fundamental risk is low an asset is "safe" from illiquidity because there are little incentives to acquire information about it. However, relying on common ignorance for liquidity provision in good times may create occasional sharp crises. When bad news arrives and fundamental risk passes a threshold, investors have incentives to learn about risk, so in principle all quasi safe claims may become illiquid. This forces sharp deleveraging, in order to restore an information-insensitive payoff structure (Gorton and Ordonez, 2014).

We now turn to consider the private response to a segmented demand for safety, particularly at time of scarce public supply of safe assets.

3.5 Safe asset creation and instability

To take advantage of the safety premium, intermediaries can promise safety by carving out safer claims and/or pledging safer assets. Diversification is the classic solution to reduce the risk of assets against which investors lend. In response to strong safety demand during the credit boom, intermediaries shared risks via loan securitization, and created safer ABS tranches that may be pledged or placed in special investment vehicles that may be funded by risk avoiding investors. Diversification via real estate loan securitization had the effect to redistribute credit risk across intermediaries, but as a consequence it led to a major increase in their return correlation. This reinforced systemic runs once risk materialized (Allen et al., 2012), all the more dramatic as investors had not fully appreciated the underlying exposure to systemic events (Gennaioli et al., 2012b, 2013).

The ability of intermediaries to issue safe claims requires first and foremost a reliable enforcement of property rights. Thus only intermediaries in countries with a solid political and fiscal position may become eligible as issuers of safe assets. Next, a nominal safe asset needs to be an unconditional promise, thus a debt claim. But debt safety may be further strengthened by contractual terms, such as collateralization (secured debt), maturity (time priority) and seniority (contractual priority at default). As the safety afforded by seniority is dominated by maturity and collateralization, the literature has focused on the latter two features.

Debt is the claim least sensitive to value fluctuations. The corporate finance literature has further highlighted how debt is most robust to adverse selection and moral hazard issues.
3.5.1 Safety through short-term debt

In traditional banking models, intermediaries have incentives to issue short-term debt to satisfy either money demand for transaction purposes (Perotti and Suarez (2011), Stein, 2012) or liquidity demand (Diamond and Dybvig (1983), Gorton and Pennacchi, 1990). The associated liquidity transformation enables banks to capture the convenience yield or liquidity premium, even when it creates a liquidity risk externality. From the perspective of safety, debt of shorter maturity is better because asset risk is less likely to materialize during a shorter interval. Hanson et al. (2015) argue that banks can replicate the inexpensive funding associated with deposit insurance by giving their investors an early exit option in the form of short-term claims.

However, there are more subtle reasons why short-term debt is safer. First and foremost, short-term creditors enjoy special protection, as they can demand repayment ahead of debt with contractually higher priority when default appears imminent. This idea is advanced by Brunnermeier and Oehmke (2013b) in a novel, supply-driven motivation for short term debt. In their model, short-term creditors can frequently adjust their claim to new information at the rollover date, in contrast to long-term creditors. This repricing dilutes long-term creditors, so short-term creditors are de facto senior. This can create a spiral of increasing shorter term funding, even if all agents are risk neutral.

As debt becomes more short term, its rollover risk becomes more salient. In the extreme case of demandable debt, a coordination problem may occur even when fundamentals are sound. Essentially, the sequential service format of immediate payments makes it impossible to reprice claims so as to encourage rollover, which creates extreme strategic complementarity among investors (Diamond and Dybvig, 1983). As withdrawals force costly liquidation of assets and reduces the value left for those who roll over, inefficient runs may occur even in solvent states (Rochet and Vives (2004), Goldstein and Pauzner, 2005). Bank runs may also be triggered by temporary asset liquidity risk, even when fundamental risk is arbitrarily small (Matta and Perotti, 2015).

As discussed earlier, short-term debt enhances the consequences of runs triggered by shocks to beliefs, such as in a sudden emergence of Knightian uncertainty (Caballero and Farhi, 2017), or sudden recognition of an unanticipated loss state (Gennaioli et al., 2012b, 2013).

Demandable debt turns out to be the optimal insurance contract that intermediaries may issue to meet the demands of extremely risk averse agents (Ahmert and Perotti, 2015). Besides avoiding any dilution, a demandable claim may be withdrawn by safety-seeking investors even when default risk is minimal. As these investors run more easily, also less risk averse agents may be induced to run to avoid dilution, even when the intermediary offers a significant rollover premium. The possibility of induced runs implies that ensuring absolute safety for some investors may increase aggregate instability. Yet because of its low cost, safety seeking funding will remain attractive to private intermediaries, which will accept more instability in exchange for a higher

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15Risky debt is analogous to riskless debt and a short position on a put option, so its value decreases in its maturity.
return in good states.

### 3.5.2 Safety through secured debt

The credit boom saw a massive expansion in the creation of financial collateral. Banks increased their effective leverage by securitizing loans and shifting their senior tranches off balance sheets, funded by inexpensive short term debt. Shadow banks sought to replicate the safety and liquidity of bank liabilities by relying on collateralized financial credit (repos as well as margins on derivatives). This funding source grew enormously in 2002-2007 (Gorton and Metrick, 2012), until shadow bank credit surpassed total assets held by traditional intermediaries.

Thanks to the pledge of tradeable securities, repo debt can largely eliminate credit and counterparty risk.\(^{16}\) Short term repo adjusts haircuts on a frequent basis, so it can be designed to be virtually riskless. Crucially, its absolute safety derives from its exemption from automatic stay in bankruptcy. Repo lenders can immediately take possession of collateral upon default and sell it. It is impossible to achieve such propriety by contract alone, as the exemption grants a proprietary right that holds in all contingencies against any third party. Secured debt provides the most safety to creditors, and is preferred over (uninsured) short term debt by risk avoiding investors.

A key question is whether the use of secured lending contributes to aggregate risk. Martin et al. (2014) argue that issuing only secured debt is stabilizing as it eliminates panic-based runs when payoffs are "first come, first serve" by solving the common pool problem.\(^{17}\) However, a critical issue is its indirect effect on its collateral value and on other debt.

The effect of repo repossession on pledged collateral has been studied more extensively. While intermediaries may use unencumbered assets to raise repo debt in an emergency, once a default is triggered secured lenders have strong incentives to immediately resell collateral (Perotti (2013), Duffie and Skeel, 2012).\(^{18}\) Correlated fire sales depress asset prices, inducing more runs. While runs on some intermediaries may be justified by fundamental risk, withdrawals may become self reinforcing as agents seek to avoid dilution (Goldstein and Pauzner, 2005).

More recent work considers explicitly the interaction of secured and unsecured debt. Matta and Perotti (2015) show how a strong demand for safety induces intermediaries to pledge liquid collateral to repo lenders, to capture the associated safety premium. A direct effect is to increase risk bearing for each unit of unsecured debt. Thus while repo is so safe that it never chooses to run, it makes other debt less secure and thus run-prone. While a social planner may reduce inessential runs by leaving high rollover rents to unsecured creditors, a private intermediary will tend to minimize funding costs. As a result, the private choice of repo debt results in more inefficient runs and default...

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\(^{16}\)In general, collateral reduces credit frictions caused by limited verifiability, moral hazard or asymmetric information. For a review on collateral in corporate borrowing, see Coco (2000).

\(^{17}\)They show that some market structures (trilateral repo market without "unwind") are more stable than bilateral repo transactions.

\(^{18}\)They might be unwilling or unable to hold the asset, have incentives to front-sell (Oehmke, 2014), and may need to sell to avoid any legal challenge on their priority.
risk than the social optimum.

While most of the literature focuses on repo debt, the role of derivatives in safe asset creation is still underexplored, hampered by limited data availability. Margins pledged on derivatives also enjoy the bankruptcy privileges of secured debt. Bolton and Oehmke (2014) show how this privilege may induce risk shifting at the cost of unsecured lenders, and the associated higher cost of funding contributes to more frequent default.

3.6 Policy implications

3.6.1 Macroeconomic effects of a decline in safe assets

When trust in quasi safe assets is lost, it represents a drastic decline in the stock of safe assets. There are different theories on how this can affect the macroeconomy. A common theme is that they associate an insufficient supply of safe assets with a recession. Policy then should boost the supply of safe assets. We will discuss this in the next section.

In adverse selection models where safe assets serve as information-insensitive collateral, a shortage of safe assets as collateral constrains the flow of credit to productive agents (Gorton and Ordonez (2014), Moreira and Savov, 2017).

In the incomplete markets setup of Brunnermeier and Sannikov (2016), agents hold safe assets for precautionary reasons against idiosyncratic risk. There, banks act as diversifiers. When the stock of inside money shrinks, agents must bear more idiosyncratic risk, which in their model distorts production decisions. This effect is amplified by a supply side response. When the economy weakens, intermediaries’ net capital drops substantially. This deteriorates their risk-bearing capacity as they wish to remain solvent to preserve their charter value. They decrease their leverage, which shrinks further the supply of safe assets available to investors. Moreover, the associated increase in the safety premium further deteriorates intermediaries financial position as the value of their liabilities increases.

J Caballero and Farhi (2017) argue that a sharp decline in (quasi-)safe assets can lead to a situation called the safety trap. While the market for safe assets usually clears via a reduction in the safe rate when there is a drop in supply, this is not possible at the zero lower bound. The only possible adjustment is through a deep recession that reduces demand for safe assets via a wealth effect. In contrast to the Keynesian liquidity trap, where there is a shortage of assets in general, the safety trap represents a shortage of safe assets. Therefore, policies such as forward guidance that increase the value of risky assets are futile in the safety trap.

3.6.2 Preventive policy

The literature we reviewed suggests that financial intermediaries have incentives to issue quasi-safe claims such as short-term or secured debt to take advantage of their low cost. As investors value safety and liquidity, a private supply of (quasi) safe assets (such as short-term or secured claims) is socially beneficial. It has long been appreciated that issuing short-term debt creates a risk externality, so intermediaries may issue too much of it. Short-term debt can trigger large-scale fire-sales that have real implications
as they lead to pecuniary externalities by creating quantity constraints on access to credit and thus do not just imply a wealth transfer. A distinct demand for safety produces a potentially large reinforcement of this effect. The key insight is that even a minimal drop in perceived safety will lead to self-protective actions by safety-seeking investors.

Issuing secured debt also creates a risk externality, as creditors have incentives to immediately sell the collateral once they run or default is triggered. In some repo markets during the financial crisis, debt was rolled over at higher haircuts (Gorton and Metrick, 2012). While this type of deleveraging has no direct external effects, we reviewed literature that emphasized the indirect effect it has on the propensity of unsecured creditors to run.

Macroprudential policy has the task to adjust the private choice of credit volume, as it may differ from the social optimum. Rules need to be adjusted over the credit cycle, targeting excessive creation of short-term debt.

Rules that limit borrowing (Lorenzoni, 2008) can be implemented via capital requirements. Other authors propose Pigouvian taxation of short-term liabilities, which forces intermediaries to internalize the social costs of short-term funding (Jeanne and Korinek (2010), Kocherlakota et al., 2010). While Pigouvian taxation can achieve the first best allocation when risk incentives are moderate, direct limits may become necessary when solvency incentives deteriorate (Perotti and Suarez, 2011). Stein (2012) argues for a cap-and-trade approach, where the regulator issues tradable permits for banks to issue short-term debt. In contrast to Pigouvian taxation, the regulator may remain uninformed about individual banks characteristics, since each of them optimally acquires the right amount permits in line with the quality of their loan pool. Such a policy can be implemented with countercyclical reserve requirements and interest on reserves (Kashyap and Stein, 2012).

A systemic risk tax on non-core funding has also been suggested to manage unstable foreign inflows (Shin, 2011).

Prudential policies also need to target risk creation outside of the regulatory perimeter, least new rules drive safe debt issuance into the shadow banking system. The empirical literature we reviewed documented that an expansion in (short-term) government debt crowds out the creation of financial sector short-term debt via market prices. The size and composition of government debt could thus be used as a Macroprudential tool to manage financial sector short-term debt issuance.

Clearly, the amount of government debt should be traded off against the distortions from taxation (Gorton and Ordonez (2013)). Another consideration is that its ability

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19 As a result, marginal rates of return are no longer equalized, leading to welfare losses (Lorenzoni, 2008).

20 Hahm et al. (2013) offer cross country evidence that more non-core bank liabilities (such as wholesale and foreign flows) is associated with erosion of risk premia and greater vulnerability.

21 The government has a comparative advantage to the private sector in providing safe assets due to its power to tax, thereby being able to pledge more than private agents can (J Caballero and Farhi (2017)). Government debt also serves as safe collateral. Issuing Treasuries against pools of privately produced collateral can reduce the information-sensitivity of privately produced collateral (Gorton and Ordonez (2013)).
to serve as a safe asset may be compromised when it approaches some fiscal limit (Farhi et al. (2011), Farhi and Maggiori, 2016). Such a situation could lead to a strong reversal in investor flows.

An interesting argument suggests that government should issue long term debt in good times. Long-term public debt is a rare case of a large scale asset with negative beta, i.e. it appreciates in time of distress when safe rates drop. This makes it a good hedge in a portfolio of riskier assets (J Caballero and Farhi (2017), Moreira and Savov, 2017). By itself, however, improving portfolio diversification does not produce absolute safety.

A key question is whether short-term government debt is a closer substitute for short-term financial sector debt. This implies that the Treasury could decrease its debt maturity to counter excess short-term debt creation (Greenwood et al., 2015). Then, the effect on financial stability should be traded off against the fiscal risk associated with short-term funding. Carlson et al. (2014) advocate that the central bank should maintain a large balance sheet, holding mostly less liquid or long-term safe assets and selling short-term Treasuries. A swap of short versus long term Treasury, a so-called twist operation, decreases the maturity of public debt held in private hands while absorbing some interest rate risk. At this stage it is unclear whether such a policy has an effect on risk premia (Krishnamurthy and Vissing-Jorgensen, 2011). The traditional approach employed during the recent crisis involves central bank purchase (or refinancing on favorable terms) of less liquid private assets, which has a direct effect on prices and increases the supply of safe bank reserves.

Greenwood et al. (2014) note that the Federal Reserve and the Treasury canceled each other out recently in supplying near-money assets. While the Federal Reserve lengthened the maturity of its assets (mainly due to quantitative easing), in the process providing more near-money assets, the U.S. Treasury was lengthening the maturity of it’s debt (to reduce roll-over risk), thereby pulling in the opposite direction. Since the relevant amount and composition of government debt is the amount held in private hands, the Treasury and Federal Reserve policy should be coordinated to provide more safe assets.

3.7 Conclusion

We review the recent literature on safe assets. The demand for safe assets appears historically quite stable. The financial sector endogenously creates "safe" assets to fill any "gap" left by insufficient government debt, as safety premia increase. Privately produced safe assets are mostly in the form of short-term or secured debt, issued by banks or the shadow banking system. While safe in most circumstances, they are vulnerable to inessential runs by risk avoiding investors. In addition, the contractual forms chosen to promise safety may lead to induced runs, when even risk tolerant investors run in response to the threat of dilution or increased adverse selection. In conclusion, the emerging literature highlights how demand for safety has the potential

22While interest-rate risk has welfare effects by inhibiting tax-smoothing, Greenwood et al. (2014) argue there is a net gain from shortening public debt maturity.
to explain credit cycles, maturity mismatch and ultimately aggregate risk.

This leaves a major role for public policy. When the supply of private safe assets shrunk during the crisis, central banks intervened to compensate with stable funding and abundant liquidity, while governments expanded the supply of public debt. Such intervention is certainly justified during a crisis. A deeper consideration concerns the public interest in private safe asset production outside crisis periods. If an increasing amount of safe debt simply reflects investor preferences, a policy intervention would involve a trade off between individual safety needs and aggregate stability. But as risk intolerant investors may respond to even minimal risk by protective actions, they may trigger defensive action by more risk tolerant investors. Short term debt demand may be self reinforcing, exceeding the natural level of demand. The pursuit of self protection by investors may then force intermediary funding to become increasingly short term (Brunnermeier and Oehmke, 2013b), or to require pledging of collateral. Ultimately, this process may increase instability while decreasing the volume of credit. Thus encouraging the creation of quasi safe assets may be destabilizing, if it leads to a maturity race or induces more run vulnerability even by risk tolerant agents.

Finally, a separate issue is whether those governments able to issue safe debt should seek to provide insurance on a global scale, accepting any amount of safety-seeking inflows.

Overall, many open issues remain in this new literature calling for new research on this fundamental theme.
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Samenvatting (summary in dutch)

Dit proefschrift bevat drie Essays in Financial Economics. In het eerste essay documenteer ik dat bedrijven in de jaren na hun beursgang steeds minder investeren. Een interessant bevinding is dat meer dan de helft van de daling van de investeringen geen verband houdt met hun grootte of winstgevendheid. Deze bevinding gaat in tegen de klassieke economische theorie, waarin de daling van de investeringen na een beursgang de geleidelijke groei van bedrijven naar hun efficiënte schaal weerspiegelt.

Ik bouw een dynamisch investeringsmodel met daarin verschillende verklaringen voor de daling van de investeringen conditioneel op omvang en winstgevendheid. Bedrijven groeien naar hun efficiënte schaal, leren over hun efficiënte schaal, worden meer rigide, ervaren mean-reversion in productiviteit en een daling in de volatiliteit van hun productiviteit. Vervolgens schat ik de parameters van het model met gegevens van Amerikaanse beursgenoteerde bedrijven. Door gebruik te maken van de gezamenlijke dynamiek van investeringen, winstgevendheid en marktwisseling kan ik een onderscheid maken tussen deze bronnen en hun individuele bijdrage afleiden in de afname van voorwaardelijke investeringen. Ik concludeer op basis van deze analyse dat (i) de unieke combinatie van groeien in de richting van de efficiënte schaal en toenemende rigiditeit, het (ii) leren over de efficiënte schaal, en (iii) afnemen van de volatiliteit van productiviteit allemaal ongeveer een derde van de daling in voorwaardelijke investeringen verklaren. Ik herzie ook de interpretaties van verschillende verschijnselen, zoals waarom de markt-boekwaardeverhouding van bedrijven daalt, waarom hun winstgevendheid daalt en waarom bedrijven minder reageren op de fundamentals in de jaren daarna nadat ze openbaar zijn geworden.

Het tweede essay is geïnspireerd op het verrassingselement van de recente financiële crisis in 2008. De risico’s van door activa gedekte waardepapieren en de onderliggende hypotheken kwamen plotseling aan het licht toen de huizenprijzen in de VS landelijk daalden en foreclosures snel toenamen. Een gangbare opvatting is dat deze financiële producten optimaal ondoorzichtig zijn ontworpen om de hoeveelheid informatie over de onderliggende activa te beperken voor de handelende partijen. Dit vergemakkelijkt namelijk de handel omdat er weinig angst is om uitgebroken te worden als de andere partij meer weet.

Ik laat theoretisch zien dat de verstrekkers van de door activa gedekte waardepapieren in de verleiding kunnen komen om te veel informatie te verdoezelen. In mijn model heeft ondoorzichtigheid ook een schaduwkant: als handelspartijen geen informatie verwerven, zijn de koersen van de financiële producten ook minder informatief. Dit kan leiden tot booms gevoed door de onwetendheid wat betreft de ware aard van de activa. De overdreven ondoorzichtigheid resulteert in een free-riding probleem dat zich voordoet wanneer de activa van verschillende financiële producten aan vergelijk-
bare risico's worden blootgesteld, bijvoorbeeld hoe gevoelig ze zijn voor huizenprijzen. Aan de ene kant zouden ze allemaal baat hebben bij buitenstaanders die informatie produceren. Maar individueel profiteren ze van het verdoezelen van informatie om hun eigen financiële producten gemakkelijk verhandelbaar te maken, wat hun financiering goedkoper maakt. Het model suggereert regelgeving die de informatieverstrekking stimuleren, waardoor overinvesteringen kan worden ingeperkt.

In het derde essay (samen met Enrico Perotti) onderzoeken we de opkomende literatuur over veilige activa. Centraal in dit essay staat dat de fundamentele vraag van beleggers naar veiligheid anders is dan de vraag naar liquide activa die gemakkelijk verhandelbaar zijn. We constateren dat er aanzienlijke bewijs is voor een sterke en stabiele vraag naar veilige activa. Perioden van lage voorziening van overheidschuld, de veiligste activa, hebben de neiging de financiële sector ertoe aan te zetten (quasi-)veilige activa te produceren in de vorm van kortlopende schulden om aan de vraag te voldoen. Dit lijkt gepaard te gaan met een kredietuitbreiding en een toename van de netto-langetermijninvesteringen. We bespreken de recente theoretische contributies in de literatuur, waarin wordt benadrukt hoe de druk om aan de vraag naar veilige activa te voldoen leidt tot contractvormen die uiteindelijk risico's creëren en uitdragen. Dit had grote gevolgen tijdens de financiële crisis van 2008, waarin onverzekerde bankschulden helemaal niet zo veilig bleken te zijn als gedacht. Risico-intolerante beleggers vluchten naar overheidschuld en lieten het financiële systeem achter zonder financiering mogelijkheden. We sluiten het literatuuronderzoek af met de inzichten wat betreft financiële stabiliteit en mogelijke regelgeving die uit de literatuur naar voren komen. Van bijzonder belang hierin is de rol van overheidschuld als een mogelijk instrument om financiële stabiliteit te creëren.
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