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Thesis title:

Essays on the Economics of Corporations

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Abstract

The first chapter investigates the link between operating leverage and the decline in business dynamism. Operating leverage is the share of fixed over total operating costs. I document its increase among U.S. listed firms over the last forty years and show that, behind this pattern, lies the entry of innovation-intensive firms that have larger R&D expenditures, more patents, and more volatile sales. I estimate operating leverage with the error correction model, which builds over the standard methodology of costs elasticity with respect to sales. I then argue that larger fixed costs are consistent with the recent decline in business dynamism from the perspective of a standard heterogeneous firms model: a lower number of firms that enter and survive upon entry. This prediction is indeed consistent with long-term industry patterns. If innovation brings upon larger fixed costs, by its nature, then it also comes naturally a lower level of business dynamism.

The second chapter investigates the corporate saving glut. Since the 2000s, the non-financial corporate sector moved from net borrower to net lender in many advanced economies – what has been labelled the corporate saving glut. Using firm-level data on U.S. listed firms, I document that the firms behind this widespread pattern are the largest corporations. Unless evidence suggests otherwise, I argue that the glut is only the consequence of the corporate sector having reached its steady state, in which the profit share is naturally larger than the investment share, while dividends not adjusting completely because of their stickiness. Indeed, I find no explanation able to empirically account for this pervasive phenomenon: neither increasing deleveraging, nor increased uncertainty (measured as both realized volatility and analysts' earnings expectations), nor increased market power (measured as both industry concentration indexes and effective tax rates) are meaningfully correlated with the emergence of the glut.

The third chapter investigates the link between cash holdings and operating leverage. Since the 1970s, average cash holdings of U.S. publicly listed firms more than doubled. This article assesses whether this phenomenon may be due to the increase in average operating leverage, which captures the rigidity of the firm's cost structure. First, I show how operating leverage exerts a positive influence on optimal cash holdings, with a simple trade-off model of precautionary savings. Then, I document such relationship in the data, concluding that operating leverage is at least as important as other known factors, such as capital, R&D expenditures or sales volatility, as a driver of the secular increase in cash holdings.

Contents

Chapter 1

Operating leverage and the decline in business dynamism

1.1 Introduction

Over the last forty years, the average share of fixed operating costs of U.S. listed firms has doubled, from less than 10% percent to almost 20% percent. This pattern is mostly due to a compositional change: old firms have been replaced by newer firms with larger fixed costs and a focus on innovation-related activities. At first glance, this change is a welcoming phenomenon. Nevertheless, recent evidence points to a deterioration in this process: lower rates of entry, both for startups and new listings, and also lower rates of growth, as high-growth firms contribute less to employment creation. In other words, there is a slow-down in the process of creative destruction, which allows the most productive firms to replace the less productive ones. What are the causes of this decline?

I argue that this recent decline in business dynamism is consistent with the preceding entry of innovative firms: they have changed the competitive environment by increasing the level of fixed costs, in turn reducing the chances for new firms to profitably enter the same market. Indeed, now only the most productive firms are able to cover the fixed costs, while the less productive ones are unprofitable and so will exit. In addition, young firms might also fail more easily during their growth phase, even if productive enough in the long run. Indeed, in the presence of financing constraints and since revenues only build up slowly over time, larger initial losses (due to larger fixed costs) can induce exit or failure. That is, we might not get as many Tesla[1] as we should. Therefore, the entry of innovative firms can, in fact, have decreased innovativeness itself: a lower level of business dynamism, in which increasing fixed costs act as a barrier to entry, as new entrants must be increasingly productive to survive.

The contribution of this article is twofold. First, I document the increase in average operating leverage and I relate it to the entry of innovation-intensive firms with larger R&D expenditures, more patents, and more volatile sales. This is done in section 1.2, which also describes the estimation methodology for operating leverage: differently from the current approach, which is based on estimating the simple cost elasticity of sales from

[1] I take Tesla as an example of a high-growth firm, which is (assumed to be) productive in the long run and faces large fixed cost (e.g. R&D), making it unprofitable during its growth phase as revenues are still building up.

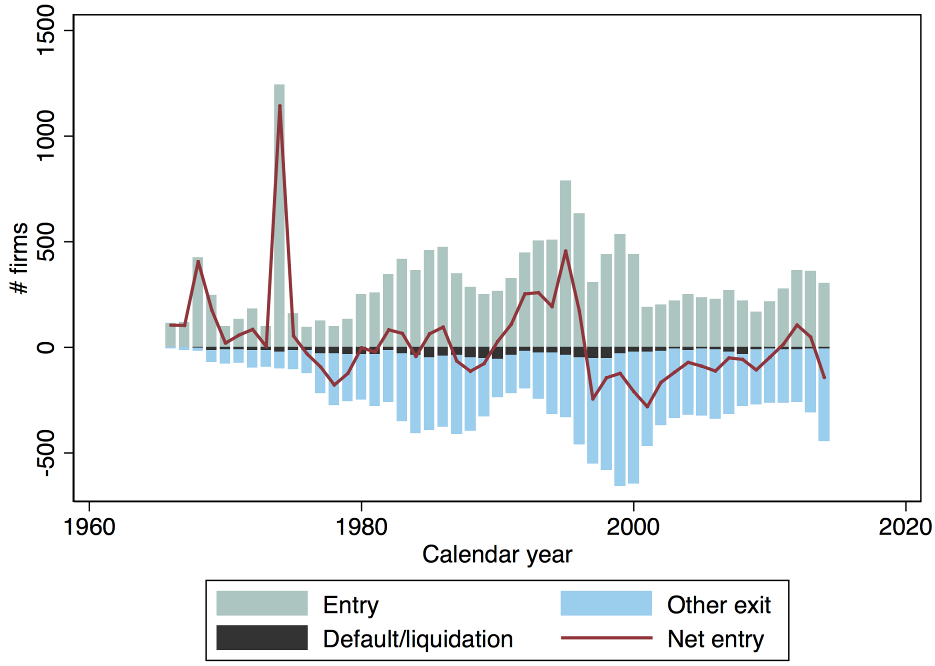
a time-series regression at the firm-level, I adopt the error correction model. Second, I argue that this secular increase can help to explain the decrease in business dynamism. Through the lenses of a standard industry model based on the classic framework of Melitz (2003), larger fixed costs are consistent with lower entry rates and higher exit rates (from a static perspective) and lower survival rates (from a dynamic one). I provide supportive evidence in section 1.3. Finally, in subsection 1.3.4, I discuss the relationship between the contemporaneous increases in operating leverage and market power, arguing that they are different phenomena. But to begin with, I now briefly offer further details on the two actors of this story: business dynamism and operating leverage.

Declining business dynamism. Business dynamism refers to the process of creation, destruction, expansion, and contraction of firms. Aggregate productivity growth depends to a great extent on allocative efficiency: a dynamic economy allows the most productive firms to displace less productive incumbents. However, recent evidence points to a decline in business dynamism, which can constrain productivity growth even in the midst of rapid technological progress; see Decker et al. (2016a, 2017b). Regarding creation and destruction, not only the start-up rate (i.e. the number of start-ups relative to the number of firms) has been declining over the last decades, but also the likelihood of start-ups of a given quality level to realize their potential declined sharply from the late 1990s, even though financing of new companies has massively increased; see Guzman and Stern (2016). Regarding expansion and contraction, the number of high-growth firms, which historically contributed to a large part of net job creation, is declining as well: the skewness of the growth distribution is shrinking, due to a fall in the right tail, especially after 2000; see Decker et al. (2016b). This is true not only across the U.S. economy as a whole, but also in high-tech sectors and among public companies, which in fact showed increasing dynamism until 2000; see Haltiwanger et al. (2014).

Figures 1.1 and 1.2 report these stylized facts for a sample of U.S. listed firms: the decline in entry rates and the decline in high-growth firms. Following a peak in net entry in the late '90s, all the following years witnessed a net outflow of firms, except for 2012. Exit occurs mainly because of mergers and acquisitions, while failures (either because of bankruptcy or of liquidation) are relatively few, due to the nature of this selected sample of listed firms. Such decreasing number of listed firms has been noticed by Doidge et al. (2015) and named the "U.S. listing gap." Similarly, high-growth firms are disappearing: the skewness of the distribution of firm employment growth rates is declining, following a peak just before 2000. Growth rates are defined to take into account entry and exit (according to eq. (1.8)) and the distribution of growth rates is weighted by employment, to capture patterns that are relevant for aggregate behavior, while time series are HP-detrended (with a parameter set to 100). The decline is particularly evident for the P90-50 differential, both for all firms and for high-tech firms only; the median growth rate (not reported) cyclically moves around 0% with no trend over time.

While the after-mentioned evidence on business dynamism is broader, these figures only capture a selected sample of the U.S. economy: the group of listed firms. However, the decline is evident also among this group and, since it is possible to estimate operating leverage only for this group of listed firms, such focus is a necessity. The only caveat to bear in mind is that there could be confounding dynamics that we cannot really control for, due to varying costs/benefits of being a listed firm; see e.g. Fama and French (2004)

Figure 1.1: Entry and exit of U.S. listed firms: 1975-2015.

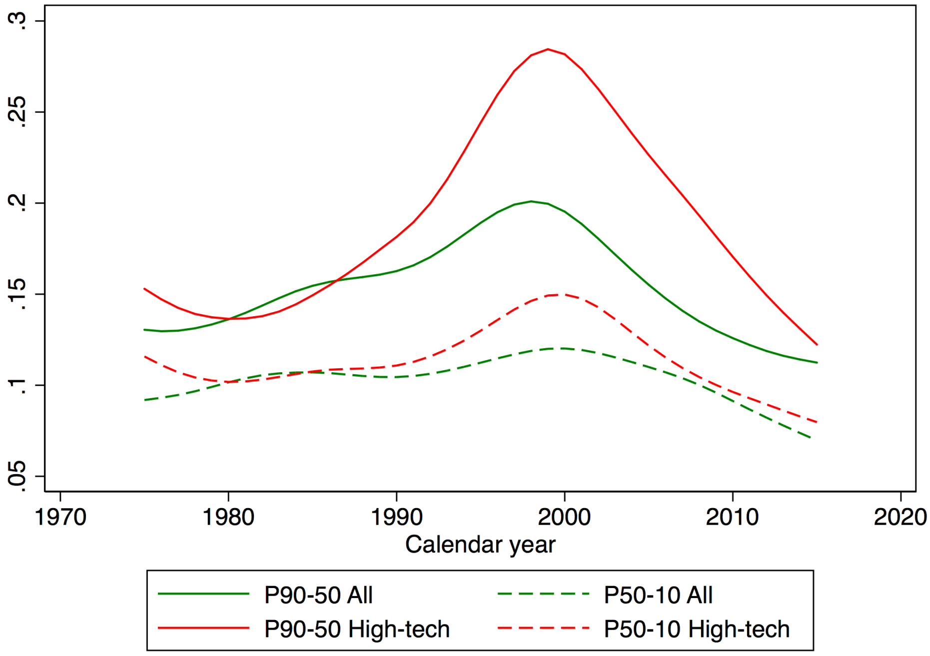


for a discussion about listing/delisting dynamics. Moreover, entry in the stock exchange usually does not concern very small business start-ups, but more young firms that have already a well-defined structure: hence, entry in this sample should be interpreted as a middle step in the growth process: a young firm that is moving to be a mature player in the industry.

Increasing operating leverage. I argue that one of the causes of the detected decline in business dynamism lies in the changing costs structure of firms: the share of production costs that are fixed in the short term (i.e. at a yearly horizon) is increasingly large. Indeed, there has been a steady increase in operating leverage among U.S. listed firm: the cross-sectional average is now twice than in the '70s, at about 18%; see figure 1.3. Such increase has been driven mostly by the entry of new firms: in particular those that spend more on R&D, hold relatively more patents, and have more volatile sales. Indeed, operating leverage appears to be a slow-moving firm characteristic with relatively small variation within firm. Empirically, I estimate operating leverage as the elasticity of operating costs with respect to sales, under the assumption that costs are fully flexible in the long run. This is equivalent to assume that sales and costs are cointegrated, which is the novel assumption that I introduce with respect to the literature.

What are the implications of larger fixed costs? I discuss this question in a standard heterogeneous-firms model à la Melitz (2003). First of all, fewer firms manage to successfully enter and produce, since only the most productive are able to cover the fixed cost of production, while the others immediately exit. In addition, firms with larger fixed costs are also more likely to fail during the growth phase: they might not be able to sustain the larger initial losses, as revenues build up only slowly over time due to demand frictions, if they have to rely mainly on internally generated funds. This might happen even though

Figure 1.2: (HP-filtered) Skewness of the firm employment growth rates distribution (employment-weighted): 1975-2015.



the firm would be profitable over the long run. Given that these kind of firms are the most innovative, a higher failure rate is consistent with a diminishing number of high-growth firms. Empirically, firms with larger fixed costs are indeed more likely to exit, *ceteris paribus*. Figure 1.4 shows how the marginal probability of default (bankruptcy or liquidation) increases in operating leverage; the logit regression behind the figure is detailed in section 1.3.3. That is, not all of the high-growth firms might survive the young and unprofitable age.

This idea is also consistent with the evidence in Decker et al. (2017a): there has been a decline in business responsiveness to productivity shocks (in terms of employment growth), rather than a change in the productivity shocks distribution. While they suggest that increasing adjustment frictions might be behind this pattern, also larger fixed costs are consistent with this decline in responsiveness: when costs – and inputs – are fixed, any productivity shock (which is measured as a residual: sales that are not accounted by inputs) will not generate any change in inputs, at least in the short-run.

To conclude, I would like to briefly highlight what could be some more general issues for which operating leverage is important. First of all, it is relevant for corporate financial policies, as much as financial leverage is; e.g. the cash holdings decision. Second, fixed costs of production are a common parameter in many economic models, in the trade literature in particular, so that having a more direct empirical proxy is certainly important. Third, the secular increase in operating leverage can also be related to the increasing robotization and automation of the economy and to the capital vs. labor share debate, even though it is yet unclear how to relate fixed/variable costs to labor/capital inputs. Finally, fixed costs can also be related to price and wage setting dynamics, as fixed costs might be subject to different pricing dynamics than variable costs, plausibly leading to

Figure 1.3: Cross-sectional average/median/P25/P75 operating leverage: 1960-2015.

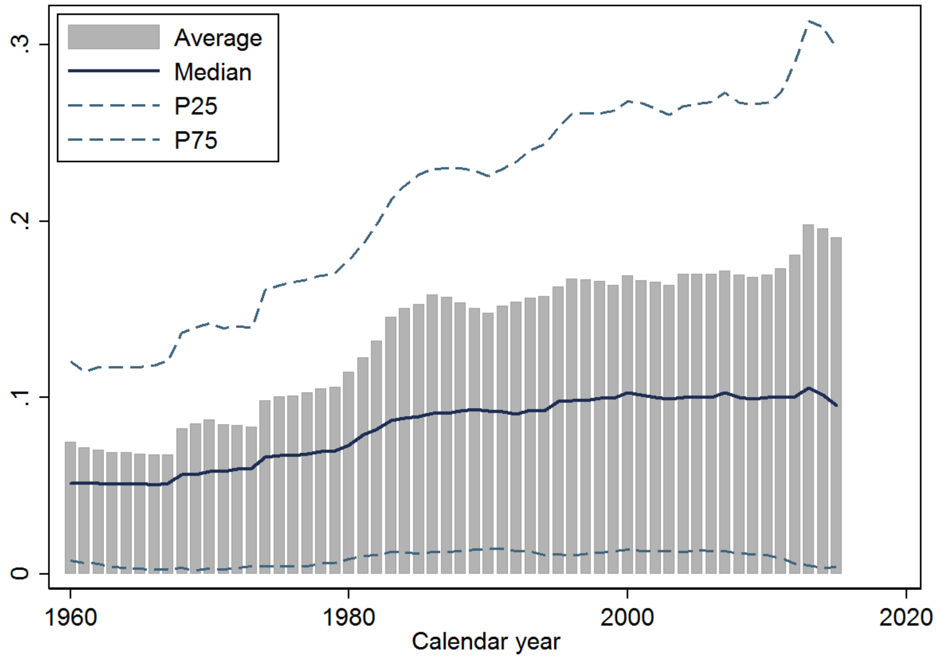
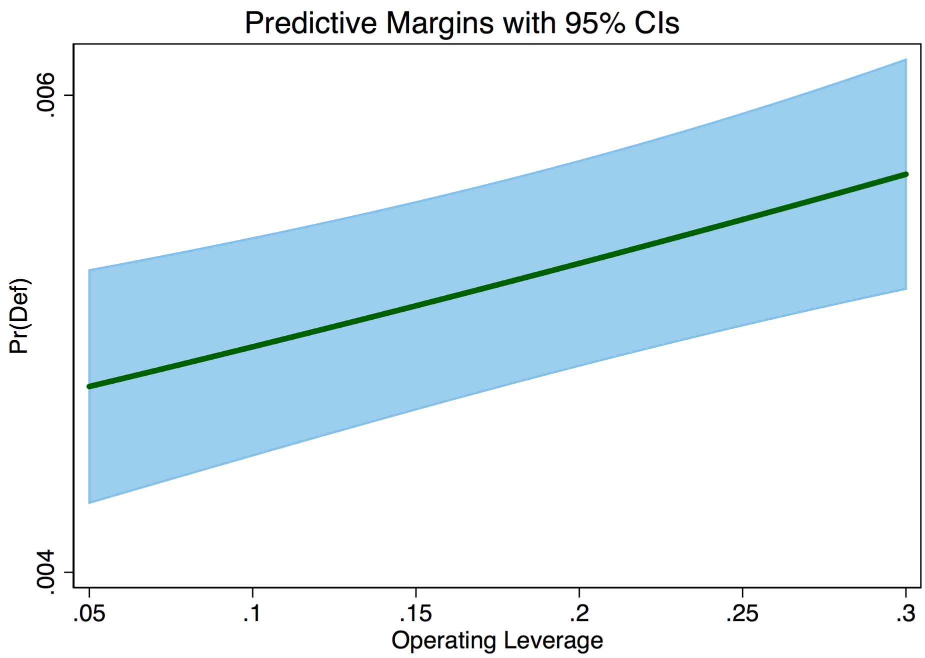


Figure 1.4: Probability of default against operating leverage; from a logit regression with industry and time fixed effects and firm-level control variables.



greater price stickiness.

1.2 Operating leverage: the last forty years

1.2.1 Data and sample

All data come from Compustat, which collects balance sheets data on publicly listed firms in U.S. stock markets. I focus on the 1960-2015 period and select the sample as follows.

First, I exclude financial firms (SIC 6000-6799) and regulated utilities (SIC 4900-4999). Second, I exclude observations that have unreported or negative values of sales, unreported values or less than $50 thousands of total assets, negative values of capital expenditures and of common/ordinary equity, and observations whose growth rate of sales exceeds 500%. Third, I exclude firms with gaps in their reported values of sales and of operating expenditures. Appendix B.1 details the definition of control variables used in this article. In general, any variable is either in real terms, i.e. adjusted for inflation using the CPI index from BLS with 1982-84 U.S. dollars, or divided by total assets. I winsorize all ratios or estimates at one and ninety-nine percentiles. The remaining sample includes 17102 firms, for a total of 184504 observations, with an average (median) number of 11.25 (8) observations per firm.

1.2.2 Related literature

Recently, the literature on operating leverage focused on asset pricing and the value premium, i.e. the greater risk-adjusted return of value stocks over growth stocks. Indeed, as production costs play much the same role as debt servicing in levering the exposure of a firms' assets to underlying economic risks, value stocks should then earn higher returns since they have higher operating leverage, i.e. systematic risk; see Carlson et al. (2004), Cooper (2006), Aguerrevere (2009), or Novy-Marx (2010). Also researchers in accounting focused on the area of cost behavior: Anderson et al. (2003), for instance, introduce the idea of cost stickiness, which is the degree of asymmetry in the reaction of costs to increases/decreases in sales, while Dichev and Tang (2008) and Donelson et al. (2011) analyze the decreasing correlation between revenues and expenses, which seems to be due by an increasing number of expenses recorded as special items. However, to the best of my knowledge, there are no articles that document the increasing degree of operating leverage in the last decades.

Lev (1974) was among the firsts to theoretically formalize the link between operating leverage and risk at the firm-level. Empirically, operating leverage has been firstly estimated as the elasticity of earnings with respect to sales, a method pioneered by Mandelker and Rhee (1984). With a linear cost function $C = f + v \cdot S$ and operating earnings $E = S - C$, the degree of operating leverage (known as DOL) is:

$$
\begin{aligned}
DOL &= \frac{\partial E}{\partial S} \cdot \frac{S}{E} \\
&= \frac{(1-v)\,S}{E} = 1 + \frac{f}{E}.
\end{aligned} \tag{1.1}
$$

However, such definition is empirically problematic: when earnings are positive DOL is greater than one, but when they are negative DOL is lower than one, but only after reaching extremely high values as $E \to 0$. Moreover, since elasticities are usually estimated in logarithms, one has either to disregard observations with negative earnings or has to deal with them is some way; e.g. García-Feijóo and Jorgensen (2010) apply an accounting transformation that allows them to keep them.

Alternatively, we can define operating leverage as (one minus) the elasticity of operating costs with respect to sales to avoid all these issues. Such definition has much better properties, since fixed costs can only be a ratio of total costs, bounded between zero and one. Indeed, it is the definition that I use, rather than DOL, and it is silently becoming common practice in the literature; which is well-reviewed in García-Feijóo and Jorgensen (2010).

Another important issue that has been extensively discussed in the literature is that sales, costs, and earnings are potentially non-stationary series. O'Brien and Vanderheiden (1987) were the first to notice and addressed it using a linear time-trend to make costs and sales time-series stationary. Other detrending methods have also been applied; e.g. Kahl et al. (2013) use compounded annual growth rates. In practice, if data are non stationary, the general solution boils down to using first differences,

$$\frac{\mathrm{d}\log(\Delta C)}{\mathrm{d}\log(\Delta S)}.$$

However, estimating the elasticity of first differences would not be appropriate if, in fact, sales and costs are cointegrated. Indeed, the lack of the error correction term would introduce a bias in the estimate. On the other hand, the error correction model is much more robust: not only it allows for both non-stationary and stationary series, but also takes care of serial correlation in the residuals, which is a concern even under the assumption of cointegration[2].

1.2.3 Empirical estimation

For any firm i, define operating leverage as

$$\omega_i = 1 - \beta_{i,0}, \tag{1.2}$$

where $\beta_{i,0}$ is the operating costs elasticity with respect to net sales. Unfortunately, it is not possible to distinguish between variations in prices and quantities; this imposes to focus on a broader definition of operating leverage, in which fixed costs are characterized by any variation in sales that is not matched by a corresponding variation in costs, not only variations in quantities. Assuming a linear cost function such as $C_i = f_i + v_i \cdot S_i$, we

[2]Notice that, under the hypothesis of cointegration, a simple OLS static regression would deliver super consistent estimates, i.e. converging faster to their true values. However, although consistent, these estimates can be substantially biased in small samples, due to serial correlation in the residuals. This is indeed a concern, as residuals appear to be very much correlated in the sample: the average correlation is .42 and testing for serial correlation (using command *xtserial*, from) strongly rejects the null of no serial.

have that definition (1.2) corresponds[3] indeed to the share of fixed over total costs:

$$\omega_i = 1 - \frac{\partial C_i}{\partial S_i} \cdot \frac{S_i}{C_i} =$$
$$= 1 - v_i \cdot \frac{S_i}{f_i + v_i \cdot S_i} = \frac{f_i}{f_i + v_i \cdot S_i}.$$

Now introduce a time index, denote the logarithm of variables with smaller case letters, e.g. $s_{i,t} = \log S_{i,t}$, and the log difference with the delta operator, e.g. $\Delta s_{i,t} = s_{i,t} - s_{i,t-1}$. Operating costs ($C_{i,t}$) are item *xopr* in Compustat, while net sales ($S_{i,t}$) are item *sales*. Their difference is *ebitda* (i.e. earnings before interest, taxes, depreciation and amortization). To estimate operating costs elasticity, I use the error correction model (ECM) with the following specification:

$$\Delta c_{i,t} = \alpha_{i,0} + \beta_{i,0}\Delta s_{i,t} + \gamma_i \left(s_{i,t-1} - c_{i,t-1}\right) + \nu_{i,t} \tag{1.3}$$

where the estimate of operating leverage is $1 - \hat{\beta_{i,0}}$, that is, one minus the coefficient on the log change in sales. The gap between log sales and costs $(s_{i,t-1} - c_{i,t-1})$ is the error correction term; it also approximates the operating markup, defined as operating earnings[4] over costs, i.e. $\mu_{i,t} = \left(S_{i,t} - C_{i,t}\right)/C_{i,t}$. This specification allows deviations from the long-run equilibrium to influence short-run dynamics, where the coefficient γ captures the speed of adjustment (or correction). Regression equation (1.3) is run independently for each firm, over all the available observations. Notice that, similarly, costs elasticity $\beta_{i,0}$ corresponds to the share of variable costs.

In fact, it is also possible to run a rolling estimate, over a period of, say, five or ten years. However, allowing operating leverage to change over time for the same firm does not seem to change much the general picture, as well as focusing only on firms with no fewer than five or ten years of data; see figures 1.6 and 1.7 and the related discussion in section 1.2.4. Moreover, estimating operating leverage at the industry-level, rather than at the firm-level, thus avoiding the small-sample problem at the cost of assuming it equal for all firms in each industry, does not qualitatively matter for the general patterns; see Appendix A.2.

Table 1.1 reports the summary statistics of the estimates. The average firm has about 14% percent of fixed costs over total operating cost, while the middle half of the distribution is in between 1% and 22%. Figure 1.5 shows the empirical distribution of operating leverage, which is skewed to the right. The error correction coefficient is .44, which dictates that about half of any gap that arises in any period will disappear in the following period. Finally, the average operating markup is 10%, while its interquartile range is 4-19%.

[3]We can also relate this measures to DOL through the following equivalence:

$$\omega = (DOL - 1) \cdot {}^{\bar{E}}/_{\bar{C}},$$

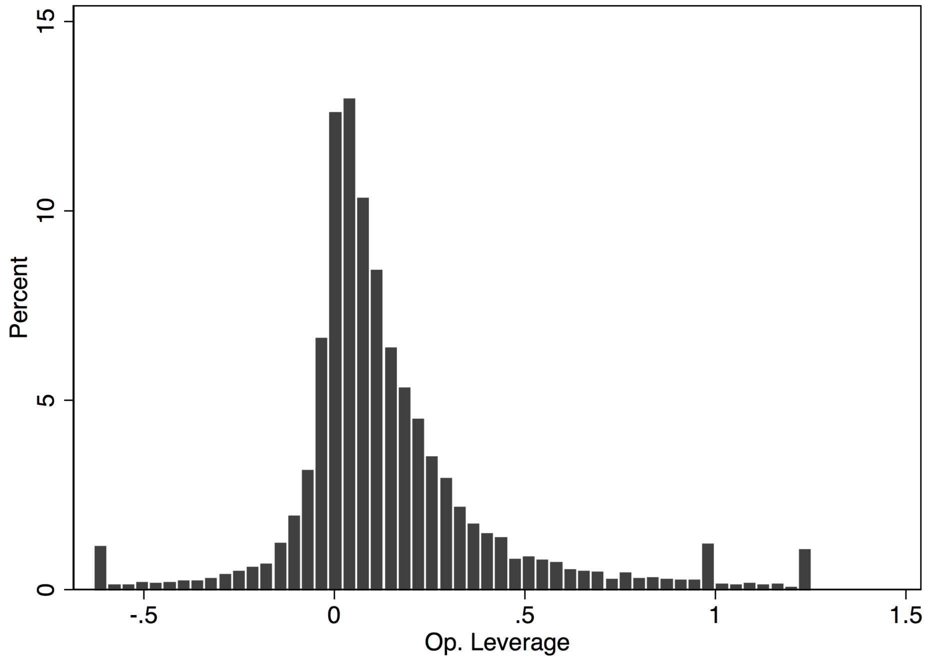
where ω and DOL are elasticities estimated over the relevant time-period, while values for $\bar{E}$ and $\bar{C}$ are averages over the same horizon.

[4]I refer to operating earnings as item *ebitda*: earnings before interest, taxes, depreciation and amortization, i.e. the difference between sales and operating costs.

Table 1.1: Summary statistics (ECM).

Variable	Obs	Mean	Std. Dev.	P10	P25	P50	P75	P90
Operating Leverage	175468	.14	.26	-.06	.01	.08	.21	.42
Error correction	175468	.44	.41	.04	.18	.37	.62	.94
Markup	180102	.1	.33	-.05	.05	.11	.19	.34

Figure 1.5: Empirical distribution of estimated operating leverage.



Advantages of the Error Correction Model. Sales follow a random and dynamic process, which is peculiar to each firm. In principle, sales can be either a stationary or non-stationary process. In the sample I am using, estimating a simple AR(1) model for each firm's sales series yields a median autoregressive coefficient of 0.85, with lower and upper quartiles of 0.94 and 0.67. Values in the upper decile are all near or above the unit. That is, sales are often either a strongly autoregressive or a permanent memory process; ex ante, they can be said a nearly integrated process. Furthermore, we cannot reject the null hypothesis of a unit root process in the time-series of aggregate sales: a Dickey-Fuller test delivers a t-stat of -0.185, very far from the 10% critical value of -2.598 to reject the null. Using the average, i.e. the aggregate divided by the number of firms in the sample, delivers the same picture.

Therefore, the error correction model (ECM) is better suited than standard time-series techniques for short-memory processes, which might deliver biased or inconsistent estimates. Even though the ECM has historically been developed for cointegrated series, we can safely use it also when data are, in fact, stationary; see De Boef and Keele (2008) for a very clear discussion on the issue. In fact, the only concern regards the estimation of long-run relationships, which is not precise and efficient when the processes are not integrated and/or their errors are correlated – but that does not really matter since we are focusing on a short-run elasticity; see again De Boef (2001).

The generalized version of error correction model is equivalent to an autoregressive distributed lag (ADL) model. Consider the following ADL(1,1;1) dynamic specification[5] case of sales and costs, with just one lag:

$$c_{i,t} = \alpha_{i,0} + \alpha_{i,1} c_{i,t-1} + \beta_{i,0} s_{i,t} + \beta_{i,1} s_{i,t-1} + u_{i,t}. \tag{1.4}$$

Then, to obtain the ECM specification in (1.3), impose the restriction that sales and costs have a long-run equilibrium relationship,

$$c_i = k_i + s_i, \tag{1.5}$$

where e^{k_i} is the share of sales that covers operating costs, $C_{i,t}/S_{i,t}$; this is also equal to one minus the gross operating margin, which is earnings over sales. That is, assume that sales and costs are cointegrated of order one. In the long run, when sales and costs are at their equilibrium values, $s_{i,t} = s_i$ and $c_{i,t} = c_i$, and there are no shocks, equation (1.4) becomes:

$$c_i = \frac{\alpha_{i,0}}{1-\alpha_{i,1}} + \frac{\beta_{i,0} + \beta_{i,1}}{1-\alpha_{i,1}} s_i.$$

The restriction in equation (1.5) imposes that $\frac{\beta_{i,0}+\beta_{i,1}}{1-\alpha_{i,1}} = 1$. This is equivalent to assume that the long-run costs elasticity is equal to one, i.e. all costs are flexible in the long run[6], which seems a very innocuous and plausible assumption. Hence, we can define

[5] The equivalent general ECM specification is: $\Delta c_{i,t} = \alpha_{i,0} + (\alpha_{i,1} - 1) c_{i,t-1} + \beta_{i,0} \Delta s_{i,t} + (\beta_{i,0} + \beta_{i,1}) s_{i,t-1} + u_{i,t}$.

[6] Similarly, notice that the estimated costs elasticity β_0 also approximates the ratio of the marginal cost over the average cost, $\beta \cong \frac{\partial C}{\partial Q} \cdot \frac{Q}{C} = MC/AC$, if we let sales ($S$) approximate quantity ($Q$). This ratio should be one in the long run under perfect competition, since firms should produce at their minimum average cost, which realizes when the marginal cost is equal to the average cost.

$\gamma_i = 1 - \alpha_{i,1} = \beta_{i,0} + \beta_{i,1}$ and rewrite equation (1.4) as equation (1.3).

The cost of moving from equation (1.4) to equation (1.3) is the restriction in equation (1.5), which is appealing because of its theoretical basis; the benefit is that we can avoid to estimate one coefficient, which is convenient with small samples. Indeed, the average number of observations per firm is about 11 years and the lower quartile is just 3 years. The accuracy of the estimation is of course a concern, which I address in the following subsection. The validity of such restriction can also be assessed empirically. Using equation (1.4), the estimated long-run cost elasticity has a median value of 0.006 and interquartile range of $-.052$ and .092. Clearly, this estimate is not exactly zero and there are also values far from it (e.g. the fifth and ninety-fifth percentiles are $-.418$ and .771 respectively), but, on average, it does seem sufficiently close.

1.2.4 The secular increase

Figure 1.3 shows the evolution of operating leverage from 1960 to 2015. The cross-sectional mean and median both increased over time, with the former showing a larger increase, consistent with an increase in the skewness of the distribution. There has also been an increase in the 75th percentile, while the share of firms with negligible fixed costs has remained broadly stable.

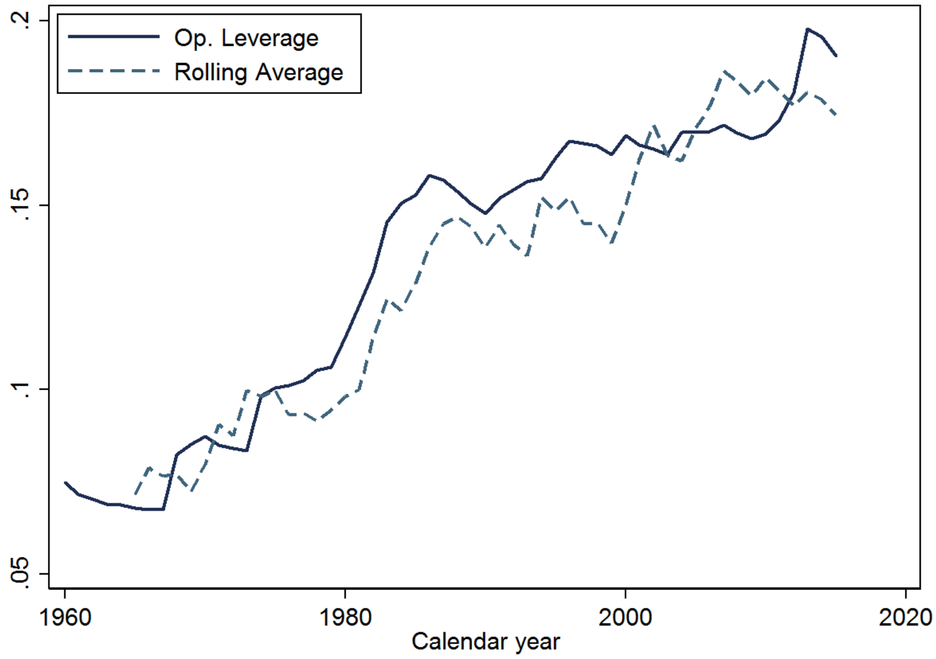
Figure 1.6 compares instead the cross-sectional average of the time-invariant estimate with the 6-years rolling estimate of operating leverage. The two measures track each other closely. Indeed, the secular increase seems mainly due to new entrants, rather than existing firms that change over time. To investigate further this assumption, I compute the average change in the rolling estimate for each firm: compared to the long-run variation of about $10-15\%$, the cross-sectional average change is about $2-3\%$, as shown in table 1.2, which also report the average change in the trend component only, using both an HP filter and the methodology proposed in Hamilton (2017): the trend as the predicted value from four lags. Henceforth, I simply assume that within-firm variation is small enough to be assumed away; this also allows to have a more precise estimate for older firms.

Table 1.2: Rolling operating leverage: within-firm variation.

Variable	Obs	Mean	Std. Dev.	P50
Avg. total change by firm	155478	.037	.748	.013
Avg. total change by firm (HP trend)	149902	.036	.603	.018
Avg. total change by firm (Hamilton trend)	132930	.026	.801	.005

The increase is not driven by firms with just few years of data, whose estimates might be imprecise: figure 1.7 reports the cross-sectional averages computed only over firms with at least 5, 10, or 15 years of data. They all show the same increasing pattern; bear also in mind that, by construction, these averages do not use any new value within 5/10/15 years of the end of the sample. Figure 1.8 shows instead the average level of operating leverage for different cohorts. Each cohort covers a five-years period. For instance, the line "1970s" tracks all the firms listed from 1970 to 1974 included, thus showing their

Figure 1.6: Cross-sectional average: rolling vs. time-invariant estimate.



Note: the rolling average is the cross-sectional average of the rolling estimate of operating leverage, which is based on a rolling window of six-years.

average operating leverage over time; this average can change after 1974 only because of firms exiting from the cohort. There are two striking patterns. First, almost any newer cohort has a higher level of operating leverage – with the exception of the 1980s cohort, which was "ahead of time" at least in its first half-decade. Second, surviving firms have a relatively lower level of operating leverage, with most of the high-leverage firms exiting from the sample after about five years. The big outlier, in fact, seems to be the 2010s cohort (which include also values for 2015, for simplicity): average operating leverage is much higher than previous cohorts and it is increasing rather than decreasing. However, this is a particularly turbulent period, following the slow down of new listings after the Great Recession of 2008/09.

How much of the increase is due to changing firms within any given industry or changing composition of industries? To answer this question, I use the following between/within decomposition:

$$\Delta\omega_t = \underbrace{\frac{1}{2}\sum_j \left(n_{j,t} + n_{j,t-1}\right)\Delta\omega_{j,t}}_{\text{within-industry}} + \underbrace{\frac{1}{2}\sum_j \left(\omega_{j,t} + \omega_{j,t-1}\right)\Delta n_{j,t}}_{\text{between-industry}} \tag{1.6}$$

where $n_{j,t}$ is the share of firms in industry j over the total number of firms, while $\omega_{j,t}$ is the average level of operating leverage in industry j. Notice that I am not weighting by sales but simply by the number of firms: not only for simplicity but also to reflect how the average is actually computed. The within-industry component captures the change due to a variation in operating leverage, keeping industries sizes (in terms of firms) constant, while the between-industry component captures the change due to a variation in industry

Figure 1.7: Cross-sectional average: younger vs. older firms.

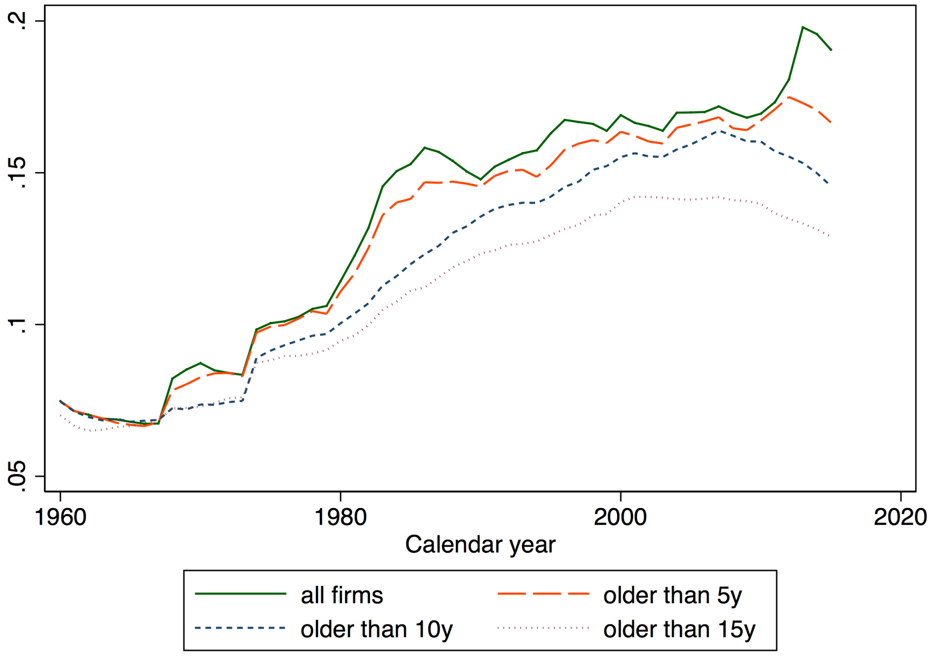
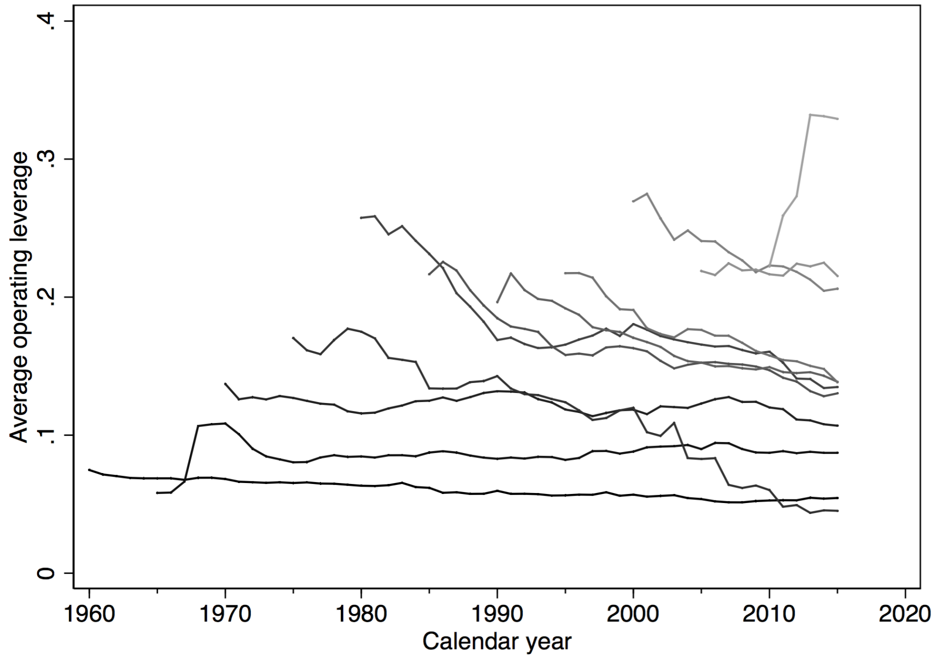
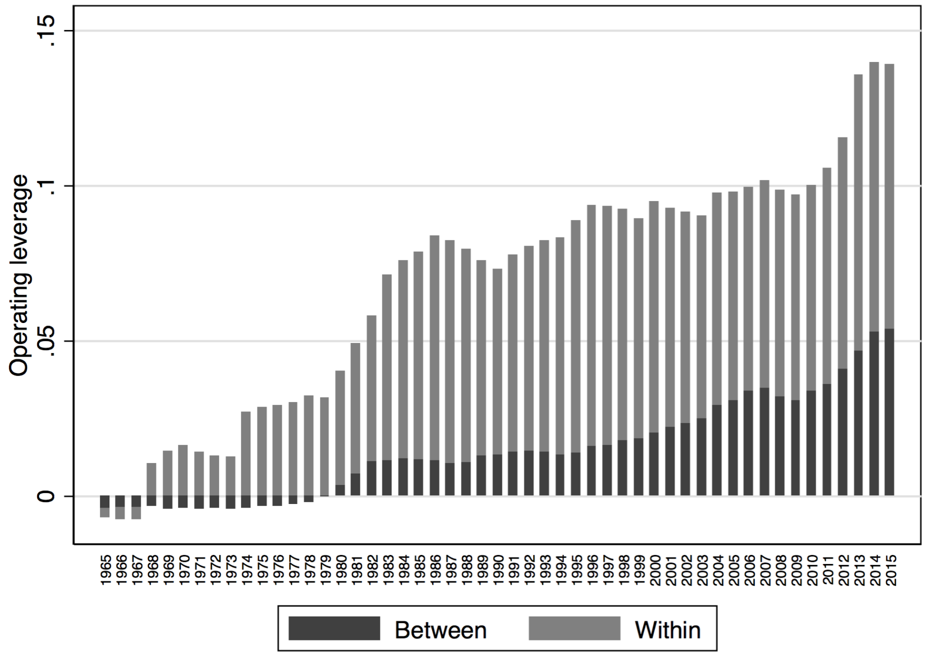


Figure 1.8: Increasing operating leverage in each new cohort: 1960–2015.



Note: each (five-years) cohort is uniquely identified by the starting of the line on the time axis; younger cohorts have also a grayer color. The number of observations in each cohort is 39522 for 1960s, 17288 for 1965s, 25508 for 1970s, 7634 for 1975s, 16410 for 1980s, 17359 for 1985s, 20042 for 1990s, 21371 for 1995s, 8577 for 2000s, 6088 for 2005s, 4705 for 2010s.

Figure 1.9: Between-within decomposition of the increase in operating leverage.



sizes, keeping operating leverage constant. The total increase in average operating leverage is $\Delta\omega_{2015-1960} = (.214 - .075) = .139$. Using the Fama-French 48 industries decomposition, the within-industry component is .085 (i.e. 61% of the total variation) while the between-industry component is .054. Figure 1.9 displays the cumulative contributions, suggesting that the between-industry component, while still minor, has played a more important role in the last decade. Similar results are obtained when using other industry classifications (e.g. SIC or NAICS 3-digits).

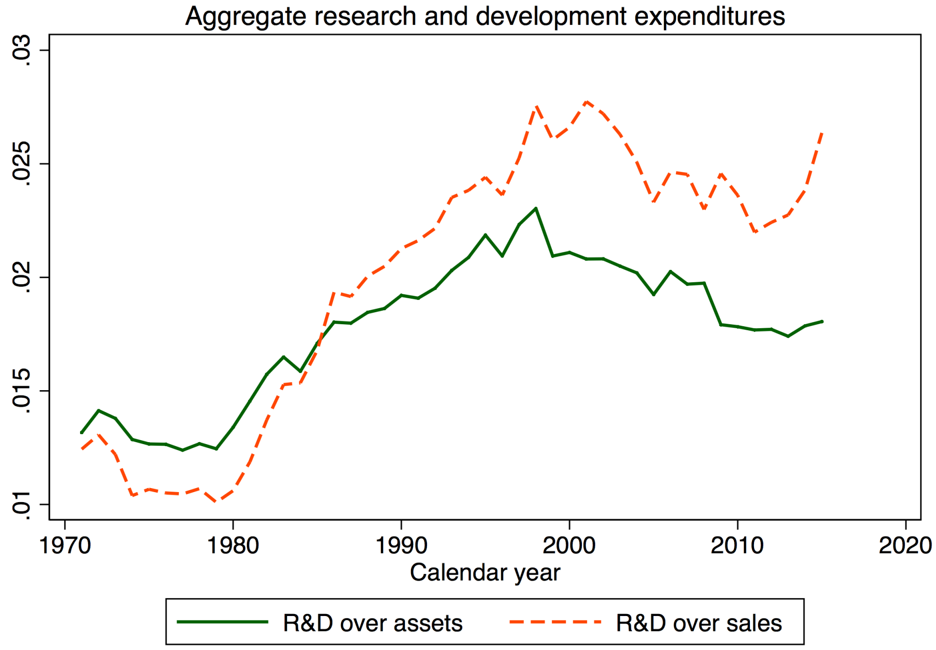
1.2.5 The role of innovative firms

R&D expenses are about $2 - 2.5\%$ of total assets or net sales, when aggregated across all listed firms in my sample. This ratio has been rising through the decades before 2000, but have remained constant and even declined afterwards; see figure 1.10. Does this matter for the increase in fixed costs?

This section assesses how much the secular increase in operating leverage is related to the entry of innovative firms. I show that high-leverage firm do not only have higher R&D expenses, which are relatively fixed, but also a more patents and a more sales volatility.

Rigidity of R&D expenses. As of now, operating leverage has been estimated from total operating costs ($xopr$). Here I look at some specific subsets of these costs: indeed, operating costs are the sum of selling, general, and administrative expenses ($xsga$) and costs of goods sold ($cogs$). This latter item includes: research and development (xrd), staff expenses (xlr), pension expenses (xpr), rental expenses ($xrent$), and advertising

Figure 1.10: The rise of aggregate R&D expenditures.



expenses (xad). That is,

$$\begin{aligned} xopr &= xsga + cogs \\ &= xsga + (xrd + xlr + xpr + xrent + xad + \ldots) . \end{aligned}$$

These costs are often not reported and some represent a tiny fraction of total costs, but it is still interesting to ask: to what extent these expenses are fixed? It is straightforward to estimate the degree of operating leverage for each of these expenditures, as for total operating costs; name it the degree of rigidity, to differentiate it from operating leverage. For instance, consider R&D expenditures: then, for each firm, run the following regression:

$$\Delta lnrxrd_t = \beta_0 + \beta_1 \Delta lnrsale_t + \gamma \left(lnrsale_{t-1} - lnrxrd_{t-1} \right) + \nu_t$$

where $\Delta lnrxrd_t$ is the log difference of inflation-adjusted R&D expenses. The estimated coefficient $\hat{\beta}_1$ delivers the elasticity of R&D expenditures, while its complement the rigidity. Table 1.3 reports the summary statistics of the rigidity of these different expenditures items. It stands out that all these expenses are relatively fixed. By construction, as total operating costs are more variable, it must be that the remaining expenses (mostly raw materials and intermediate products) are the most variable expenses.

In particular, R&D expenditures show the highest degree of rigidity, with an average estimated value of .45. It is no surprise then that firms with high operating leverage are also firms that spend more on R&D: a simple OLS regression (not reported) confirms indeed that R&D expenditures are the one expenditure item that is mostly related to operating leverage. Figure 1.11 reports the increase in average operating leverage by

Table 1.3: Degree of rigidity of different expenditures.

Variable	Obs	Mean	Std. Dev.	P5	P25	P50	P75	P95
SG&A	167234	.33	.45	-.32	.11	.32	.55	1
R&D	91315	.45	1.26	-1.23	.13	.52	.88	1.96
Staff	36359	.27	.6	-.5	.04	.25	.52	1.09
Pension	135528	.39	1.36	-1.65	-.05	.49	.95	2.11
Rental	163631	.46	.91	-.87	.1	.49	.86	1.69
Advertising	96206	.21	2.07	-2.56	-.36	.24	.91	2.78

different economic sectors: high-technology and R&D-intensive sectors show indeed the most pronounced increase, compared to retail or service sectors. That is, innovative firms, with relatively fixed R&D expenses and belonging to high technology sectors, appear to be very much related to the increase in operating leverage.

Patents and output volatility. In order to detail further the relationship between operating leverage and innovation-intensive firms, I now focus on two additional pieces of evidence:

1. the number of patents per firm, which captures a specific output of innovation activities, and

2. the level of sales volatility, which should be higher for innovation activities.

Operating leverage is indeed correlated with both these measures, suggesting that firms with relatively high fixed costs are also relatively focused on innovation activities, i.e. that produce patents and whose output is more volatile. For the first measure I use NBER patent data, which is a comprehensive and publicly available dataset that covers the period 1976-2006 and is easily matched with Compustat firms, associating the number of patents to each firm in each year. The measure of sales volatility is instead the rolling standard deviation of the sales growth rate, defined as:

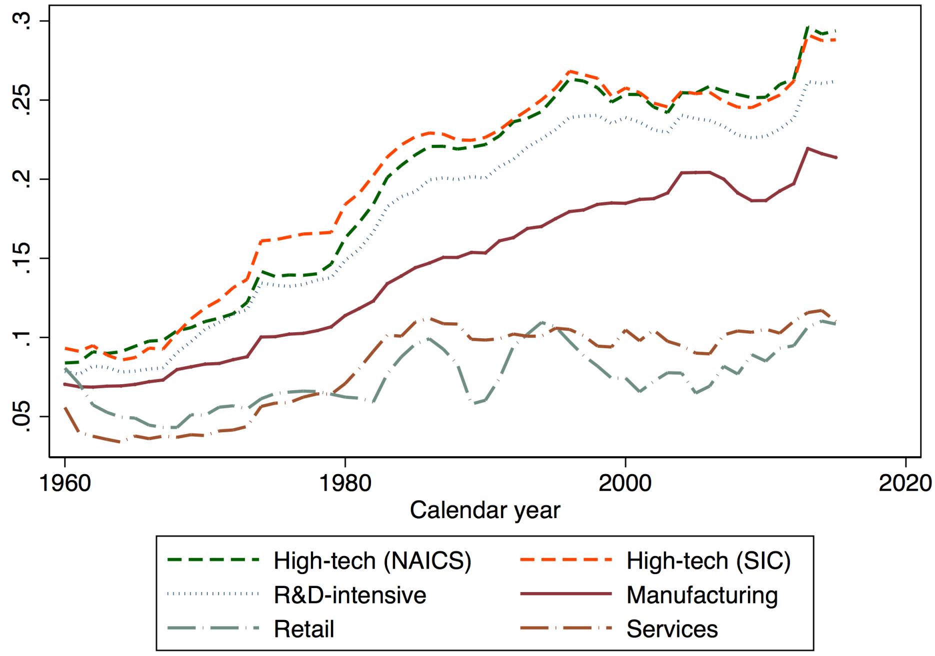
$$\sigma_{i,t}\left(S_t\right) = \left[\frac{1}{T}\sum_{\tau=0}^{T-1}\left(\gamma_{i,t-\tau}-\bar{\gamma}_{i,t}\right)^2\right]^{\frac{1}{2}} \tag{1.7}$$

$$\gamma_{i,t} = \frac{S_{i,t}-S_{i,t-1}}{\left(S_{i,t}+S_{i,t-1}\right)/2}. \tag{1.8}$$

The definition of the growth rate is more robust than the standard growth rate: it allows for entry and exit, is bounded between $[-2, 2]$, and otherwise have very similar values to growth rates as measured by the log difference; see Davis et al. (2006) who introduced this measure in the economic literature[7]. I use a rolling window of $T = 5$ years; using $T = 10$ does not change the results in a meaningful way.

[7] There is also a large literature on firm-level volatility, which documents an increasing pattern among U.S. listed firms; see Comin and Philippon (2006); Comin and Mulani (2006, 2009). However, this pattern contrasts a decreasing trend among privately held firms; see Davis et al. (2006); Davis and Kahn (2008) and Thesmar and Thoenig (2011).

Figure 1.11: Increasing operating leverage by industries: 1960–2015.



Note: the manufacturing sector is defined by NAICS codes 3100-3399, the R&D-intensive sector by SIC3 industries with average R&D expenses over assets above 2% (as in Begenau and Palazzo, 2017), the High-tech (NAICS) is defined as in Stekler and Thomas (2005), the High-tech (SIC) sector as in Brown et al. (2009), the retail sector by NAICS codes 4400-4599, the services sector by NAICS codes 4100-4999 and 5400-8999. In particular, the High-tech (SIC) sector includes: Drugs (283), Computer and Office Equipment (357), Communications Equipment (366), Electronic Components and Accessories (367), Measuring and Controlling Devices (382), Medical Instruments and Supplies (384), Computer and Data Processing Services (737).

Table 1.4: OLS regression: the relation with patents and sales volatility.

	(1)	(2)	(3)	(4)	(5)
Number of patents	-0.034***		0.055***	0.043***	0.032***
	(-9.05)		(12.52)	(9.46)	(6.97)
Sales volatility		0.26***	0.18***	0.18***	0.15***
		(85.87)	(39.76)	(38.23)	(31.06)
Log years since IPO			-0.074***	0.058**	0.040*
			(-15.80)	(3.16)	(2.15)
Log total assets			-0.28***	-0.21***	-0.23***
			(-58.79)	(-38.57)	(-39.25)
Cohort				0.11***	0.11***
				(4.87)	(4.65)
Capital exp.				0.019***	0.015**
				(4.10)	(3.05)
Acquisition exp.				-0.058***	-0.055***
				(-12.99)	(-12.48)
Dividend payer (if =1)				-0.13***	-0.11***
				(-23.25)	(-18.92)
Book leverage				-0.100***	-0.082***
				(-21.38)	(-16.98)
Market-to-book				0.10***	0.083***
				(21.30)	(17.50)
R^2	0.001	0.067	0.178	0.221	0.290
Observations	71767	102995	46517	41514	39245

Notes: operating leverage is the dependent variable. Standardized beta coefficients; t statistics in parentheses; * $p<0.05$, ** $p<0.01$, *** $p<0.001$. Time dummies are included in columns (3)-(5); NAICS 3-digits dummies are included in column (5).

Table 1.4 reports a simple OLS regression that highlight the positive correlation between operating leverage and the two measures just discussed. The first two columns report the unconditional correlation, while columns (3) to (5) add additional controls; Appendix B.1 defines the control variables. The final column also includes industry dummies (NAICS 3-digits). Magnitudes are economically meaningful. Using standardized beta coefficients, i.e. those obtained after the variances of the variables have been standardized to one, a unitary increase in the standard deviation of patents per firm delivers a 5.8% percent increase in operating leverage, while sales volatility adds a 12% increase.

Notice that I do not use R&D expenditures as a control variable because it is a component of operating costs, which we already know to be relatively fixed. Hence, the correlation would be strong and positive – which indeed it is – but mechanical, at least partially. It is also interesting to notice that capital expenditures show a positive correlation, but not anymore once we account for industry dummies. Also the logarithm of total assets (a proxy for firm size) and years since the listing on the stock market (a proxy for age) have significant and negative coefficients: bigger and older firms show a lower level of fixed costs.

There is only another article I am aware of that documents a positive cross-sectional correlation between sales volatility and a measure of costs rigidity: Banker et al. (2014), which argues that congestion costs, which are disproportionately high when sales are high, induce firms to increase their fixed costs whenever sales volatility increases exogenously[8]. On the other hand, I view both sales volatility and fixed costs as the natural consequence of being a firm that is innovation-intensive.

1.3 Implications for business dynamism

This section details how increasing fixed costs of production affect industry equilibrium. The framework is based on Melitz and Redding (2015). In particular, there are many similarities with the model outlined in Bernard et al. (2009), in which there are two types of firms differing in their fixed costs. Bustos (2011) also adopts a very similar setup. However, I do not focus neither on distinct preferences by consumers nor on the open economy set up, but I simply focus on a comparative statics exercise: what is the difference between industries with different levels of fixed costs?

The first subsection deals with a static model, while the following introduces a two-periods set-up to say more about firms growth dynamics. The aim of the model is to rationalize the following empirical patterns:

1. lower net entry rates;

2. lower number of high-growth firms.

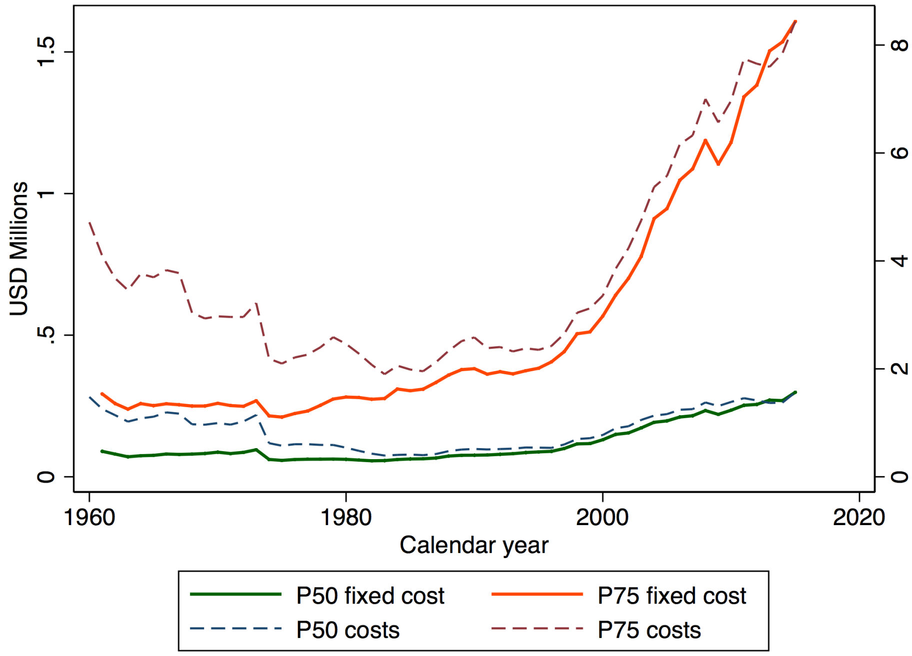
First of all, notice that this article takes as given the increase in fixed costs. Indeed, the focus is on its consequences, not on its causes: as fixed costs are associated with innovation activities, this would call the question about why firms are relatively more innovative today, which is a question that is dealt with in another economic literature. Consider the evidence on declining R&D productivity presented in Bloom et al. (2017): the number of researchers required today to achieve the famous doubling every two years of the density of computer chips (Moore's Law) is more than 75 times larger than the number required in the early 1970s; and similarly so for many other processes. This article simply acknowledges this fact and focuses on its consequences: might larger fixed costs induce a slow down in business dynamism?

To begin with, I show some further evidence about fixed costs. Figure 1.12 reports the variation over time of the P50 and P75 of the cross-sectional distribution of (inflation-adjusted) operating costs: total costs as the dashed line while fixed costs as the solid line, obtained by multiplying with the average value of operating leverage[9]. Total operating costs have a U-shaped pattern, which follow the pattern of the average firm size in the sample. However, fixed costs show instead an increasing pattern, without any decline at the beginning. In other words, firms that have about the same level of total operating costs in the 1960s and in the 2000s have instead a much larger fixed cost component today than in the past, about twice as big. The rise in fixed costs is especially evident after 2000, which is exactly when the decline in business dynamism kicks in.

[8] There are, in fact, other related articles that, by focusing on more disaggregated data in specific industries, reach contrasting conclusions; see e.g. Holzhacker et al. (2015).

[9] It is also possible to match each firm with its estimated value for operating leverage, at the cost of larger variability across firms. Nonetheless, results are qualitatively similar.

Figure 1.12: Fixed cost: P50 and P75.



1.3.1 Larger fixed costs in an industry model

Endowments and preferences. Labor L is the only factor of production and is inelastically supplied; this also indexes the size of the economy. Consumer's preferences are assumed to be a constant elasticity of substitution (CES) function over a continuum of horizontally differentiated varieties or products $i \in [0, 1]$:

$$C = \left[\int_0^1 q(i)^{\frac{\varepsilon-1}{\varepsilon}} \mathrm{d}i \right]^{\frac{\varepsilon}{\varepsilon-1}}, \tag{1.9}$$

where $\varepsilon > 1$ is the elasticity of substitution between varieties. The dual price index is:

$$P = \left[\int_0^1 p(i)^{1-\varepsilon} \mathrm{d}i \right]^{\frac{1}{1-\varepsilon}}.$$

Consumer expenditure minimization yields the following demand function for each variety:

$$q(i) = Y P^{\varepsilon-1} p(i)^{-\varepsilon}. \tag{1.10}$$

Technology. There are two types of technologies, indexed by $j = \{l, h\}$; they are mnemonic for low (l) and high (h). Production of each variety i involves a fixed production cost of f_j units and a variable cost b_j that also depends on firm productivity, which is heterogeneous across firms. The total amount of input required to produce q_j units of a variety i is:

$$l_j = f_j + \frac{b_j q_j}{\varphi}, \tag{1.11}$$

where φ is the productivity parameter. Production costs differ between technologies: the "high" technology has a higher fixed cost and lower variable cost than the "low" technology: $f_h > f_l$ and $b_h < b_l$. Given the wage w and the cost function wl_j, operating leverage is

$$\omega_j = 1 - \frac{\partial w l_j}{\partial q_j} \frac{q_j}{w l_j} = \frac{f_j}{f_j + {}^{b_j q_j}/_{\varphi}},$$

which is exactly the ratio of fixed to total costs, f_j/l_j. Notice that operating leverage depends on the optimal quantity q_j chosen by the firm: this in turn depends on the variable costs b_j, which indirectly depends on the fixed cost. To be in line with the theoretical literature on which I build, I focus on variations in the fixed cost rather than on variations in operating leverage[10]. However, as long as a larger fixed cost implies a smaller marginal cost, operating leverage is increasing in the fixed cost, so that an increase in the fixed cost is equivalent to an increase in operating leverage. Indeed, by looking at the sign of the derivative:

$$\frac{\partial \omega_j}{\partial f_j} > 0 \;\Leftrightarrow\; b_j > (\varepsilon - 1) \frac{\partial b_j}{\partial f_j}$$

which is always true, as long as $\partial b_j / \partial f_j < 0$, with $\varepsilon > 1$ and $b_j > 0$.

Firm's optimization. The market structure is of monopolistic competition. Profits maximization by the firm implies the following equilibrium price for each variety

$$p_j(\varphi) = \left(\frac{\varepsilon}{\varepsilon - 1} \right) \frac{w b_j}{\varphi}, \tag{1.12}$$

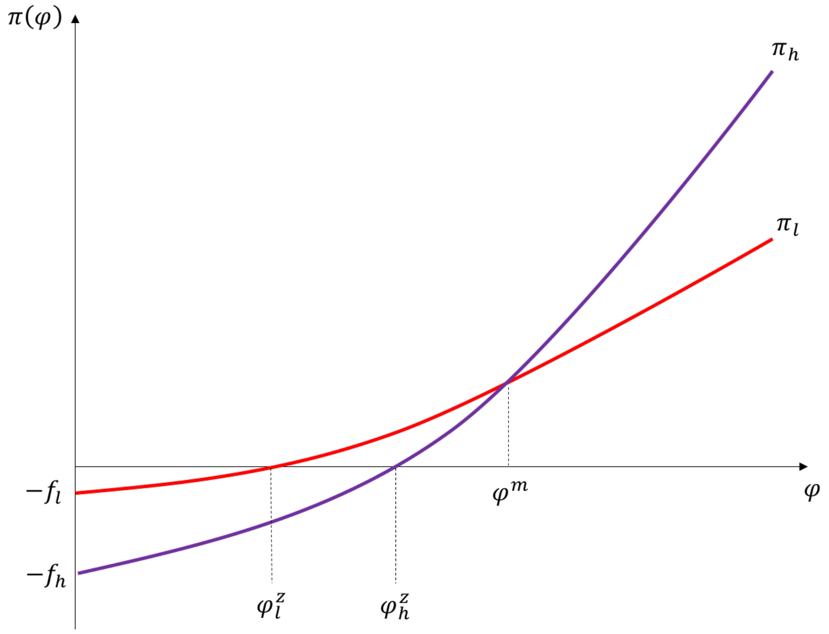
which is equal to a constant markup over the marginal cost. Let the wage be the numéraire: $w = 1$. Using the pricing rule in (1.12) and the demand function in (1.10), equilibrium firm's revenue and profits are:

$$r_j(\varphi) = B \left(\frac{\varphi}{b_j} \right)^{\varepsilon - 1},$$
$$\pi_j(\varphi) = \frac{r_j(\varphi)}{\varepsilon} - f_j.$$

where $B \equiv Y P^{\varepsilon-1} \left(\frac{\varepsilon-1}{\varepsilon} \right)^{\varepsilon-1}$ is a market demand index. Notice that increasing f_j has two effects: it directly reduces profits but also increases revenues, through the fall in the variable cost b_j. Which effect prevails depends on the level of productivity: the larger and the latter effect prevails.

[10] This choice also imposes operating leverage to depend on the productivity parameter φ. It is possible to avoid this inconvenience, by assuming $l_j = (f_j + b_j q_j)/\varphi$ instead of eq. (1.11), but the cost would be to depart from the standard terminology and to slightly complicate the analytical results, without obtaining any additional insight, since choosing f_j rather ω_j as the fundamental parameter of the analysis is in fact equivalent.

Figure 1.13: Productivity and profits for the two technologies.



Firm's profits. Any firm draws its productivity φ from $g(\varphi)$, with cumulative distribution function $G(\varphi)$ over the interval $[0, \bar{\varphi}]$, and decides whether to immediately exit or to produce. With a zero productivity draw, the firm would make the largest losses by using the high technology:

$$\pi_h(0) = -f_h < \pi_l(0) = -f_l < 0.$$

Moreover, the rate of change of profits with respect to productivity is faster with the high technology, i.e. the one with larger fixed costs and $b_h < b_l$:

$$\frac{\partial \pi_j}{\partial \varphi} = (\varepsilon - 1) B\varphi^{\varepsilon-2} \left(\frac{1}{b_j}\right)^{\varepsilon-1}, \tag{1.13}$$

which is decreasing in b_j. Therefore, since profits increase faster along with productivity with the high technology, assume there exists a productivity level φ^m such that profits are the same for the two technologies – and larger thereafter for the high technology: $\pi^m \equiv \pi_l(\varphi^m) = \pi_h(\varphi^m)$. For the sake of simplicity, assume that profits are positive at this productivity level φ^m and that expected profits (conditional on entry) are identical for the two technologies:

$$\pi^e \equiv \int_{\varphi_l^z}^{\bar{\varphi}} \pi_l(\varphi) g(\varphi) \mathrm{d}\varphi = \int_{\varphi_h^z}^{\bar{\varphi}} \pi_h(\varphi) g(\varphi) \mathrm{d}\varphi. \tag{1.14}$$

In other words, the profit distribution of the high technology is a mean-preserving spread of the profit distribution of the low technology. Figure 1.13 visually describes this setting.

Firm entry and exit. The first equilibrium condition concerns exit: any firm drawing a productivity level that is not sufficient to generate positive profits can and does exit, costlessly. This zero-profit condition yields, for each technology, the cutoff productivity φ_j^z:

$$\pi_j\left(\varphi_j^z\right)=0 \;\Leftrightarrow\; \varphi_j^z=b_j\left(\frac{\varepsilon f_j}{B}\right)^{\frac{1}{\varepsilon-1}}, \tag{1.15}$$

which characterizes the minimum level such that a firm operates.

The other equilibrium condition concerns entry: any firm can enter the market by paying a sunk entry cost of f_j^E units of the labor input, which is technology-specific. In equilibrium, the sunk-entry cost must be equal to the expected value of entry:

$$f_j^E=\int_{\varphi_j^z}^{\infty}\pi\left(\varphi\right)\mathrm{d}G\left(\varphi\right)=\left[1-G\left(\varphi_j^z\right)\right]\pi^e, \tag{1.16}$$

for $j=\{l,h\}$, in which the *ex ante* probability of successful entry is $\left[1-G\left(\varphi_j^z\right)\right]$. I assume that, since *ex post* profits are identical on average for the two technologies, the sunk-entry costs are such that each firm is indifferent over the *ex ante* choice of the production technology: $f_h^E<f_l^E$. However, once the entry cost is paid, any firm will be associated to a specific production technology for ever. This is different from Bernard et al. (2009), who instead allow firms to choose their technology/product after their productivity is revealed, thus allowing for endogenous product choice. Here instead I assume indifference in the technological choice, so that the increase in the number of high technology firms in the last decades is entirely exogenous to the model. Again, the focus is on the comparative statics, not on the causes.

Industry equilibrium. The cutoff productivity φ_j^z can be determined from the zero-profit (1.15) and the free entry (1.16) conditions. Combining them, obtain

$$f_j\cdot J\left(\varphi_j^z\right)=f_j^E,\quad J\left(\varphi_j^z\right)=\int_{\varphi_j^z}^{\infty}\left[\left(\frac{\varphi}{\varphi_j^z}\right)^{\varepsilon-1}-1\right]\mathrm{d}G\left(\varphi\right) \tag{1.17}$$

which uniquely identifies the cutoff productivity for each technology, since $J\left(\cdot\right)$ is monotonically decreasing in φ_j^z with $\lim_{\varphi_j^z\to 0}J\left(\varphi_j^z\right)=\infty$ and $\lim_{\varphi_j^z\to\infty}J\left(\varphi_j^z\right)=0$. In turn, market demand can be determined simply as

$$B=\varepsilon f_j\left(\varphi_j^z/b_j\right)^{1-\varepsilon}. \tag{1.18}$$

Profits, revenues, prices, output, and employment are then determined from φ_j^z and B. Indeed, CES preferences and monopolistic competition ensures that neither firm selection φ_j^z nor firm's performance measures will be influenced by sector aggregates, which only influence the mass of firms.

Predictions. Immediately, looking at equation (1.17), we have that a larger fixed cost f_j delivers a higher cutoff productivity φ_j^z. This is equivalent to say that the portion of the mass M_j^E of entrants that survive to become the mass M_j of active firms, which is given by

$$M_j = \left[1 - G\left(\varphi_j^z\right)\right] M_j^E \tag{1.19}$$

is decreasing in the fixed cost. That is, a larger number of firms fail upon entry and a smaller number of firms is active in the long run. This is a prediction about net entry rates: the gross inflow less the gross outflow of firms. Empirically, given the nature of the sample, we expect not only higher exit rates, but also lower entry rates (which in fact in the model are constant), since many low-productivity firms are not even close to be listed as they fail well in advance. This is indeed what seems to be the case, when looking at entry and exit rates across industries; see section 1.3.3.

1.3.2 Dynamics

Why are there fewer high-growth firms? Do fixed costs play a role? Here I conjecture that, under certain assumptions, the number of firms that survive from being young to mature is decreasing in the amount of the fixed cost. In other words, larger fixed costs decreases the number of "winners". Notice that this is different from the simple statement that fewer firms survive upon entry: it is instead about firms that grow from young to mature, not from newborns to young. If these potential firms have large fixed costs, as they are innovative firms, there is a risk that they do not survive the growth phase because of the large initial losses that they have to sustain. Indeed, the relevant assumptions are: (*i*) high-growth firms are characterized by larger fixed costs; (*ii*) young firms have smaller revenues that then grow larger; and (*iii*) exit/default is correlated with negative profits.

Consider then two periods, which can be thought of as the short and the long run: $t = 1, 2$. The only difference is about revenues:

$$r_{j,t}\left(\varphi\right) = \begin{cases} \alpha \cdot r_j\left(\varphi\right) & : t = 1 \\ r_j\left(\varphi\right) & : t = 2 \end{cases}$$

with $0 < \alpha < 1$. That is, new firms are smaller than old firms, because their revenues are smaller (by a factor α) than revenues in the long run. It is, of course, a very reduced form approach to capture a robust empirical regularity: recent research has shown that new firms are small not because they are less technically efficient, but because demand for their product is low, due to informational, reputational, or other frictions; see Foster et al. (2016) and references therein. This assumption also aligns with the negative correlation between firm size and operating leverage: by construction, operating leverage increases as revenues decrease, holding constant the fixed cost.

In the simple case of perfect information and capital markets, the zero-profit condition reads as

$$\pi_{j,1}\left(\varphi_j^{zz}\right) + \pi_{j,2}\left(\varphi_j^{zz}\right) = 0 \;\Leftrightarrow\; \varphi_j^{zz} = b_j\left(\frac{2\varepsilon f_j}{\left(1+\alpha\right)B}\right)^{\frac{1}{\varepsilon-1}} \tag{1.20}$$

so that a firm exits if the net present value of its profits is negative; assume no discounting for simplicity. Together with the free entry condition,

$$\int_{\varphi_j^{zz}}^{\infty} \left[\pi_{j,1}\left(\varphi\right) + \pi_{j,2}\left(\varphi\right)\right] \mathrm{d}G\left(\varphi\right) = f_j^E, \tag{1.21}$$

we can implicitly determine the cutoff productivity from

$$\int_{\varphi_j^{zz}}^{\infty} \left[\left(\frac{\varphi}{\varphi_j^{zz}} \right)^{\varepsilon-1} - 1 \right] \mathrm{d}G(\varphi) = \frac{f_j^E}{2f_j}. \tag{1.22}$$

Now introduce the following financial constraint: exit occurs when profits are negative. That is, even though profits are positive in net present value, they can be negative in the short run, since revenues are not yet large enough. This idea tracks back to the "internal finance theory of growth": the growth of small firms is constrained by the available quantity of internally generated finance, that is, profits; see Carpenter and Petersen (2002) or Brown et al. (2009). Then, substitute the zero-profit condition with

$$\pi_{j,1}\left(\varphi_j^{cz}\right) = 0 \iff \varphi_j^{cz} = b_j \left(\frac{\varepsilon f_j}{\alpha B} \right)^{\frac{1}{\varepsilon-1}} \tag{1.23}$$

which imposes exit if only short-run profits are negative; this is the constrained zero-profit condition. Together with the free entry condition,

$$\int_{\varphi_j^{cz}}^{\infty} \left[\pi_{j,1}(\varphi) + \pi_{j,2}(\varphi) \right] \mathrm{d}G(\varphi) = f_j^E, \tag{1.24}$$

we can again implicitly determine the constrained cutoff productivity from

$$\int_{\varphi_j^{cz}}^{\infty} \left[\left(\frac{1+\alpha}{2\alpha} \right) \left(\frac{\varphi}{\varphi_j^{cz}} \right)^{\varepsilon-1} - 1 \right] \mathrm{d}G(\varphi) = \frac{f_j^E}{2f_j}. \tag{1.25}$$

Naturally, imposing a stricter constraint on exit delivers a higher likelihood of exit. Indeed, by comparing equations (1.22) and (1.25), the cutoff productivity is higher in the case with the financial constraint: $\varphi_j^{cz} > \varphi_j^{zz}$. In particular, the larger the potential growth rate (i.e. the smaller the α) and the larger the constrained cutoff productivity. That is, firms having a greater growth potential are more at risk of failure. Furthermore, this should be increasing in the level of short-term financing constraints.

1.3.3 Evidence in the data

To sum up, moving from a low- to a high-fixed cost technology has two implications:

a) lower net entry rates;

b) lower survival rates.

I now focus on the empirical evidence regarding these two implications. Afterwards, I discuss a model's assumption: that operating leverage increases profits volatility.

a) Lower net entry rates. Any analysis of the data, unfortunately, runs against a fundamental issue: industries with higher operating leverage could be those that have witnessed more entries – otherwise operating leverage would not have changed, since it's mostly due to entry/exit. In other words, operating leverage might have increased exactly in the industries that also have seen a lot of dynamism. This is exactly the opposite of what the model tells us: increasing fixed costs might lower dynamism. Therefore, data can in principle give contradictory results.

Nonetheless, having this in mind, it is useful to analyze some empirical patterns. I focus on entry and exit rates within industries, through panel regression with industry fixed effects, which control for any level difference. Hopefully, this should capture the after-mentioned bias in associating industries with higher entry rates to increasing operating leverage, at least partially. Thus, all results depend only on time-variation across industries.

Tables 1.5 and 1.6 report fixed-effects panel regressions for various measures of entry/exit rates against the measure of (industry-average) operating leverage, using NAICS 3-digits industries[11]. Tables 1.7 and 1.7 report the same regressions using economic sectors, as defined by US Census (at the SIC 1-digit level). Table 1.9 uses entry/exit rates from the Business Dynamics Statistics, which covers the whole US economy over the period 1977-2014.

Over time, industries with increasing operating leverage show decreasing net entry rates. In particular, at a more disaggregated level (NAICS industries), exit rates seem to be crucial in driving down net entry rates, whereas entry rates appear weakly correlated with operating leverage. Instead, at a more aggregate level (sectors), it is entry rates that become significantly related with operating leverage: increasing fixed costs are accompanied by lower entry rates. When moving the focus from listed firms to the whole economy, entry remains negatively related with operating leverage, while exit switches sign: larger fixed costs are associated with lower exit rates. However, the net effect is still that net entry is decreasing where operating leverage is increasing: among listed firms, larger exit rates are driving this pattern, while among the whole economy lower entry rates are the culprit. Thus, industries or sectors with increasing fixed costs show a decreasing level of business dynamism, in terms of net entry rates.

b) Lower survival rates. Now I focus instead at the firm-level rather than at the industry-level. Table 1.10 shows results from a logit regression, in which the dependent variable is either deletion or default: deletion is straightforward disappearance from the sample, while default only comprises bankruptcy (Chapter 7) or liquidation (Chapter 11). The table presents both the univariate regression and the one including controls that account for other important determinants of deletion/default, such as financial leverage and profitability, and time and industry dummies. It appears that larger fixed costs are indeed associated to a higher likelihood of deletion and, most importantly, default: the odds are twice as likely.

The interpretation is in fact wide-ranging. Firms in Compustat are not exactly start-ups; rather, they are either young or mature firms. Hence, this evidence does not directly address the issue of the decreasing number of new start-ups, but rather points to a higher likelihood of young firms with larger fixed costs to fail before they become mature. And these firms are potentially high-growth firms, since operating leverage is related to innovating activities; see subsection 1.2.5.

[11]Similar results are obtained when using other digits aggregations and SIC classification.

Table 1.5: Gross entry/exit rates: NAICS3 industries.

	(1) Entry	(2) Deletion	(3) Exit	(4) Default
Op. Leverage	-12.38	35.71***	6.922***	1.775***
	(-1.82)	(5.53)	(10.08)	(3.54)
Observations	4670	4670	4670	4670

Table 1.6: Net entry rates: NAICS3 industries.

	(1) Net entry	(2) Net entry	(3) Net entry
Op. Leverage	-48.09***	-19.30**	-14.16
	(-4.16)	(-2.82)	(-1.97)
Observations	4670	4670	4670

Note: panel regression of various entry/exit rates (%) against industry-average operating leverage, with industry fixed effects (NAICS 3-digits). In table 1.5, the columns refers to different net entry rates: entry against deletion in (1), against exit in (2), and against default in (3). *Entry* is entry in the sample; *deletion* is disappearance from the sample, i.e. delisting; *exit* is delisting for any reason other than mergers, reorganization, or going private (if Compustat item dlrsn is different than 1, 2, 4, 7, 9, or 10); *default* is delisting because of bankruptcy or liquidation (if Compustat item dlrsn is equal to 2 or 3). The exit definition is consistent with U.S. Census Bureau's; see Duffie et al. (2007). P-values: * $p<0.05$, ** $p<0.01$, *** $p<0.001$; t statistics in parentheses; analytically weighted least squares, where the weight is total industry sales; standard errors clustered at the industry level.

Table 1.7: Gross entry/exit rates: Census sectors in Compustat sample.

	(1) Entry	(2) Deletion	(3) Exit	(4) Default
Op. Leverage	-72.06***	62.57***	10.98***	2.188*
	(-5.89)	(12.10)	(8.77)	(2.43)
Observations	448	448	448	448

Table 1.8: Net entry rates: Census sectors in Compustat sample.

	(1) Net entry	(2) Net entry	(3) Net entry
Op. Leverage	-134.6***	-83.04***	-74.25***
	(-8.32)	(-6.21)	(-6.16)
Observations	448	448	448

Table 1.9: Gross entry/exit rates: Census sectors in the whole economy.

	(1) Net Entry	(2) Entry	(3) Exit
Op. Leverage	-30.86***	-56.33***	-25.48**
	(-5.75)	(-5.52)	(-4.79)
Observations	304	304	304

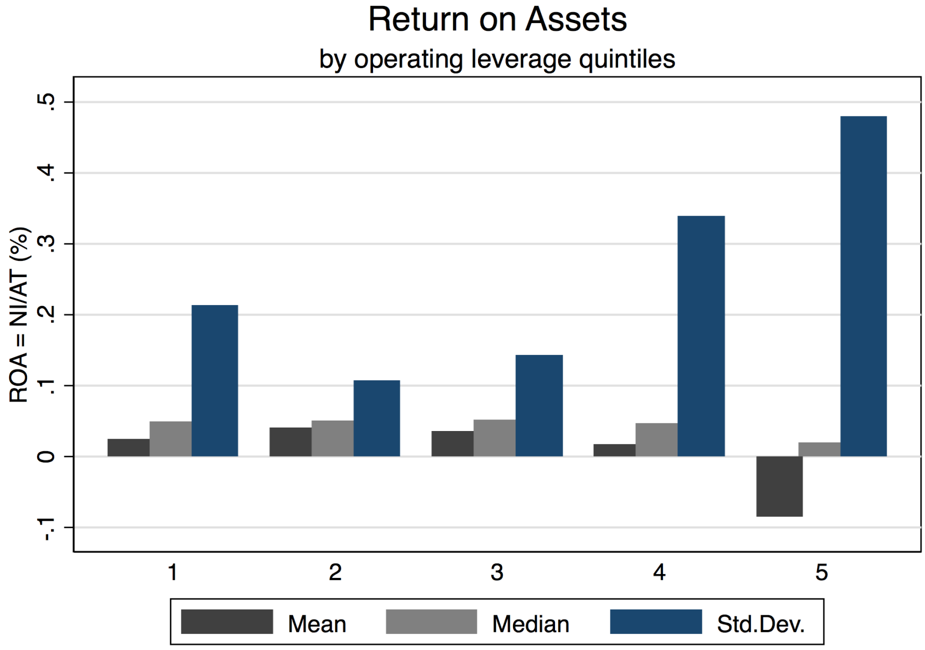
Note: panel regression of various entry/exit rates (%) against sector-average operating leverage, with sector fixed effects (CENSUS sector; SIC 1-digit). In table 1.8, the columns refers to different net entry rates: entry against deletion in (1), against exit in (2), and against default in (3). Tables 1.7 and 1.8 focus on the Compustat sample while table 1.9 uses entry/exit rates in the whole economy (data from US Census' Business Dynamics Statistics at the firm level). *Entry* is entry in the sample; *deletion* is disappearance from the sample, i.e. delisting; *exit* is delisting for any reason other than mergers, reorganization, or going private (if Compustat item dlrsn is different than 1, 2, 4, 7, 9, or 10); *default* is delisting because of bankruptcy or liquidation (if Compustat item dlrsn is equal to 2 or 3). The exit definition is consistent with U.S. Census Bureau's; see Duffie et al. (2007). P-values: * $p<0.05$, ** $p<0.01$, *** $p<0.001$; t statistics in parentheses; analytically weighted least squares, where the weight is total sector sales; standard errors clustered at the sector level.

Table 1.10: Logit regression; deletion/default and operating leverage.

	(1) Deletion	(2) Deletion	(3) Default	(4) Default
Operating Leverage	2.022***	1.317***	2.668***	2.053***
	(20.39)	(5.40)	(7.80)	(3.77)
Log years since IPO		1.163***		1.209***
		(9.90)		(3.50)
Log total assets		0.873***		0.866***
		(-16.70)		(-4.80)
Capital exp.		0.381***		0.812
		(-4.64)		(-0.31)
Dividend payer (if =1)		0.773***		0.642***
		(-7.82)		(-3.35)
Book leverage		5.708***		60.00***
		(23.70)		(17.29)
Market-to-book		0.858***		0.721***
		(-13.42)		(-4.74)
ROA (ni/at)		0.184***		0.0605***
		(-31.61)		(-18.20)
Observations	172948	119058	172948	107825

Notes: Odds ratio (i.e. exponentiated) coefficients. Time and NAICS 3-digits dummies are included in columns (2) and (4). *Deletion* is disappearance from the sample, i.e. delisting; *exit* is delisting for any reason other than mergers, reorganization, or going private (if Compustat item dlrsn is different than 1, 2, 4, 7, 9, or 10); *default* is delisting because of bankruptcy or liquidation (if Compustat item dlrsn is equal to 2 or 3). The exit definition is consistent with U.S. Census Bureau's; see Duffie et al. (2007). P-values: * p<0.05, ** p<0.01, *** p<0.001; t statistics in parentheses; standard errors clustered at the firm level.

Figure 1.14: ROA by operating leverage quintiles; increasing cross-sectional dispersion.



Operating leverage and profits volatility. There is a central characteristic of high-operating leverage firms: profits volatility. Figure 1.14 reports how statistics on return on assets (ROA, i.e. net income over total assets) vary among different quintiles by operating leverage. The most evident pattern is that profits dispersion is increasing in operating leverage. Graphical evidence is confirmed also by econometric evidence: table 1.11 quantifies how much the standard deviation and the inter-quartile range of ROA (at the firm level) are positively related to operating leverage. This holds true also after controlling for sales volatility, which is crucial: larger fixed costs increase profits volatility for any given level of sales volatility.

1.3.4 Operating leverage and market concentration

The literature has recently focused on another secular trend in U.S. markets: the increase in market concentration and market power. Autor et al. (2017) argue that markets are increasingly dominated by superstar firms, characterized by "winner take most" features and accountable for the rise in industry concentration and the fall in the labor share. Barkai (2017) shows that the secular fall in the labor share was not in fact followed by a rise in the capital share: it's the profit share that has risen. De Loecker and Eeckhout (2017) similarly find that firms mark-ups has been rising, defined as price over marginal cost. Similarly, Gutiérrez and Philippon (2017) argue that increased market power can be related to decreasing investment rates.

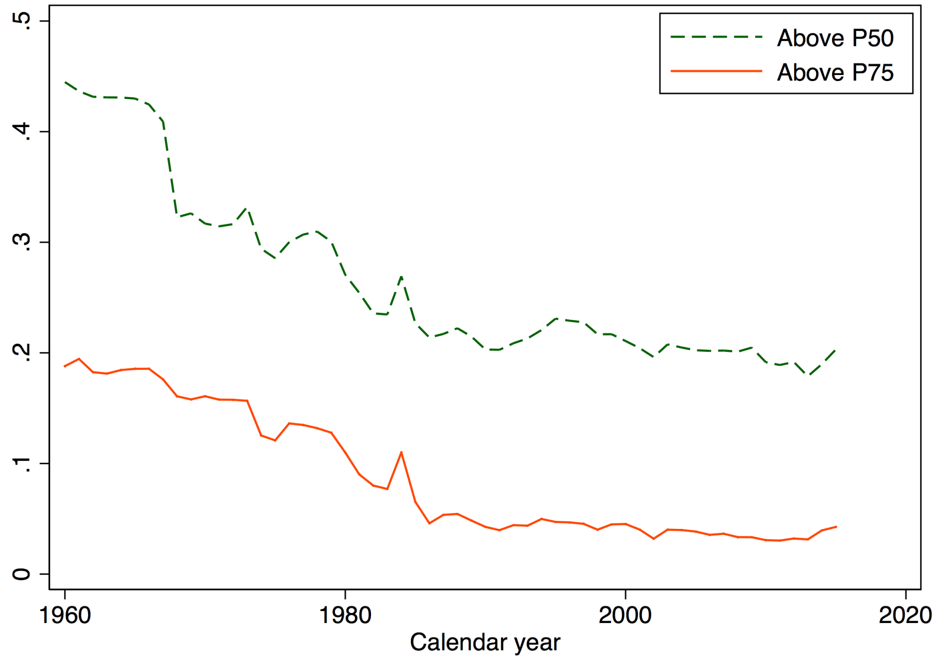
How does the increase in operating leverage fit into these stories? In fact, this rise is mostly accounted by new entrants, small, young, and innovative firms. Of course, some might already be the dominant players in the markets, such as Google or Facebook, but they are rather the exception than the rule. Figure 1.15 shows that high operating

Table 1.11: Dispersion in ROA and operating leverage; OLS regression.

	(1) ROA SD	(2) ROA IQR
Operating Leverage	0.066***	0.078***
	(58.37)	(55.86)
Log years since IPO	-0.0056***	-0.0089***
	(-13.73)	(-17.47)
Log total assets	-0.0088***	-0.0099***
	(-77.31)	(-70.14)
Capital exp.	-0.018***	-0.0084
	(-4.97)	(-1.85)
Acquisition exp.	0.021***	-0.0023
	(5.46)	(-0.48)
Dividend payer (if =1)	-0.0098***	-0.0028***
	(-21.05)	(-4.94)
Book leverage	-0.031***	-0.042***
	(-25.21)	(-27.47)
Sales volatility	0.11***	0.12***
	(67.78)	(60.52)
Market-to-book	0.0066***	0.011***
	(36.20)	(49.24)
ROA (ni/at)	-0.13***	-0.18***
	(-89.60)	(-95.52)
Observations	79697	79697

Notes: time and NAICS 3-digits dummies are included in all columns. P-values: * $p<0.05$, ** $p<0.01$, *** $p<0.001$; t statistics in parentheses; standard errors clustered at the firm level.

Figure 1.15: Share of sales accounted by firms with operating leverage above the median (P50) e the 75^{th} percentile (P75): 1960-2015.



leverage firms account indeed for a relatively smaller share of total sales: those with above-median fixed costs account for only about 30% of total sales. Therefore, we can think of them as two different phenomena: incumbent firms that manage to increase their market dominance, in turn capturing a higher share of sales and profits, and the arrival of new innovative firms, which induce an increase in fixed costs. In turn, this latter process induced a decline in business dynamism, which of course could be related also to the first process of increasing concentration, but the channels are different. I believe the relationship between these two phenomena is a fruitful avenue for future research.

There is yet an important issue to deal with: may a secular increasing trend in markups, as evidenced in De Loecker and Eeckhout (2017), influence the measure of operating leverage? I believe that it does not. In fact, these two long-term patterns might be combined into a consistent picture: increasing markups (which are measured as price over marginal costs) can in fact be offset by increasing fixed costs, so that profits remain unaffected. Why that happened? For instance, because of an increase in the love for variety: firms sustain larger fixed costs to produce more varieties, each with a larger markup; see[12] Robin Hanson on this. On the other hand, increasing market power seems to be a story about very large firms, while increasing fixed costs is about smaller firms.

Going back to the initial question, first recall that operating leverage is measured as an elasticity, from the following equation:

$$\Delta c_t = \alpha + \beta \Delta s_t + \gamma \left(s_{t-1} - c_{t-1} \right) + \varepsilon_t$$

where the difference between sales (s_t) and total costs (c_t) is the price-cost margin, which is the markup over *total* costs, not only variable costs, defined as $\mu_{i,t} \cong \ln s_{i,t} - \ln c_{i,t}$. Any

[12] http://www.overcomingbias.com/2017/08/marching-markups.html

long-run trend in such price cost margin does not in fact matter, since we are considering first differences, while the long-run estimate will be just its average. In any case, the price-cost margin that I am focusing on does not even show any relevant trend over the last decades, on average: a regression against a time index with firm fixed-effects delivers no positive correlation with time.

The relevant issue is instead the existence of a positive contemporaneous correlation between sales and markups. Indeed, a variation in sales might occur together with a variation in the markup, so that costs would appear as fixed when in fact they are not. However, in the data there is no such pattern – suggesting that increasing operating leverage is entirely a pattern due to a change in operating costs. Table 1.12 reports the correlation matrix between inflation-adjusted net sales (Sales) and the markup (Markup), both in levels and growth rates. The correlation among the variables is very weak at best. If anything, the correlation between the growth rates is even negative: an increase in sales is not matched by any increase in the markup, so that the estimate of operating leverage seemingly captures really the cost behavior. There is also no apparent change over time in these correlation, looking at OLS regressions with firm fixed-effects over different sub-periods.

Table 1.12: Cross-correlation table: markup and sales.

Variables	Markup	Markup growth	Sales	Sales growth
Markup	1.000			
Markup growth	-0.012	1.000		
Sales	0.056	0.001	1.000	
Sales growth	0.102	-0.018	-0.019	1.000

1.4 Conclusions

Average operating leverage has significantly increased in the last forty years among U.S. listed firms. This increasing share of fixed operating costs is associated to the changing composition of firms: there are now relatively more innovation-intensive firms, which spend more in R&D, produce more patents, and whose sales are more volatile. Nowadays, listed firms are not only riskier in terms of output volatility, but also in terms of their cost structure.

Can this increase be associated to the recent decline in business dynamism? I show that a standard industry model à la Melitz delivers predictions that are consistent with this idea. Indeed, an increase in fixed costs predicts a larger number of firms that fail upon entry, because their productivity is not high enough to cover the fixed costs of production. Moreover, larger fixed costs also lower the possibility that young firms successfully grow to become mature firms: if revenues take time to build up and firms face financing constraints, larger initial losses can induce firms' exit, even if they are productive enough in the long run – exactly because initial losses are large due to the fixed costs. Indeed, many young firms rely on internal financing as a source of growth, which decreases in the level of fixed costs. In the data, there are two empirical patterns that align with this story: net entry rates are declining in those industries or sectors in which operating leverage has increased and firms with higher operating leverage have also a larger failure probability.

However, much questions remain open. First of all, it would be interesting to know whether fixed costs have been rising also in the whole U.S. economy, or it is just a phenomenon peculiar to listed firms. Moreover, it would be particularly interesting to know the level of fixed costs of start-ups, that is, really young and small firms. Second, it is still unclear how much financing constraints could dampen the growth process of high-growth and high-leverage firms: on the one hand, this choice is entirely in the hand of shareholders, so that we might presume that failure or exit is optimal, while on the other hand there might be inefficiencies in this market selection process, since firms with larger fixed costs actually fail more often. The difficult is, of course, how can we say whether a firm that fails ought instead survive to eventually become a successful mature firm. We might also think about cross-country comparisons and along different financial systems. Finally, we still need sound empirical evidence on these important phenomena, moving beyond descriptive analyses and suggestive statistics: yet, it is not obvious how do solve this issue.

Chapter 2

The corporate saving glut

2.1 Introduction

Net lending/borrowing is a *flow* measure that is defined as saving less investment/consumption. Each sector of the economy does either lend or borrow; even countries do. In the corporate sector, net lending corresponds to undistributed profits less dividends (which results in *gross saving*) less investment (which results in *net saving*).

Corporations are often *naïvely* considered as net borrowers in the economy; many theoretical models hold this assumption. In principle, a firm should raise funds on the market, install productive capital, and obtain a stream of future cash flows, which will allow them to pay back the funds initially borrowed. At an aggregate level, the presumption is that there are always many more firms raising funds than paying them back. However, in the recent years, the corporate sector turned from net borrower to net lender, in many advanced economies. This macroeconomic fact has been labeled the "corporate saving glut"; see Loeys et al. (2005) and Gruber and Kamin (2015).

First of all, this article defines and identifies net lending/borrowing from firm-level data, using Compustat, showing that what we see on aggregate corresponds to what we can see among publicly listed companies. But why did this happened? Why are corporations now saving their funds, rather than investing, or at least distributing them back to shareholders?

Conventional wisdom views the glut as a puzzle. However, I believe it is not – we just need to think about the growth of sectors of the economy, not about individual firms behavior. Indeed, in many growth models, the representative firm accumulates capital until a steady-state is reached, in which the investment rate decreases to a level just enough to replace the capital that depreciates. On the other hand, the capital share is deemed to be constant, i.e. unrelated to the level of capital accumulation, if, for example, production is Cobb-Douglas. If anything, the capital share has slightly increased as capital in the economy increased over time – which happens if production is CES with an elasticity larger than one; see e.g. Piketty and Zucman (2014).

This is remarkably similar to what we have witnessed in recent decades: a constant capital share together with a decreasing investment rate, resulting in the corporate sector moving from net borrower to net lender. The only assumptions needed are: the capital share is larger than the depreciation rate, in a steady-state, and firms do not actually pay back to sharehodlers all the excess funds. Indeed I argue that, in lack of sufficient evidence suggesting otherwise, we must view the glut as a natural occurence: the corporate sector has reached its steady-state. Of course, there might be other reasons behind the glut, but we must bring evidence about them – and I strongly believe that even providing negative evidence about something is a useful. This article aims to do exactly that, focus on three major potential motives of the glut:

1. a deleveraging motive: firms are willing to lower their debt outstanding;

2. a precautionary motive: firms are willing to accumulate savings against an uncertain environment or because of better future opportunities; and

3. a strategic motive: firms are willing to accumulate funds for competitive reasons, e.g. to carry out and/or avoid acquisitions, for predatory practices, and so on.

The first motive presumes that a positive saving flow is the mechanism through which firms reduce their debt outstanding, which is deemed too much. Recent years have indeed witnessed a large number of zero-leverage firms; see Strebulaev and Yang (2013) and also Graham et al. (2015) for a longer term perspective on corporate leverage. However, these firms are relatively small and on aggregate corporate leverage remained quite constant, which is inconsistent with the emergence of the saving glut.

The second motive is about another conventional perspective: saving as a way to postpone investment or consumption. In particular, this links to the long-term decline in investment rates; see e.g. Furman (2015) or Gutiérrez and Philippon (2017). This also opens the questions on the investment determinants: for instance, Kothari et al. (2015) discuss the predominant role of profits growth and stock returns in predicting investment, while many other variables, such as interest rates, seem to be quite irrelevant, or Gennaioli et al. (2016) discuss the role of expectations in determining investment, which seem to be more adaptive than rational. Moreover, a precautionary motive can also be related to the long-term accumulation of cash and liquid assets by corporations, on which many articles focused; see Bates et al. (2009), Riddick and Whited (2009), or Falato et al. (2013). However, notice that "savings" (the stock) is conceptually different from "saving" (the flow): for example, corporations willing to strengthen their liquidity position could issue long-term liabilities and acquire liquid assets, without any change in their net lending positions; or corporations willing to deleverage could decrease investment relative to saving and use these resources to repay debt, but with no change in their cash holdings. Indeed, the accumulation of cash holdings seems to be related to risk and/or non-collateralizable assets in small firms that pay no dividends; on the other hand, the increase in net lending is about large corporations that pay dividends with no much firm-risk .

The third motive focuses instead on a more uncommon perspective: firms with enough market power can potentially invest less to maintain their dominant position, while accumulating assets with their saving flows[1]. This links to recent articles that point to a broad rise in market power in the U.S. economy; see e.g. Council of Economic Advisers (2016), Ohlhausen (2016), Grullon et al. (2017), Barkai (2017), or Autor et al. (2017). Furthermore, there is also evidence about predatory behavior and the accumulation of liquid assets; see Bolton and Scharfstein (1990), Fresard (2010), and Frésard and Valta (2016).

[1]See, e.g., Paul Krugman's "Robber Baron Recessions" on April 18, 2016, and "Profits Without Production" on June 20, 2013, *The New York Times*.

Related literature. There are only few papers focusing on the recent pattern of corporate net lending, mainly from an empirical perspective: Loeys et al. (2005), Cardarelli and Ueda (2006), André et al. (2007), and recently Gruber and Kamin (2015). They all document that, while profits remained high and constant over time, corporations sensibly decreased their capital expenditures (together with a sharp decrease in their relative price), paying out to investors only a share of the increased net resources available. Furthermore, Koo (2009) argues that, for Japanese corporations, deleveraging has a been central driver of the move from borrowing to lending.

Other articles have a more theoretical flavor, trying to explain the glut by some modeling features. Armenter and Hnatkovska (2014) discuss the increase in corporate saving as the consequence of changes in taxation, in a framework with financial frictions. Bacchetta and Benhima (2015b) and Bacchetta and Benhima (2015a) discuss the role of intangible capital in the increase in corporate saving. Chen et al. (2017) also use firm-level data, showing that neither size, nor age, nor being a multinational has any role in the saving glut, which is instead a very pervasive phenomena. Their model takes the decrease in prices of investment goods and interest rates to explain the glut, relating it also to the fall in the labor share; however, investment rates should also increase, while in fact they have not.

Interestingly, at about the same time, the net lending/borrowing position of other sectors (or sectoral imbalances) attracted a lot of attention, both in academia and in policy circles. First, the "global saving glut", i.e. the current account surpluses of emerging economies that financed the current account deficits of some advanced economies, the U.S. in particular. The term was coined in a couple of influential speeches by the former FED governor Bernanke (2005; 2007). Second, the government deficits, i.e. the excess of expenditures over taxes, that characterized much of the discussion following the worst economic crisis since the Great Depression. Noticeably, the discussion over this topics focused as much on the causes as on the consequences, while on corporate imbalances the literature is struggling on the causes, let alone discussing the consequences. The standard textbook view on the current account balance is the inter-temporal approach to the current account, which sees it as a problem of optimal allocation of consumption and investment across time; see Obstfeld and Rogoff (1996). This standard view had in fact created a famous puzzle in international economics: why doesn't capital flow from rich to poor countries? See Lucas (1990). Recent works tried to rationalize this fact by adding financial frictions to the story, to explain why China is financing the United States current account deficit; see Caballero et al. (2008) in particular. However, it is difficult to imagine how corporations lend to the rest of the economy because they lack investment opportunities in financial markets, due to a sector-specific financial friction. Rather, they might lack investment opportunities in the real sector, but it is very difficult to assess this hypothesis in practice.

Another strand of literature deals with the government position. On the policy side, since the General Theory of Keynes (1936), government deficits are just the immediate consequence of fiscal policies, aimed at controlling the aggregate demand (either ad hoc or due to automatic stabilizers). But such literature addresses a short-term issue, while in fact we are looking at long-term patterns. And indeed there are important articles looking at the role of public debt as safe liquid asset in the economy, from a long-term perspective; see Holmström and Tirole (1998), Holmström and Tirole (2002), Caballero (2006), or Caballero and Farhi (2013).

2.2 Flows of funds of U.S. listed firms

The corporate saving glut has been firstly identified from aggregate data, using national accounts statistics. Here I address the question of whether firm-level data delivers a similar picture and, if yes, what are the firms driving the glut.

Census data registered 5,734,538 firms in the United States in 2010: most of them are privately held, as only 3,716 (or 0.06%) were listed on a U.S. exchange. However, as the glut is an aggregate phenomenon, looking at the biggest firms only (or at least those that are publicly listed) should be appropriate. Indeed, the literature has recognizing that the biggest firms have a disproportionate impact on aggregate variables, since the firm-size distribution is fat-tailed; see Gabaix (2011).

2.2.1 Definition

The notion of "saving" also applies to firms. Gross saving identifies the amount of undistributed profits, while net saving is net of investment expenditures. Net saving can be either negative or positive; in fact, it is more commonly identified with net lending/borrowing,

$$\begin{aligned}\text{Net lending/borrowing} &= \overbrace{(\text{Profits} - \text{Dividends})}^{\text{Gross saving}} - \text{Investment} \\ &= \Delta\text{Financial assets} - \Delta\text{Financial liabilities}\end{aligned}$$

which is also equivalent to the net accumulation of financial assets, i.e. the second line. This must be the case because of the double-entry accounting system. This relationships can be rearranged as follows, to highlight, on the left and on the right hand-side respectively, the sources and the uses of funds,

$$\text{Profits} + \Delta\text{Financial liabilities} = \text{Investment} + \text{Dividends} + \Delta\text{Financial Assets}.$$

2.2.2 Sample

Data comes from Compustat, which includes all the publicly listed firms in U.S. stock markets, from 1960 to 2015. I focus on the nonfinancial corporate sector; hence, I exclude financial firms (SIC 6000-6799) and regulated utilities (SIC 4900-4999). Then, I also exclude observations that have unreported or negative values of sales, unreported values or less than \$50 thousands of total assets, negative values of capital expenditures and of common/ordinary equity, and observations whose growth rate of sales exceeds 500%. I exclude firms with gaps in their reported values of sales and of operating expenditures. Finally, I winsorize all variables at one and ninety-nine percentiles.

2.2.3 Sources and uses of funds

Net lending/borrowing is an economic flow. In order to better understand where does it come from, it is useful to discuss the related accounting flows: the sources and uses of funds, at the firm-level. Below I describe how to empirically define them.

There are two sources of funds: internal and external. I classify flow payments to the holders of equity and debt, i.e. dividends and interest payments, as uses of funds; accordingly, sources of funds are defined gross of them. Internal financing (iFin) is equal to net income (before dividends but after extraordinary items) plus depreciation allowance, interest payments, and R&D expenditures; this is to avoid double-counting R&D expenditures, which I consider as investment that is a use of funds – in accordance with recent national accounting practices[2]. External financing (eFin) is instead equal to net funds from equity-holders (new stock issuance net of stock repurchases) plus net funds from debt-holders (long-term debt issuance, net of debt reductions, plus current debt changes). Definition of external finance are common in the literature; see e.g. Rajan and Zingales (1995) or Eisfeldt and Muir (2016). In Compustat alphabet,

$$\begin{aligned} \text{iFin} &= \text{ni} + \text{dp} + \text{xint} + \text{xrd}, && (2.1) \\ \text{eFin} &= (\text{sstk} - \text{prstkc}) + (\text{dltis} - \text{dltr} + \text{dlcch})\,. && (2.2) \end{aligned}$$

These available funds, in turn, can be used either for payouts or for real, financial, or other kinds of investments. Flow payouts (pay) is as the sum of total dividends paid and interest expenses. Real investment (rInv) is the sum of capital and R&D expenditures, plus the net change in inventories. Financial investment (fInv) is the change in cash and cash equivalents, which are mainly short-term liquid assets. Finally, other investment (oInv) is the residual balancing term, which captures all the uses of funds that are not captured in the other categories. Not to say that other investment is negligible in value, but the variety of the specific uses does not allow for a meaningful categorization at this level of analysis. In Compustat alphabet:

$$\begin{aligned} \text{pay} &= \text{dvt} + \text{xint}, && (2.3) \\ \text{rInv} &= \text{capx} + \text{xrd} + \text{invch}, && (2.4) \\ \text{fInv} &= \text{chech}, && (2.5) \\ \text{oInv} &= \text{iFin} + \text{eFin} - \text{rInv} - \text{fInv}. && (2.6) \end{aligned}$$

To sum up, the following balancing equation must hold:

$$\text{iFin} + \quad \text{eFin} = \text{pay} + \text{rInv} + \text{fInv} + \text{oInv}. \quad (2.7)$$

Now, using these definitions, we can define net lending/borrowing as

$$\begin{aligned} \text{netLB} &= \text{iFin} - \text{pay} - \text{rInv} && (2.8) \\ &= \text{fInv} + \text{oInv} - \text{eFin} \end{aligned}$$

[2]See Corrado and Hulten (2010) on the relevance of treating R&D expenditures as investment, rather than current non-capital expenditures.

where the second line simply reminds us that net lending/borrowing is also equal to the change in financial assets less the change in financial liabilities; this is a feature of every double-entry accounting framework and, in principle, we could also use the variations in the stocks of assets and liabilities to derive it. So-defined, net lending/borrowing is in accordance with its aggregate definition (i.e. profits, less dividends, less investment) and also notice that, by a straightforward substitution, the following holds true:

$$\text{netLB} \;=\; (\text{ni} + \text{dp}) - (\text{dvt}) - (\text{capx} + \text{invch})\,. \tag{2.9}$$

Notice how do we account R&D expenditures: they are accounted as investment, but also as internal funds, so that they cancel out exactly when defining net lending/borrowing. That is, considering them either as investment or as expenditures is neutral to net lending/borrowing. On the other hand, if R&D were capitalized, then it would be very similar to the accounting of capital expenditures: there are depreciation and amortization expenditures (dp) on the sources of funds and capital expenditures (capx) on the uses of funds, which in fact do not cancel out exactly, but only with lags, over the depreciation period.

Net lending/borrowing is rather similar to another measure that is sometimes found in the literature: the financing gap, which captures the extent of a firm's financing needs and is broadly defined as the difference between investment and internal funds available; see Hennessy and Whited (2005). The disputable issue is what we can consider as available internal funds: do dividends affect this availability? If yes, we can define, in our framework, the financing gap as

$$\begin{aligned} \text{fgap} &= \text{rInv} - (\text{iFin} - \text{pay}) \\ &= -\text{netLB} \end{aligned} \tag{2.10}$$

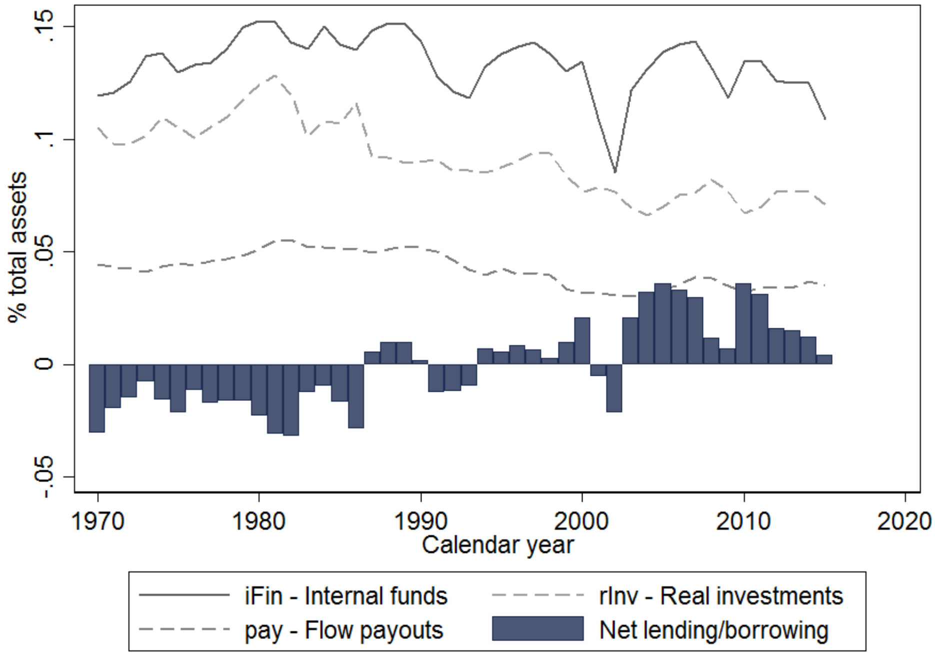
which then is exactly equal to the (opposite of the) measure of net lending/borrowing. Alternatively, considering dividends as not strictly necessary, we would obtain the following definition: $\text{fgap}' = -\text{netLB} - \text{pay}$. Nevertheless, rather than the financing gap definition, I prefer use net lending/borrowing definition, even if the two are equivalent, exactly because we are talking about positive net lending – the corporate saving glut is the reversal of the financing gap.

2.2.4 The saving glut

First of all, it is necessary to establish whether there is a saving glut or not also among publicly listed firms. Figures 2.1 and 2.2 reports the net lending/borrowing measure, each with a different set of variables used to compute the measure, as in equations (2.8) and (2.9), respectively. The values are aggregate value, computed as the cross-sectional sum of all firms in the sample and divided by the cross-sectional sum of total assets.

What happened to the determinants of net lending/borrowing? Few facts stand out: (*i*) internal funds and profits are subject to cyclical swings, especially a drop in 2001, but are still high, even though slightly lower than the levels of the late '70s; (*ii*) real investment shows an evident decreasing pattern, even after taking into account R&D expenditures; and (*iii*) flow payouts are remarkably stable over time.

Figure 2.1: Net lending/borrowing: from sources and uses of funds.



As a consequence, more or less at the start of the new millennium, firms started lending rather than borrowing. Therefore, the corporate saving glut appears to characterize also U.S. listed firms, in a similar fashion to what national accounts data tells us. The magnitudes are in the interval of -4/4% of total firm assets; in proportion to U.S. GDP, values are pretty similar, perfectly in line to the values coming from national accounts data. For instance, in 2011 GDP was \$15'520 billions while net lending was \$693 billions: that is 4.47% of GDP (or 2.7% of total assets). Notice that shares are computed over total assets of all firms.

Figure 2.3 shows how the measure of net lending/borrowing changes when considering not only flow payouts to shareholders (dividends) but total payouts: dividends, plus shares repurchases, less share issued; items dvt + prstkc − sstk. The pattern is a bit more nuanced, slightly closer to zero in most of the years, with an increasing relevance of share buybacks in particular after 2000, but the increasing trend is still apparent. That is, the recent upsurge of equity buybacks lowers the amount of net lending, but it rather seems a phenomenon symmetrical around zero, i.e. in the '70s equity issuance lowered a bit the amount of net borrowing.

It is of interest also to show what happened to the relative sources and uses of funds. Figure 2.4 shows the share of external financing (eFin) over all the sources of funds (eFin + iFin): while it averaged around 10-15% in the '70s, '80s and '90s, since year 2000 the share drops to zero, or even negative. That is, external financing, in terms of debt and equity net issuance, is mostly irrelevant as a source of financing – firms, on aggregate, do self-finance themselves with internal funds. There is only a little spike upwards around the end of the time-horizon (2015), which might reflect firms finally taking advantage of the zero-interest-rates environment.

Figure 2.2: Net lending/borrowing: profits, less dividends, less investment.

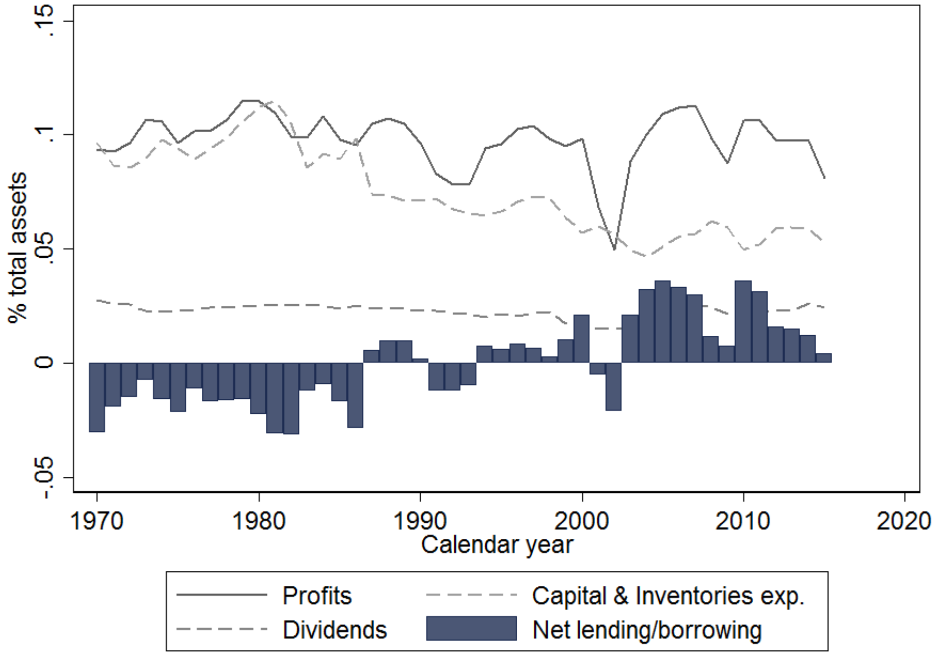


Figure 2.3:

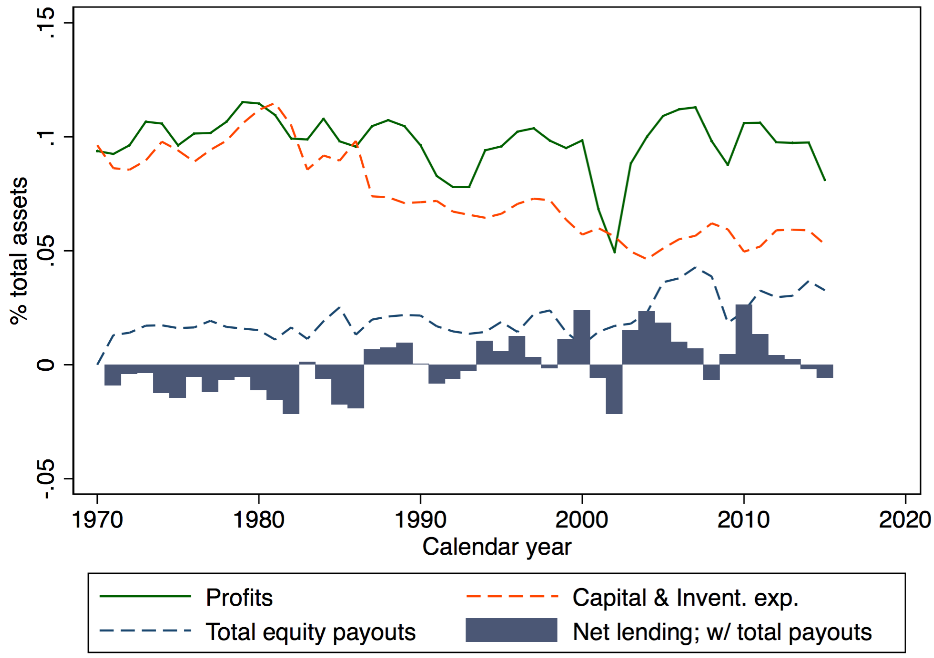
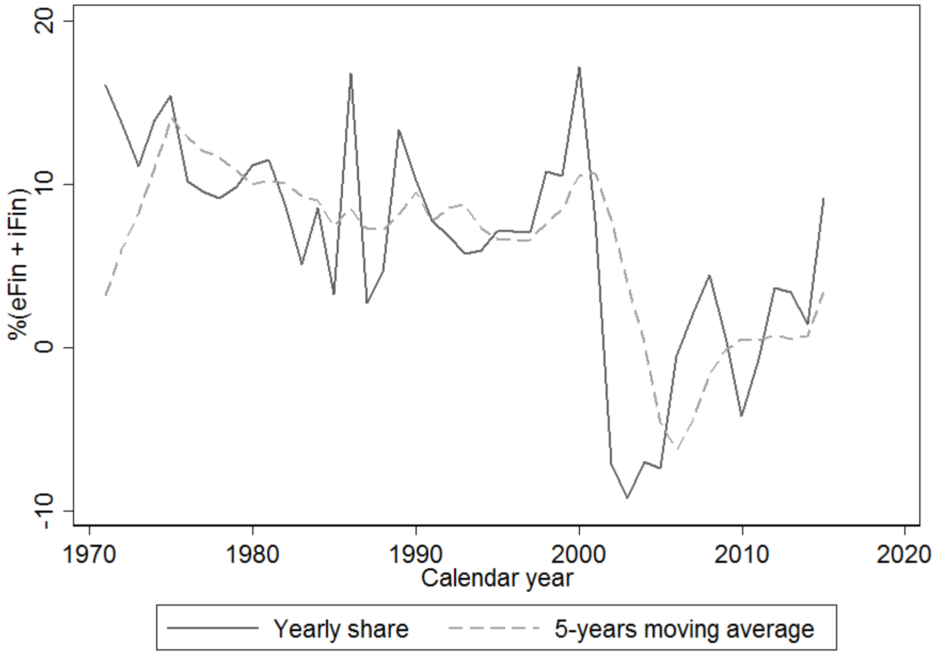


Figure 2.4: Relative sources of funds: eFin vs. iFin.



2.2.5 The saving glut: which firms?

What are the firms behind these patterns? Of course, the biggest firms are *a priori* the obvious suspects, since we are discussing about aggregate patterns. Indeed, figure 2.5 shows that the largest firms are behind the glut: the top 100 and top 500 firms (by sales) pattern of net lending/borrowing matches almost completely the aggregate pattern. But is this pattern shared among all firms – or is it particular to only a subset of them?

Figures 2.6 and 2.7 divide firms among quartiles (by net lending/borrowing) and report averages of various variables. Figure 2.6 shows that the gap between profits and investment is the major determinant of the glut: firms that are borrowing have either small profits and/or high investment, while firms that are lending have either large profits and/or low investment. Notice in particular the difference between the second and third quartiles; larger profits and lower investment. On the other hand, dividends play a minor role. Figure 2.7 shows instead the what correlates with net lending. First, firms with large R&D expenditures do in fact borrow; thus, the emergence of the glut as a consequence of an inability to borrow because of intangible capital seems in contradiction with this fact. Second, larger values[3] of net lending/borrowing are peculiar to smaller firms; which is quite obvious and does in fact tell us much about anything. Third, larger cash holdings are associated both to borrowing firms, who might hold them for precautionary motives[4], and to lending firms, who might accumulate financial assets as consequence of the yearly saving flows. Fourth, the latter "mechanical" motive might also apply to a reduction in debt, which is more pronounced in lending firms.

[3]Above 5.6% or below −5.6% relative to firm's assets, which are the P25 and the P75 of the distribution.

[4]See e.g. Acharya, Almeida, Campello (2007).

Figure 2.5: Net lending/borrowing: top 100 and top 500 patterns.

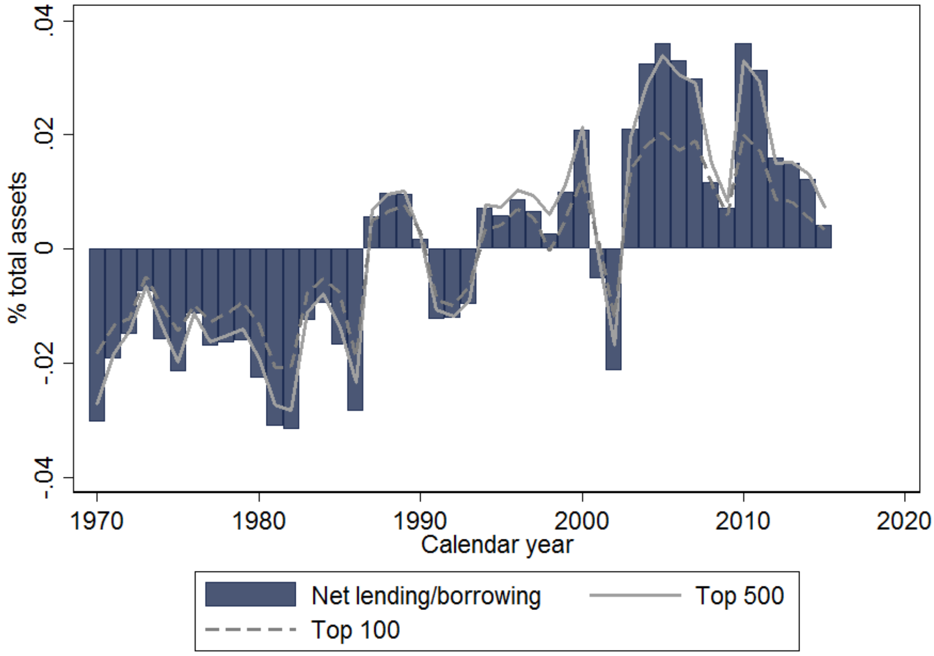


Figure 2.6: Net lending/borrowing and its components; by quartiles.

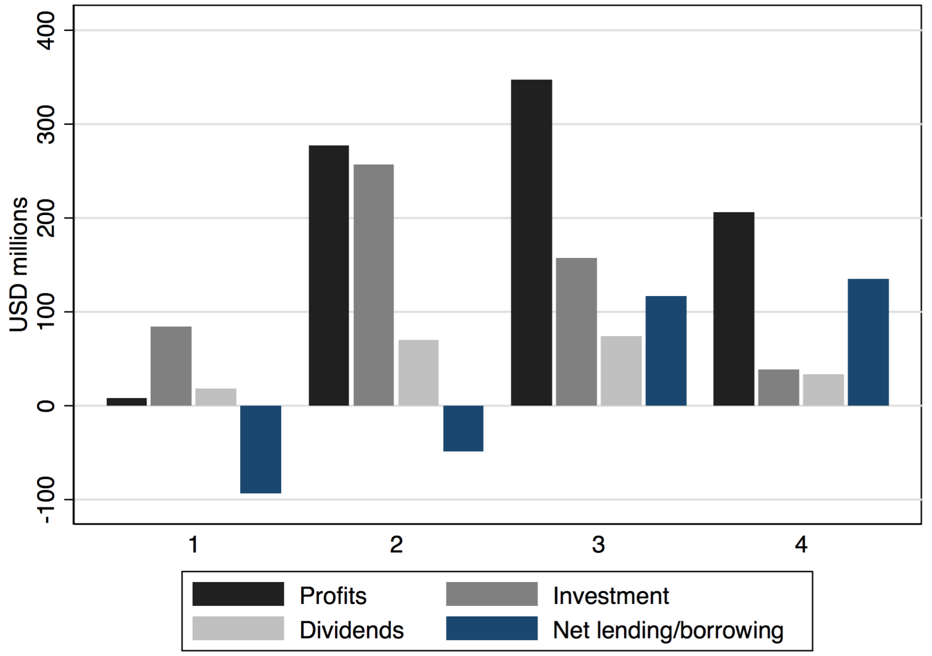


Figure 2.7: Net lending/borrowing and other variables; by quartiles.

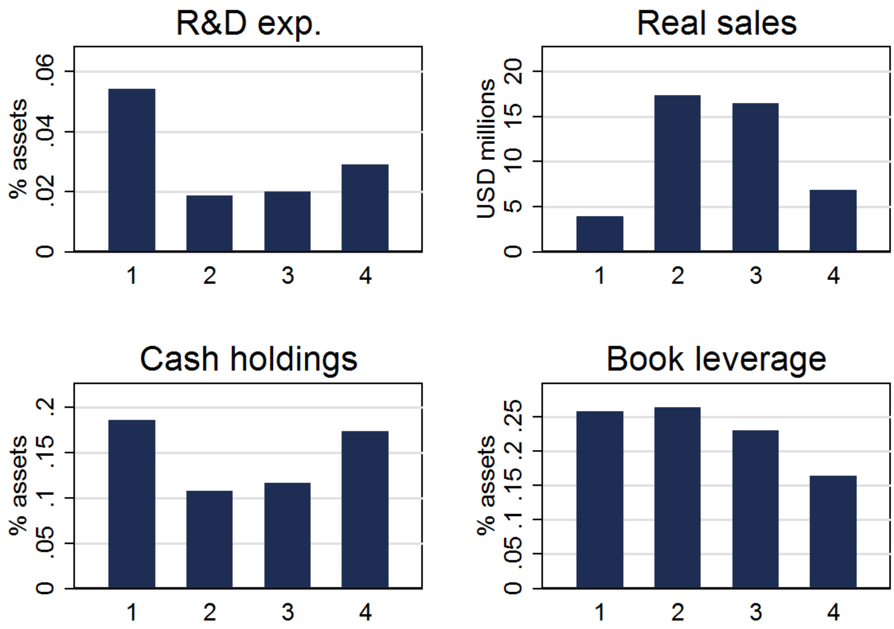


Figure 2.8 reports instead the median value of net lending/borrowing for different five-years cohorts, based on the year in which each firm appears for the first time on Compustat. That is, the first cohort reports the median value among all firms that entered the sample between 1960 and 1964; and so on. Even though the graph may appear confusing at first – each line identifies the cohort that starts where the line starts – the main point is that all firms behave similarly. In particular, notice how during downturns every cohort looks alike. The only exception is about some cohort that, when relatively young, are still net borrowers.

Finally, figure (2.9) reports the measure of aggregate net lending/borrowing by some economic sectors: manufacturing (NAICS 31-33), retail (NAICS 44-45), services (NAICS 41-49 and 54-89). I also use the following classification: I&T sector (SIC 7370-79, 4800-99, 3570-79 and NAICS 51), and high tech sector (NAICS 3254, 3341-42, 3344-45, 3364, 5112, 5161, 5179, 5181-82, 5413, 5415, 5417). The latter has been used by Hecker (2005) and Decker et al (2016). Overall, there seems to be absolutely no sector-specific pattern, as all sectors are displaying the same pattern of increasing net lending. This points to really broad and aggregate phenomena, which encompass all sectors.

2.3 Why the glut?

Now comes the question. First, I briefly discuss the most plausible explanation, at least to me. Second, I empirically investigate the role of alternative explanations, however without finding any compelling evidence.

Figure 2.8: Net lending/borrowing: median by cohorts.

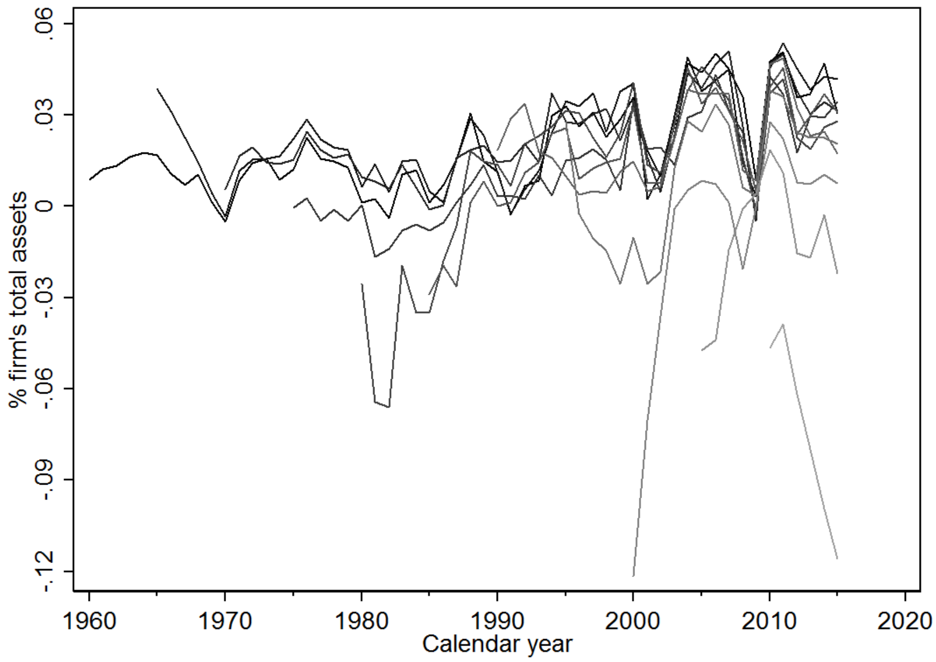
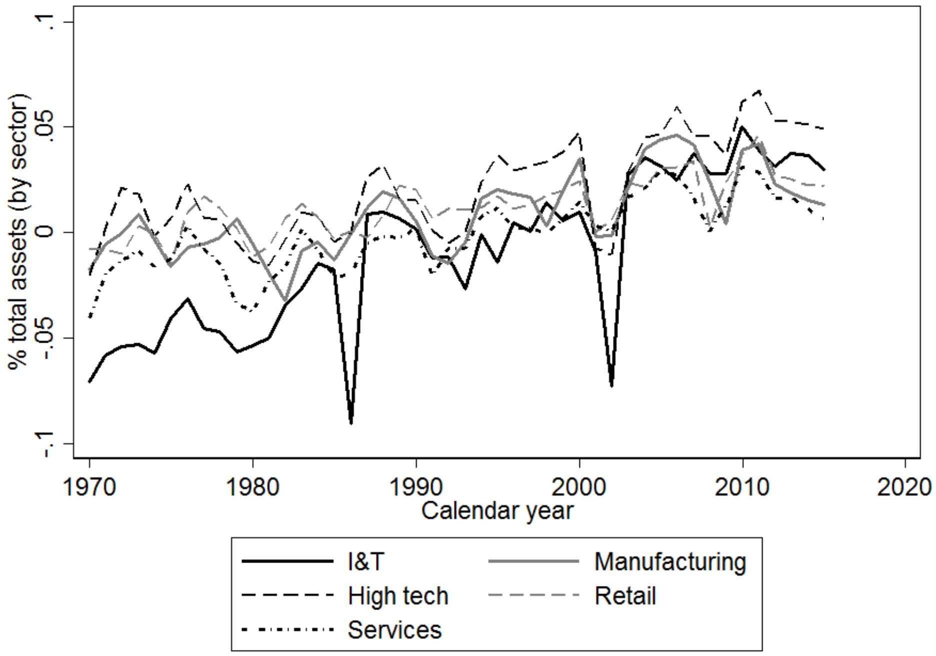


Figure 2.9: Net lending/borrowing: aggregates by economic sectors.



2.3.1 Capital vs. Investment shares

There are three relevant ingredients: the capital share, the investment share, and dividends.

The capital share can be derived from the aggregate production function. For instance, with Cobb-Douglas technology, $Y = AK^{\alpha}L^{\beta}$, and competitive factors markets, so that $r = \partial Y/\partial K$, the capital share is equal to

$$rK = \alpha Y,$$

where typically $\alpha \sim 30/35\%$ is assumed empirically. Most importantly, this share is independent of the level of capital K in the economy.

The investment share, on the other hand, depends on the level of capital in the economy. In the basic Solow growth model, the steady state[5] level of investment I^* is just enough to compensate for capital depreciation and population growth, so as to maintain constant the level of capital. Using the expression of the steady-state level of capital K^*, obtain

$$\frac{I^*}{Y} = \frac{\delta K^*}{Y} = \delta \left(\frac{s}{\delta + n}\right)^{\frac{1}{1-\alpha}}$$

which gives numbers around 10/15%, when assuming standard values for depreciation, saving rate, and population growth: $\delta \sim 10/15\%$, $s \sim 10/15\%$, and $n \sim 2/4\%$.

Finally, dividends are relatively sticky over time. Even accounting for total flows to equityholders, including shares issuances and buybacks, does not change much the long-term pattern of dividends: always around 3/5% of corporate profits.

Therefore, by subtracting the investment and dividend shares to the capital share, given reasonable parameters, one remains with a positive value: that is, positive corporate net lending. In other words, the fact that the corporate sector is not anymore borrowing to finance its capital accumulation should not surprise, but instead should be seen as a natural consequence of reaching a steady-state level of capital in the economy – which, sooner or later, we have to reach. This should be the baseline view of the glut, unless evidence suggests otherwise.

2.3.2 Alternative motives: looking for evidence

I believe that there can be three different and major alternative stories:

1. *deleveraging* glut: firms are saving to decrease their leverage, which in turn shows up as net lending;

2. *precautionary* glut: firms are saving against an uncertain environment and/or because a more promising future; or

3. *strategic* glut: firms are saving to increase their market power, in order to pursue acquisitions or predatory practices.

[5]which is not necessarily the optimum. Indeed, with Cobb-Douglas, the Golden-rule optimal saving rate is $s^g = \alpha$, which allows the maximum level attainable of consumption.

In brief, do corporations have fear of debt, of the future, or of themselves? Of course, there could also be other stories, but the alternatives that came to my mind were not much promising[6].

The first story can account for an increasing relevance of binding credit constraints. However, while this could apply to smaller and R&D-intensive firms that use intangible capital that cannot be collateralized, it seems at odd with the largest listed corporations easiness of financing and the increasing financialization of the economy.

The second and third stories also account for another pattern that affected advanced economies: decreasing investment rates, even after accounting for R&D expenditures. This might have been because firms have chosen to decrease their investment rates, either due to precautionary motive[7] or in line with the aim of maximizing profits, given an increasing amount of market power. That is, both stories explain both the *investment dearth* and the *saving glut* at the corporate level, not only the second one.

Against the third story lies a theoretical motivation: in which sense does saving help a firm? Why the saving flow is different from the savings stock, such as cash holdings, in this respect? On the other hand, it is an intriguing line of research, with important policy implications.

Deleveraging glut. If too much leverage is the problem that firms are willing to solve, thereby diminishing their borrowing and even saving, then we should see a pattern of decreasing leverage in aggregate data. In fact, in the last forty years, aggregate debt outstanding has remained broadly stable.

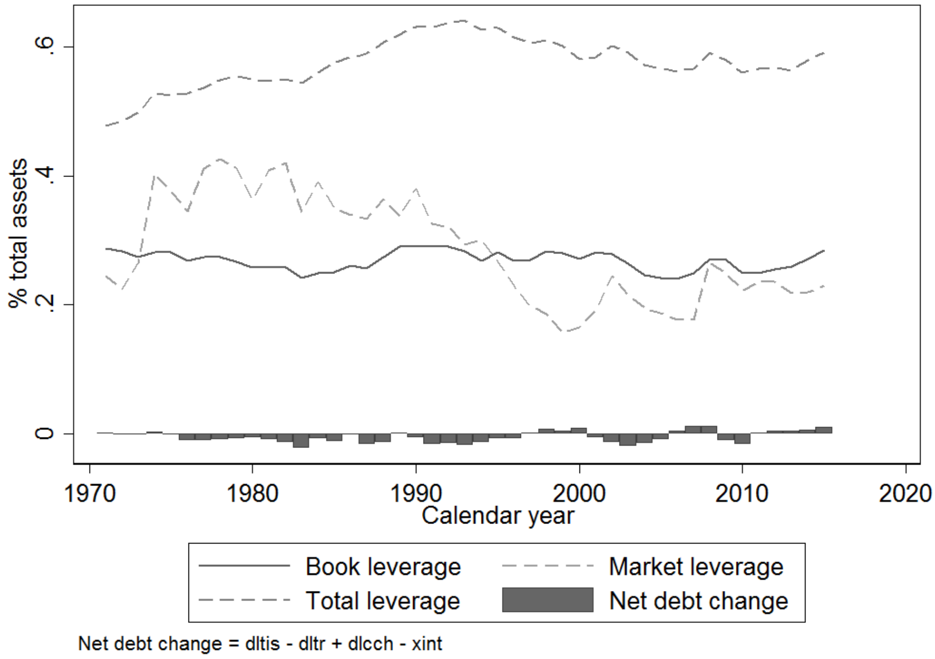
Figure 2.10 shows three measures of leverage: book leverage (debt in current and long-term liabilities over total assets, i.e. (dlc+dltt)/at), market leverage (debt in current and long-term liabilities over debt plus equity, i.e. (dlc+dltt)/(dlc+dltt+csho*prcc_f), and total leverage (total liabilities over total assets, i.e. lt/at). Only market leverage shows a sharp decrease in the 1990s – which is mostly driven by the equity market boom of those years. The other measures remain flat and stable. Even by netting out debt with cash and liquid assets we barely change the picture (not shown in the figure) – but that has mostly to do with the changing composition of assets, not of liabilities. In addition, also net debt change (i.e. issuance of new debt less purchase of outstanding debt and interest expenses) does not indicate a decrease in leverage; rather, it shows the opposite, since it turns positive only in some years around and after 2000.

On the other hand, the median firm shows in fact a decline in leverage over time, from a book leverage of 20-25% of assets in the '70s and '80s, to about 15% in the 2000s, with

[6]For instance, another story could have been that firms are becoming corporate venture capitalists, thus lending funds to other companies/projects rather than investing on their own. Consider Alphabet Inc.: in addition to its largest business subsidiary, Google, it also owns Google Ventures (founded in 2009) and Google Capital (founded in 2013). They both are aimed at venture capital financing, at either initial or later stages of growth. This corporate structure is not uncommon, with many companies now also holding an investment arm. This would partially show up as net lending - i.e. accumulating other financial assets. However, the economic magnitudes do not add up. Estimates point at about $5-10 billions invested each year by corporations in venture capital financing. In comparison, the saving glut is around $500 billions.

[7]There is an extremely huge literature on investment behavior and, in particular, on the effects of uncertainty. Of course, there is no definite answer, neither theoretical nor empirical, but the majority of articles point to a negative relationship; see e.g. Dixit and Pindyck (1994). Often, one of the crucial assumption is the presence of irreversible expenditures.

Figure 2.10: Financial leverage. Aggregate over total assets.



a small reversal in the period 2010-15. For the median firm, netting out cash holdings also implies an almost zero net leverage; see Strebulaev and Yang (2013). Therefore, it is mainly small firms who have low net leverage – and decreasing; at the aggregate level, where large corporations play the game, there is basically no change in leverage, and thus no signs of deleveraging. That is, the increase in net lending does not seem to have much in common with the choice of the capital structure.

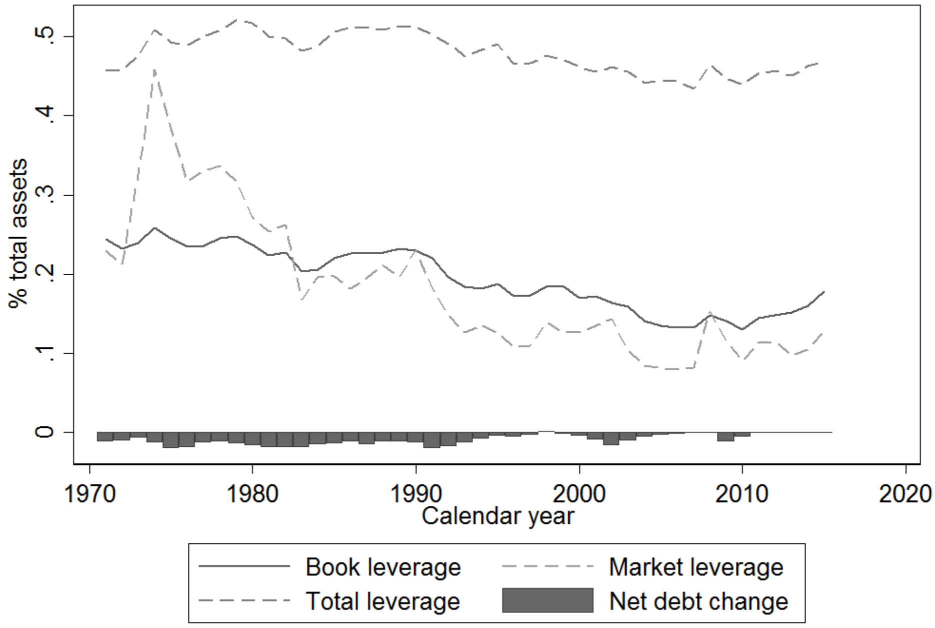
Precautionary glut. Now I move to panel regressions at the firm-level. But before looking in depth at some specific hypothesis, it is useful to point out some basic facts. Table 2.1 reports the results of panel regression performed over the whole sample of firms and only on the top 500/100 firms by sales (in each year), to better focus on the largest corporations. That is,

$$\text{netLB}_{i,t} = \alpha_i + X_{i,t}\beta_{i,t} + Z_i\gamma_i + \delta_t + \varepsilon_{i,t}, \tag{2.11}$$

where α_i are firm fixed-effects, $X_{i,t}$ and Z_i are time-varying and time-fixed variables, δ_t is a set of time dummies, and $\varepsilon_{i,t}$ is the residual component. Notice that must avoid explanatory variables that are in a linear relationship with net lending/borrowing, which is, by construction, a linear function of profits, less investment, less dividends. For instance, capital expenditures over assets would show up as extremely significant, with a negative coefficient – but that just because of a mechanical relationship.

Size appears to be the most important variable in the whole sample specification, together with R&D expenditures: indeed, small and R&D intensive firms are borrowing, while only the largest corporations are lending, as we have already pointed out. Once we focus on the biggest firms, only book leverage, market-to-book ratio and net working

Figure 2.11: Financial leverage. Median over total assets.



Net debt change = dltis - dltr + dlcch - xint

capital hold a significant impact on net lending/borrowing. In particular, the market-to-book ratio is the one that gains the most explanatory power. Of course, a higher market-to-book ratio can be associated with large market power – as well as many other different things, e.g. a high ratio could be associated with positive investment. Further investigation is needed.

Let's now move to the precautionary hypothesis: firms are lending because they do not see many profitable opportunities today and rather prefer to move (financial) resources in the future.

First, I look at volatility measures: the rolling standard deviation of the growth rate in the last six[8] years of sales, earnings before interest taxes depreciation and amortization (EBITDA), operating cash flows (OCF), and net cash flows (NCF); further details are described in appendix B.1. Second, I look at uncertainty measures: analysts expectations about the median forward earnings per share (EPS), its growth rate from the previous year, and the median long-term estimate of the firm's earnings growth rate, together with its standard deviation and its difference with the current EPS growth rate. Data is obtained from the I/B/E/S database. For the sake of simplicity, I focus only on firms belonging to the S&P500 index, as of September 2016. Tables 2.2 and 2.3 report the results of the baseline regression (as in table 2.1) with the added explanatory variables for volatility and uncertainty.

Quite surprisingly, the coefficients on both realized volatilities have the "wrong" sign: negative. That is, an increase in volatility is associated with a decrease in net lending. On the other hand, EPS estimates have different effects: the current and future growth rates exhibit a negative correlation, which is in fact rather weak in magnitude; the coefficient

[8] I use a six-years window instead of the standard ten-years window since it keeps a larger number of observations. Nevertheless, results do not change in a meaningful way.

Table 2.1: Panel regression: net lending/borrowing and some basic explanatory variables.

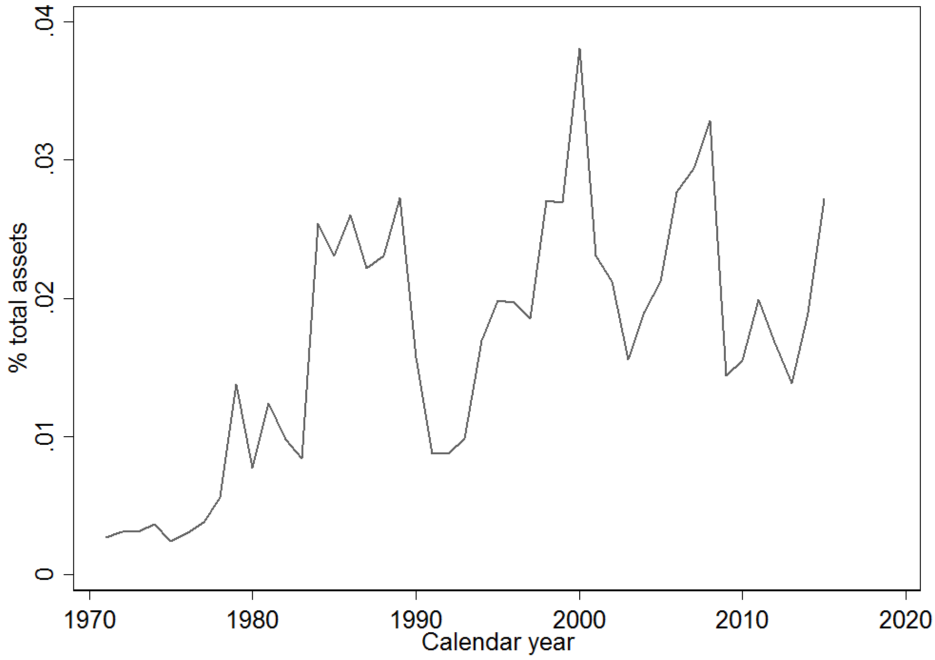
	(1) all	(2) top500	(3) top100
Log total assets	0.367***	0.059***	0.051
	(58.26)	(3.77)	(1.35)
Years since IPO	0.023***	0.019	0.022
	(3.58)	(1.33)	(0.57)
Book leverage	-0.191***	-0.223***	-0.135***
	(-57.02)	(-21.97)	(-5.65)
Market-to-book	0.052***	0.219***	0.210***
	(17.63)	(22.73)	(8.95)
Dividend payer (if =1)	-0.060***	-0.060***	-0.058**
	(-16.92)	(-6.39)	(-2.98)
Net working capital	0.285***	0.213***	0.103***
	(72.31)	(16.62)	(3.64)
R&D exp.	-0.367***	-0.081***	-0.004
	(-89.42)	(-5.99)	(-0.13)
Acquisition exp.	0.023***	0.041***	0.005
	(9.95)	(4.87)	(0.22)
Acquisition-to-assets, SIC4	0.010***	0.030***	0.043*
	(3.98)	(3.39)	(1.96)
Op. Leverage	-0.139***	0.034*	0.046
	(-24.66)	(2.40)	(1.17)
Observations	116921	15677	2934

Standardized beta coefficients; t statistics in parentheses

Time and firm FE are included in all regressions.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 2.12: Acquisitions.



on the expected growth in the growth rates (i.e. long-term less current growth rate) has instead a positive sign, so that a higher growth in the future (relative to the present) is correlated with higher net lending – which is in accordance with a precautionary or "postponing" behavior. Finally, the consensus estimate for the forward 12 months EPS shows a positive correlation, with the greatest magnitude. However, caution is needed in the interpretation of this latter coefficient: indeed, net lending is also a function of profits, so that this might simply be a mechanical correlation, even though EPS is computed per share (which, in fact, their number is quite constant over time).

Strategic glut: the "cash-cow" hypothesis. The story behind this motive is that a profitable firm with market power finds optimal to both decrease investment, since there is no need to keep up with competitors, and to accumulate financial resources, instead of paying them out to shareholders, in order to maintain its market power. There is a small literature focusing on the value of cash for competitive reasons, but not really on the value of saving flows; see e.g. Fresard (2010) and Valta (2012). This is what I want to investigate.

First of all, to substantiate more this hypothesis, we could look at the pattern of corporate acquisitions; see figure 2.12. There are very large swings, which is a well-known fact in the finance literature, that make it difficult to see any long-term pattern. But we can look at the peak-to-bottom variation over decades: this is increasing, from 0-1% in the '70s, to 1-2.5% in the '80s, up until 1.5-4% after 2000. Not really impressive, but not even contrary to the hypothesis of increasing market power and in turn increasing competition through acquisitions. Notwithstanding, having a positive net lending position over time may allow a firm to arrive in a better shape to counter these M&A waves: with lower debt, higher cash, larger equity – so that it becomes easier to acquire than being acquired.

Table 2.2: Panel regression: net lending/borrowing and volatility.

	(1)	(2)	(3)	(4)
Log total assets	0.304***	0.303***	0.267***	-0.006
	(35.95)	(33.24)	(28.98)	(-0.19)
Years since IPO	-0.024**	-0.023**	-0.029***	0.049
	(-3.14)	(-2.85)	(-3.64)	(1.95)
Book leverage	-0.233***	-0.240***	-0.235***	-0.128***
	(-51.93)	(-48.79)	(-48.12)	(-6.00)
Market-to-book	0.117***	0.123***	0.121***	0.237***
	(29.83)	(28.27)	(27.91)	(9.98)
Dividend payer (if =1)	-0.069***	-0.063***	-0.075***	-0.101***
	(-14.01)	(-11.71)	(-13.87)	(-5.23)
Net working capital	0.272***	0.289***	0.274***	0.105***
	(50.79)	(49.26)	(46.71)	(4.06)
R&D exp.	-0.358***	-0.342***	-0.334***	0.045
	(-64.39)	(-57.35)	(-56.67)	(1.80)
Acquisition exp.	0.035***	0.036***	0.037***	0.015
	(11.16)	(10.44)	(10.96)	(0.67)
Acquisition-to-assets, SIC4	0.007*	0.008*	0.008*	0.047*
	(2.24)	(2.23)	(2.11)	(1.99)
Op. Leverage	-0.116***	-0.128***	-0.112***	0.026
	(-14.75)	(-15.55)	(-14.04)	(1.07)
Sales volatility	-0.089***		-0.077***	-0.011
	(-21.03)		(-16.53)	(-0.54)
OCF volatility		-0.017***	-0.004	-0.006
		(-4.14)	(-0.97)	(-0.32)
EBITDA volatility			-0.049***	-0.041*
			(-9.10)	(-2.11)
NCF volatility			0.003	-0.076***
			(0.66)	(-3.87)
Observations	79535	68724	68706	2562

Standardized beta coefficients; t statistics in parentheses

Time and firm FE are included in all regressions.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.3: Panel regression: net lending/borrowing and uncertainty.

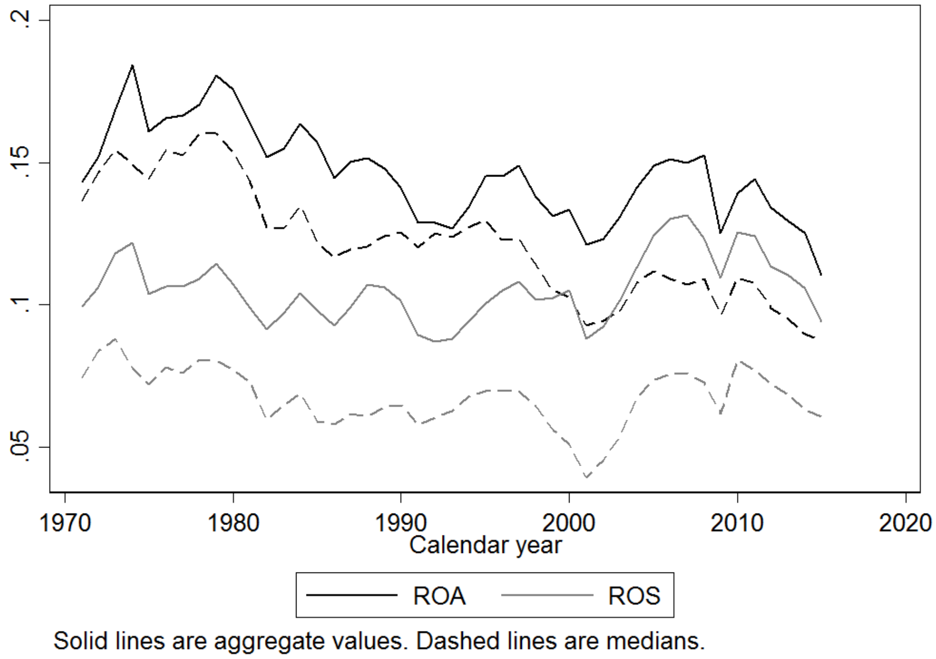
	(1)	(2)	(3)	(4)	(5)
Log total assets	0.089***	0.028	-0.008	0.122***	0.082***
	(3.96)	(1.16)	(-0.33)	(5.46)	(3.45)
Years since IPO	0.027	0.045	0.037	0.037	0.046
	(0.95)	(1.66)	(1.37)	(1.30)	(1.59)
Book leverage	-0.169***	-0.147***	-0.149***	-0.164***	-0.156***
	(-11.98)	(-9.34)	(-9.53)	(-11.51)	(-10.08)
Market-to-book	0.281***	0.302***	0.291***	0.303***	0.288***
	(19.66)	(18.25)	(17.64)	(21.21)	(18.79)
Dividend payer (if =1)	-0.068***	-0.076***	-0.075***	-0.073***	-0.069***
	(-4.25)	(-4.35)	(-4.35)	(-4.52)	(-4.07)
Net working capital	0.206***	0.204***	0.194***	0.217***	0.198***
	(11.93)	(10.76)	(10.31)	(12.55)	(10.59)
R&D exp.	-0.148***	-0.032	-0.030	-0.152***	-0.087***
	(-7.67)	(-1.58)	(-1.47)	(-7.89)	(-4.25)
Acquisition exp.	0.041***	0.032*	0.032*	0.042***	0.036**
	(3.38)	(2.41)	(2.45)	(3.41)	(2.80)
Acquisition-to-assets, SIC4	0.011	0.018	0.011	0.020	0.021
	(0.86)	(1.37)	(0.82)	(1.59)	(1.56)
Op. Leverage	0.064**	0.063**	0.069**	0.055*	0.054*
	(2.70)	(2.86)	(3.19)	(2.36)	(2.28)
EPS 12m forward	0.168***		0.145***		
	(10.44)		(8.29)		
Median long-term EPS growth		-0.055***	-0.066***		
		(-3.42)	(-4.09)		
St.dev. long-term EPS growth		-0.058***	-0.050***		
		(-4.60)	(-3.98)		
EPS 12m growth rate				-0.052***	
				(-5.11)	
EPS long vs short growth					0.059***
					(5.54)
Observations	6392	5479	5479	6391	5803

Standardized beta coefficients; t statistics in parentheses

Time and firm FE are included in all regressions.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 2.13: Profitability measures.



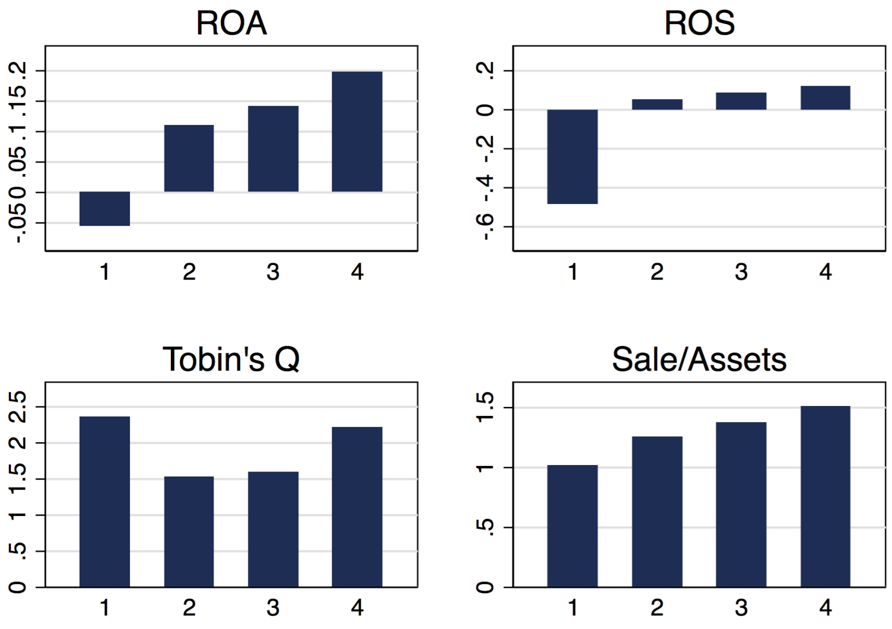
But how to directly gauge the degree of market power? We can start by looking at some profitability indexes. Figure 2.13 report the measures of return on assets (ROA, i.e. EBITDA over total assets) and return on sales (ROS, i.e. EBIT over sales) at the median and at the aggregate level. The most evident pattern is that profitability is much higher at the aggregate than at the median level, even increasingly so, which is consistent with larger firms obtaining larger profits – and possibly enjoy greater market power. In fact, it might just be that larger firms are larger precisely because they are more profitable, and did grow more!

Figure 2.14 shows some (average) profitability measures by quartiles of net lending/borrowing. The lending firms are much more profitable than the average; also Tobin's Q is larger, even if not as much as borrowing firms. The idea that comes to mind is that these lending firms are "cash-cow" firms that enjoy some non-negligible degree of market power.

One of the most direct and common measure of competition is the Herfindahl–Hirschman Index (HHI), i.e. the sum of squared market shares within a given industry. Figure 2.15 reports the median values of various HHI: both when computed over defined SIC or NAICS 3-digits industries and when computed over a more refined definition of industries, i.e. using text-based algorithms to associate together clusters of similar firms, either with a fixed number of different industries (FIC300) or with an evolving one (TNIC). See Hoberg and Phillips (2010, 2016) for precise definitions and details on this latter approach; data is available only from 1997 onwards. If we disregard the HHI computed over SIC industries, which is the most "obsolete" classification system, and the swings of its median value, the other measures all show an increasing level of concentration.

Clearly, HHI are problematic: industries can be badly defined, not representing the true field of competition; sales values can be missing, e.g. private firms are not reporting

Figure 2.14: Profitability by net lending/borrowing quartiles.



sales on Compustat; concentration is not even an obvious sign of market power or bad outcomes, since there are many other factors at play, e.g. economies of scale; and so forth. However, again, there is no apparent evidence against the hypothesis of increasing market power.

Tables 2.4 and 2.5 report the estimated coefficients on the various HHI, first over the whole sample and second over the restricted sample of the top 500 biggest firms. However, almost all of them are either not significant or have very small magnitudes, suggesting a very weak relationship between net lending/borrowing and industry concentration measures.

Tables 2.6 and 2.7 do a similar exercise with another potential proxy of market power: tax rates. Indeed, large corporations with huge market power might also be able to pay lower taxes than weaker and smaller firms. I include different tax rates in the regression. However, there is no apparent nor significant relationship between net lending and such measures. That is, the evidence in favor of the "cash cow" hypothesis is in fact weak.

2.4 Concluding remarks

Positive saving (or net lending) by the aggregate corporate sector in the U.S. is a quite recent phenomena, which is driven by the behavior of the largest U.S. listed corporations. Why are they saving, instead of borrowing? Neither a deleveraging, nor a precautionary, nor a strategic motive seems to account for it – at least from the modest empirical perspective pursued in this article. Indeed, aggregate leverage is remarkably constant; realized volatility at the firm-level has a negative correlation with net lending; EPS estimates show no meaningful or significant correlations; industry concentration ratios, such

Table 2.4: Net lending/borrowing and HHI. All firms.

	(1)	(2)	(3)	(4)	(5)
Log total assets	0.392***	0.392***	0.325***	0.367***	0.367***
	(39.21)	(39.55)	(43.54)	(58.10)	(58.19)
Years since IPO	0.020	0.019	0.031***	0.023***	0.023***
	(1.69)	(1.64)	(4.12)	(3.56)	(3.54)
Book leverage	-0.187***	-0.188***	-0.188***	-0.191***	-0.191***
	(-31.31)	(-31.29)	(-45.39)	(-57.01)	(-57.01)
Market-to-book	0.093***	0.093***	0.051***	0.052***	0.052***
	(19.70)	(19.55)	(13.98)	(17.63)	(17.64)
Dividend payer (if =1)	-0.087***	-0.088***	-0.059***	-0.060***	-0.060***
	(-14.85)	(-14.90)	(-12.85)	(-16.92)	(-16.91)
Net working capital	0.278***	0.278***	0.301***	0.285***	0.285***
	(43.67)	(43.53)	(63.43)	(72.27)	(72.26)
R&D exp.	-0.408***	-0.406***	-0.379***	-0.367***	-0.367***
	(-57.62)	(-57.32)	(-77.37)	(-89.22)	(-89.33)
Acquisition exp.	0.024***	0.024***	0.023***	0.023***	0.023***
	(6.02)	(6.03)	(7.90)	(9.94)	(9.95)
Acquisition-to-assets, SIC4	0.014***	0.014***	0.011***	0.010***	0.010***
	(3.49)	(3.34)	(3.52)	(3.99)	(3.98)
Op. Leverage	-0.097***	-0.097***	-0.137***	-0.139***	-0.139***
	(-11.12)	(-11.14)	(-21.18)	(-24.63)	(-24.66)
HHI TNIC	-0.004				
	(-0.81)				
HHI FIC300		0.002			
		(0.38)			
Fitted-HHI			-0.008		
			(-1.47)		
HHI SIC3				0.001	
				(0.34)	
HHI NAICS3					-0.002
					(-0.34)
Observations	39416	39111	76301	116921	116921

Standardized beta coefficients; t statistics in parentheses

Time and firm FE are included in all regressions.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 2.15: Concentration measures: median HHI by industries.

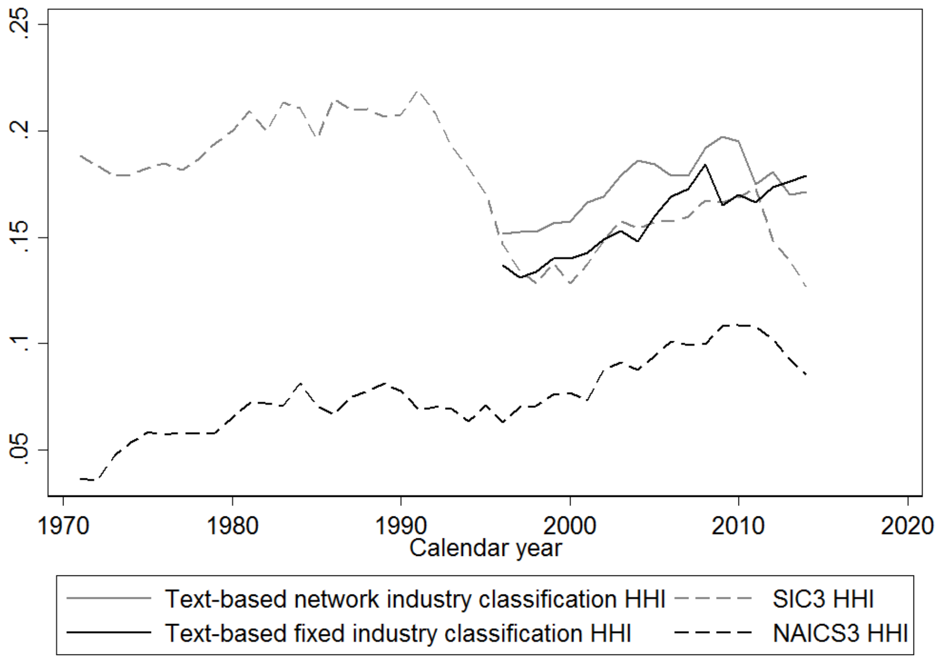


Table 2.5: Net lending/borrowing and HHI. Top 500 firms by log sales.

	(1)	(2)	(3)	(4)	(5)
HHI TNIC	-0.012				
	(-0.76)				
HHI FIC300		0.037*			
		(2.07)			
Fitted-HHI			-0.008		
			(-0.51)		
HHI SIC3				-0.021	
				(-1.76)	
HHI NAICS3					-0.039**
					(-3.18)
Observations	4125	4068	9446	15677	15677

Standardized beta coefficients; t statistics in parentheses

Controls, time and firm FE are included in all regressions.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.6: Net lending/borrowing and taxes. All firms.

	(1)	(2)	(3)	(4)
	txt	txw	txfed	txfo
Total tax rate	0.086***			
	(35.36)			
Worldwide tax rate		0.061***		
		(24.28)		
Federal tax rate			0.034***	
			(7.12)	
Foreign tax rate				0.032***
				(6.68)
Observations	116911	95288	26390	26781

Standardized beta coefficients; t statistics in parentheses
Controls, time and firm FE are included in all regressions.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.7: Net lending/borrowing and taxes. Top 500 firms by log sales.

	(1)	(2)	(3)	(4)
Total tax rate	0.066***			
	(8.97)			
Worldwide tax rate		0.059***		
		(7.27)		
Federal tax rate			0.060***	
			(4.88)	
Foreign tax rate				0.019
				(1.58)
Observations	15677	11457	4892	5421

Standardized beta coefficients; t statistics in parentheses
Controls, time and firm FE are included in all regressions.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

as the HHI, are mostly not significantly correlated. That is, there is no evidence in favor of any particular story that might explain the saving glut. Therefore, what we should conclude about the glut is the simplest explanation: the corporate sector has reached its steady-state, in which the profit share is naturally larger than the investment share, whose excess is not entirely paid back to shareholders simply because of the degree of inertia and stickiness of dividends.

Chapter 3

Cash holdings and operating leverage

3.1 Introduction

In the last forty years, U.S. publicly listed firms increased their liquidity holdings from less than 10% to more than 20% of their total assets, on average. In 2015, total cash and marketable securities amounted to 3 trillions of U.S. dollars; this is a huge amount, equal to 16.7% of U.S. GDP in that same year. Figure 3.1 reports the evolution of the cash-to-assets ratio, over the cross-section of firms in my sample.

Most of the literature investigating this stylized fact focused its attention on the precautionary demand for cash: hoarding cash is optimal when cash flows are risky and access to capital markets poor. Indeed, smaller and newly listed firms are important determinant of this aggregate pattern. Furthermore, among the most important firms characteristics associated with increased cash holdings is the increase in firms' cash flows riskiness; see e.g. Bates et al. (2009).

This article focuses on a source of cash flows riskiness: the rigidity of the cost structure, which characterizes how sales, that can have themselves some idiosyncratic volatility, go down the line to operating cash flows. This is measured by the degree of operating leverage, which is defined by the elasticity of costs to sales and indirectly captures the share of fixed over total costs. As an illustration, consider two firms with different relative amounts of fixed costs of production: following any given unexpected variation in sales, the firm with higher fixed costs is relatively less able to adjust its total costs to the new level of demand, in turn making its profits relatively more volatile. For instance, pharmaceutical, software or oil and gas extraction companies are characterized by large amount of fixed costs; on the other hand, retail stores and transportation services are characterized by low operating leverage.

Basic finance textbooks say that operating leverage matters in the precautionary demand for cash; see e.g. Brealey et al. (2011). Accordingly, this article validates this belief: indeed, operating leverage has increased in the last decades, in turn inducing a larger demand for cash. From my estimations, operating leverage can explain almost 10% of the increase in average cash holdings, which is larger than the explanatory power of many other variables known in the literature to affect optimal cash holdings, such as sales volatility or R&D expenditures.

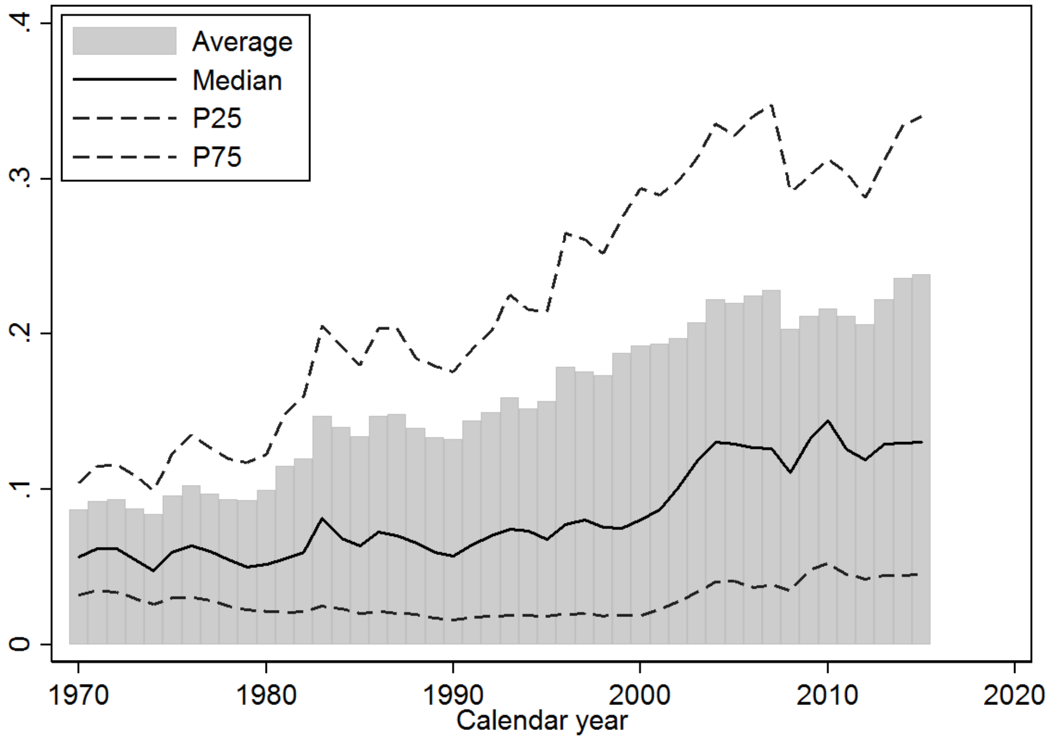


Figure 3.1: Cash and short-term investments over total assets.

Section 3.1.1 discusses the literature while section 3.1.2 presents some preliminary and anecdotal evidence about the mechanism here investigated. Section 3.2 presents a simple trade-off model of the cash holdings decision, which accounts for operating leverage and its role in determining the optimal level of cash. Section 3.3 provides an empirical measure of operating leverage and investigates its relationship with cash holdings. Finally, section 3.4 concludes.

3.1.1 Related literature and contribution

This paper belongs to two different strands of literature; on corporate cash holdings and on operating leverage. Its contribution is to introduce operating leverage as a novel determinant of the secular increase of the cash-to-assets ratio of U.S. listed firms. Below, I briefly review the related literature.

Literature on cash holdings. There is a large literature on optimal cash holdings, which greatly expanded at the turn of the millennium; see Opler et al. (1999) for a classic reference. Despite the numbers of articles, there seems to be a broad consensus on the basic determinants of a firm's cash holdings decision, which conform well to a static trade-off model that balances costs and benefits of holding cash. While older literature, such as Baumol (1952) or Miller and Orr (1966), focused on the transaction motive to hold cash, recent articles mostly refer to the precautionary motive to hold cash, which dates back to Keynes (1936).

More recently, researchers focused on the long-term increase in cash holdings of U.S. listed firms; Bates et al. (2009) offer the most widely-known documentation and investigation of this fact. Although there are some factors that have been associated with such build-up of cash (i.e. increased cash flow volatility and R&D expenditures, together with decreased inventories and capital expenditures, which all tend to correlate with higher cash balances), the magnitude of this secular trend remains puzzling, given also the increasing financialization of the economy, with an ever-increasing number of financial instruments available to firms, such as credit lines or derivative-based hedging contracts.

One major cause of this cash build-up is regarded to be an increase in firms idiosyncratic volatility of cash flows. For instance, Irvine and Pontiff (2009) argue that such increase is due to a more intense economy-wide competition. In fact, this increase is also mirrored into the increase in idiosyncratic return volatility in the stock market; see Rubin and Smith (2011) for an overview on the topic. Therefore, cash holdings increased because of a precautionary motive in the presence of financial constraints; see e.g. Kim et al. (1998) for one of the first articles analyzing this mechanism. Almeida et al. (2004) introduced the notion of cash flow sensitivity of cash: the fraction of incremental cash flows that is retained by the firm as additional cash; see also Han and Qiu (2007) and Riddick and Whited (2009) among others. In addition, Acharya et al. (2007) discuss the difference between cash and debt capacity; indeed firms might issue debt to hoard part of it as cash so to transfer liquidity from good to bad states of the world. However, the role of operating leverage has not yet been investigated and the empirical definition of firm riskiness (e.g. which cash flow measure to consider?) remains elusive in most of the literature[1].

Another motive behind the secular rise in cash holdings might come from the changing organizational structure of firms. Duchin (2010) argues that a decrease in corporate diversification, by increasing investment opportunities and cash flows, can partially account for the long-term pattern in cash holdings. However, it is difficult to gauge a precise estimate of the contribution of this factor, also because it is not even clear theoretically whether diversification does indeed help to reduce firm's riskiness; see e.g. Banal-Estañol et al. (2013) for a detailed view.

Also, firms may hoard cash for tax avoidance motives. Foley et al. (2007) argue that repatriating foreign profits would entail taxes, which can be avoided by simply keeping them as cash. However, the recent buildup in cash seems to be a broader phenomenon that does not only affect foreign-exposed firms.

Finally, firms may hold different amount of cash holdings depending on their corporate governance. Agency theory predicts that, in firms with poor governance, managers are more likely to retain larger cash reserves and to extract private benefits out of them; see e.g. Dittmar and Mahrt-Smith (2007), Faulkender and Wang (2006), or Pinkowitz et al. (2006) for supportive evidence. However, the literature also presents contrasting empirical evidence, in particular when focusing in within-country variations across firms; see e.g. Harford et al. (2008). Given this lack of robust evidence, especially about variations over

[1] There is also a large literature on the evolution of firm riskiness. See Comin and Philippon (2006) for evidence of increasing sales and employment volatility of U.S. listed firms, while Davis et al. (2006) for opposite evidence in privately held firms; see also Thesmar and Thoenig (2011) for a rationalization of these two facts. Yet, when moving from sales to cash flows, the literature adopted many different definitions and there is, in fact, not a clear agreement on the evidence.

time, agency problems find hard time in explaining the long-term increase in cash holdings.

When talking about the cash holdings decision, departures from friction-less models of the firm are unavoidable. From a modeling perspective, this has been done mainly on the lines of a liquidity vs. illiquidity trade-off, in which a firm can either invest in an illiquid long-term project or hoard liquid assets. The literature on liquidity is incredibly vast. See Almeida et al. (2014) for a review on corporate liquidity management and Strebulaev and Whited (2011) for a review on dynamic models of corporate liquidity.

In fact, the cash holding decision is similar to the optimal inventory decision, which has received much attention in the managerial literature. The problem of finding the optimal stocking quantity under uncertain demand, also known as the news-vendor problem, involves a trade-off between holding costs and shortage costs; see Porteus (1990) for an overview. Whilst the methodological approaches are very similar, one major modeling difference is that the cost of holding liquidity is paid ex ante in the cash holdings literature, while it is paid only ex post in the news-vendor problem. Finally, as of methodology, I adopt a similar framework to Johnson and Myatt (2006) in characterizing cash flow volatility and linking it to operating leverage.

Literature on operating leverage. The classic contribution is Lev (1974), who formally set up the link between operating leverage and firm's risk. Another important contribution is Mandelker and Rhee (1984), who pioneered the empirical estimation of operating leverage, as the elasticity of earnings with respect to sales.

In the last decade, the literature on operating leverage has mainly moved its focus on asset pricing, as many authors put forward operating leverage as an explanation of the value premium, i.e. the greater risk-adjusted return of value stocks over growth stocks. Indeed, as production costs play much the same role as debt servicing in levering the exposure of a firms' assets to underlying economic risks, value stocks should then earn higher returns since they have higher operating leverage, that is, systematic risk; see Carlson et al. (2004), Cooper (2006) or Novy-Marx (2010). Also, Aguerrevere (2009) discusses the role of market competition in shaping the relationship between operating leverage and asset returns. García-Feijóo and Jorgensen (2010) offers a good review of the literature, besides providing further evidence of the positive association between stock returns, operating leverage and the book-to-market ratio. Indeed, the latter relationship has been the focus of most of this literature, which explores mechanisms through which operating leverage is associated to book-to-market ratio, in order to propose operating leverage as an explanation of the value premium earned by higher book-to-market stocks; they are riskier because of their costs structure. Other authors also have looked at the relationship with financial leverage; Kahl et al. (2013) point out the positive association with cash holdings, in a similar spirit with this article.

Researchers in management accounting have also produced some noticeable findings in the area of cost behavior. Some articles recently focused on cost stickiness, which is the degree of asymmetry in the response of costs to increases or decreases in sales; see e.g. Anderson et al. (2003) or Calleja et al. (2006). Others focused instead on cost rigidity, which is indeed the concept of operating leverage as determined by the elasticity of the cost function with respect to variation in sales. For instance, Banker et al. (2013) discuss the positive relationship between realized demand uncertainty and cost rigidity, which is somewhat against conventional wisdom and is certainly an issue that warrants further research.

Furthermore, other articles focused on the relationship between sales and costs, which shows a decreasing contemporaneous correlation over the last decades; see e.g. Dichev and Tang (2008) and Donelson et al. (2011). It seems that an increasing number of expenses recorded as special items, which are primarily related to economic events and not to accounting practices, is responsible of this changing correlation.

3.1.2 Preliminary evidence

Below I briefly point out two facts. First, firms that account for much of the increase in the cash-to-assets ratio (those who do not pay dividends) are also those that account for much of the increase in operating leverage. Second, the correlation between sales and costs has been decreasing in the last decades, in accordance with the hypothesis of increasingly fixed costs.

Notice that I am focusing only on a sub-sample of U.S. firms, i.e. publicly listed firms that belong to Compustat database, which might not represent the behavior of all U.S. firms; e.g. Davis et al. (2006) offer evidence of divergent volatilities between publicly traded firms and privately held firms. Nonetheless, the aim of this paper is to investigate the relationship between cash holdings and a firm's cost structure, so that focusing on just a sub-sample of U.S. firms does not really matter.

Dividend vs. nondividend payers. One of the most remarkable facts of the secular increase in cash holdings is the role of firms that do not pay dividends: they account almost exclusively for the increase in cash holdings, since dividend payers firms show no evident pattern in their cash-to-assets ratio. Taking for granted how to get an estimate of operating leverage (which I discuss in section 3.3), it is interesting to notice that nondividend payers also account for much of the increase in average operating leverage. Figure 3.2 reports averages of the cash-to-assets ratio and operating leverage across the two subsamples of firms, highlighting a positive and strong association between cash holdings, not paying dividends, and operating leverage.

Can we think of other stories about cash accumulation and nondividend payers? Nondividend payers firms have since long been investigated for agency problems, in which managers are reluctant to pay out cash to shareholders. However, evidence favoring the view of increased agency problems behind the increase in cash holdings has been hard to find; see e.g. Bates et al. (2009). Hence, accumulating cash for precautionary motives, either because cash flow riskiness has increased or access to capital markets has become more difficult (which is often associated to the choice of not paying dividends), seems the most compelling explanation for the secular trend in cash holdings. Indeed, this article argues that operating leverage played a prominent role.

Decreasing correlation between sales and costs. The two variables I focus on are sales (item `sale`) and operating costs (item `xopr`, which is also the sum of items `cogs`

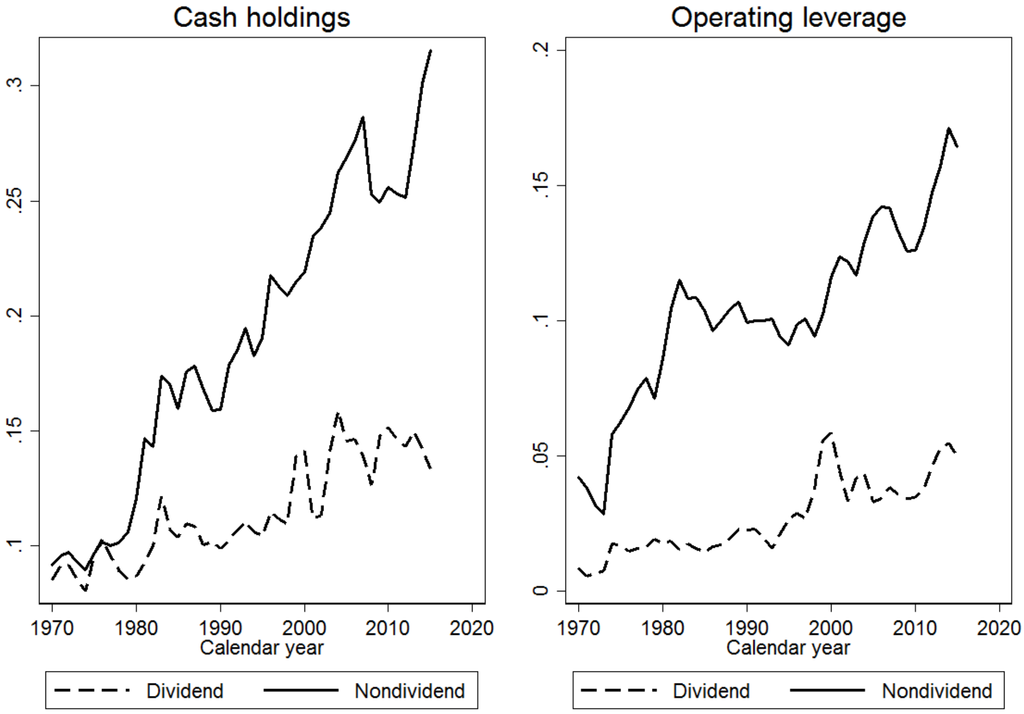


Figure 3.2: Average cash holdings and operating leverage for dividend vs. nondividend payers.

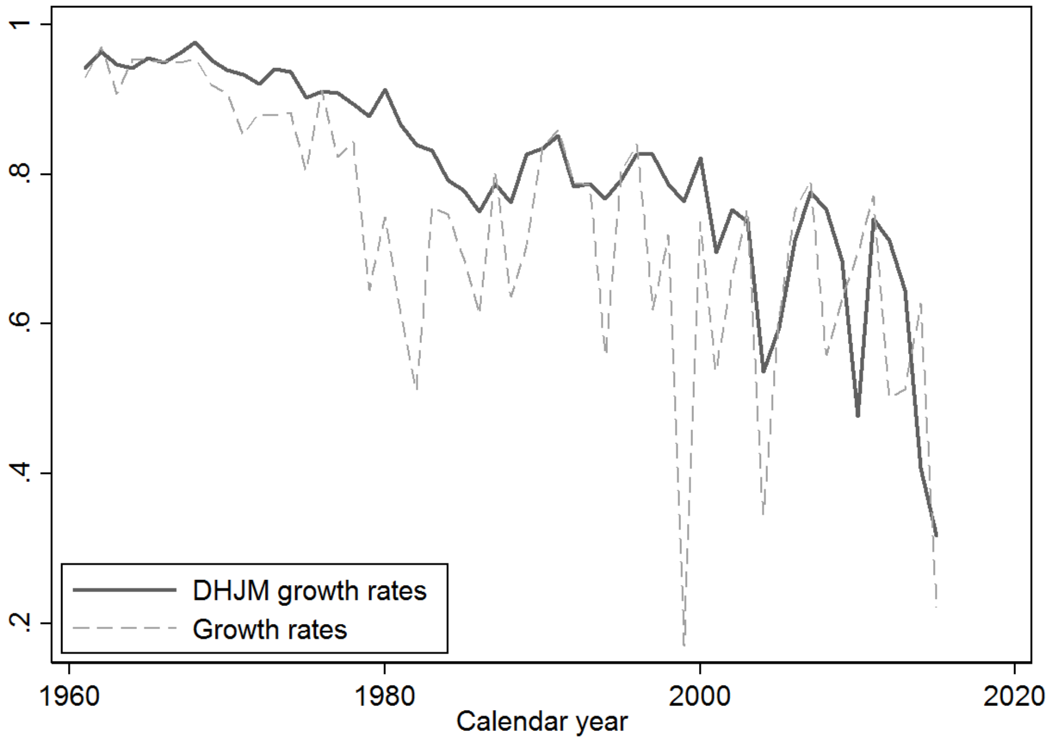


Figure 3.3: Average correlation between sales and costs.

and `xsga`), both in real terms. Their difference corresponds to a firm's operating cash flow (item `oibdp`, i.e. operating income before depreciation), which is also equivalent to earnings before interest, taxes, depreciation and amortization (item `ebitda`). In levels, sales and costs have a particularly high correlation; hence, I focus on growth rates. Following Davis et al. (2006) and Comin and Philippon (2006), I define the growth rate of variable $x_{i,t}$ as

$$\gamma_{i,t} = \frac{x_{i,t} - x_{i,t-1}}{\left(x_{i,t} + x_{i,t-1}\right)/2}, \tag{3.1}$$

which provides a symmetric measure that also takes into account entries and exits from the sample. For instance, when a firm enters the sample, its growth rates is equal to two instead of being missing.

Figure 3.3 reports the average correlation coefficient, in each year, between sales and costs growth rates; for comparison purposes, I also use the standard growth rate definition. The decreasing trend is apparent, with average correlation almost below the 0.5 mark at the end of the 2000s. During the first decade of the sample, any increase in sales was almost completely matched by an equivalent increase in costs; nowadays, this is less so, with costs following not so neatly changes in sales. This is an indication that costs are becoming more and more decoupled with sales.

3.2 A Model with Operating Leverage

This section presents a simple trade-off model of a firm's cash holdings decision, in which the essential and novel feature is operating leverage. The model also yields some empirical predictions, which find supportive evidence in the empirical section 3.3.4.

3.2.1 Defining operating leverage

There is not a unique definition of operating leverage in the literature. Some textbooks define it as the ratio of fixed-to-variable costs, e.g. Damodaran (2010). Others define it as the elasticity of earnings with respect to sales, e.g. Brealey et al. (2011), or to quantity sold, e.g. Ross et al. (2008). Notwithstanding, they all share the same meaning: the relative importance of fixed costs, or the rigidity of the cost structure. To be the most consistent with the empirical analysis, for each firm i, I define operating leverage as

$$\omega = 1 - \varepsilon, \tag{3.2}$$

which is the complement to one of the elasticity of operating costs with respect to quantity sold, which itself is defined as

$$\varepsilon = \frac{\partial \ln c(q)}{\partial \ln q} = \frac{\partial c(q)}{\partial q} \frac{q}{c(q)}, \tag{3.3}$$

where $c(q)$ is the operating costs function and q is the quantity sold. This definition characterizes operating leverage through the responsiveness of the cost function, with a high degree of operating leverage associated to a lower responsiveness of total costs to variations in quantity.

Notice that this definition boils down to the share of fixed over total costs, if we assume that variable costs are linear. Indeed, with a cost function such as $c(q) = c_v q + f$, where c_v is the variable per-unit cost and f is the fixed cost, it is immediate to show that definition in equation (3.2) is equal to

$$\omega = \frac{f}{c_v q + f}. \tag{3.4}$$

Thus, operating leverage describes a firm's flexibility in cutting (or raising) its costs following a variation in quantity. Notice that the kind of real flexibility deriving from operating leverage is different from investment flexibility, i.e. the degree of irreversibility of investment decisions, which of course is important but I am not considering in this article. Indeed, it only derives from the assets in place. Also, notice that operating leverage is a function of the quantity sold q. Indeed, being an elasticity, it is a local definition, since it characterizes how costs vary following a deviation of quantity from a specific level. Here I am taking a very reduced form approach, since I do not characterize why a firm should produce exactly that specific quantity, but just assume that there is one.

3.2.2 The effect on cash flow volatility

This section wants to show that the volatility of operating cash flows is increasing in operating leverage, ceteris paribus. In this section, I use profits, operating cash flows and cash flows interchangeably; of course, I will be more precise in the empirical section.

Assume a continuum of otherwise identical firms, indexed by $i \in [0,1]$, and ordered by increasing operating leverage, i.e. $\omega_i < \omega_{i+1}$ for all i. All firms face the exogenous demand function, characterized by the distribution $F(\cdot)$, symmetric around the mean $E[q] = \bar{q} > 0$ with finite variance. Operating leverage is defined at such expected quantity,

$$\omega_i = 1 - \left.\frac{\partial c_i(q)}{\partial q}\right|_{q=\bar{q}} \cdot \frac{\bar{q}}{c_i(\bar{q})}. \tag{3.5}$$

Firm's profits are a function of the quantity q that will realize in the market and on a firm's operating leverage ω_i. That is,

$$\pi_i = s(q) - c_i(q;\omega_i), \tag{3.6}$$

where $s(q)$ is the sales function and $c_i(q;\omega_i)$ is the cost function, which are both increasing in q. For the sake of simplicity, assume that expected profits are equal for all firms, $E[\pi_i] = \int_0^\infty \pi_i(q)\,\mathrm{d}F(q) = \pi^e \geq 0$ for all i, as well as profits at the expected mean quantity, $\pi_i(\bar{q}) = \bar{\pi}$ for all i, so that firms are equal but for their degree of operating leverage. From the distribution of quantity sold, $F(\cdot)$, we can derive the distribution of profits

$$\begin{aligned} P(\pi_i \leq x) &= P\left(q \leq \pi_i^{-1}(x;\omega_i)\right) \\ &= F\left(\pi_i^{-1}(x;\omega_i)\right) \equiv G(\pi_i;\omega_i) \end{aligned}$$

which will be denoted with $G(\cdot;\omega_i)$ and is parametrized by the degree of operating leverage. That is, profits follow

$$\pi_i \sim G(\cdot;\omega_i). \tag{3.7}$$

Consider now the variation in profits following a variation in quantity, computed at expected quantity $\bar{q}$,

$$\begin{aligned} \left.\frac{\partial \pi_i}{\partial q}\right|_{q=\bar{q}} &= \left.\frac{\partial}{\partial q}\left(s(q) - c_i(q)\right)\right|_{q=\bar{q}} \\ &= \left.\frac{\partial s(q)}{\partial q}\right|_{q=\bar{q}} - \left.\frac{\partial c_i(q)}{\partial q}\right|_{q=\bar{q}} \\ &= s^{'}(q) - (1-\omega_i)\frac{c_i(\bar{q})}{\bar{q}}, \end{aligned}$$

where the last line uses the definition of operating leverage, as in equation (3.5). The first term, which is the marginal revenue, is equal for all firms; the second, which is the marginal cost, is instead decreasing in operating leverage ω_i,

$$\left.\frac{\partial^2 c_i(q)}{\partial q \partial \omega_i}\right|_{q=\bar{q}} = -\frac{c_i(\bar{q})}{\bar{q}} < 0, \tag{3.8}$$

and, as a consequence, the derivative of profits is increasing in operating leverage:

$$\left.\frac{\partial^2 \pi_i}{\partial q \partial \omega_i}\right|_{q=\bar{q}} = \frac{c_i(\bar{q})}{\bar{q}} > 0. \tag{3.9}$$

More general results can be easily obtained:

PREDICTION 1A. The variance of operating costs is decreasing in operating leverage, and

PREDICTION 1B. The variance of operating cash flows is increasing in operating leverage, if sales and costs are sufficiently correlated.

Indeed, equations (3.8) and (3.9) just characterize local variations, but are silent about variance over the whole distribution, which instead is the target of the two predictions. Of course, generality requires some additional assumptions. The first prediction simply requires the marginal cost to be decreasing in operating leverage, i.e. $c_i'(\cdot;\omega_i) \geq c_j'(\cdot;\omega_j)$ almost everywhere, for $\omega_i < \omega_j$, and absolutely continuous on the interval ℓ. The prediction then automatically follows; see Tang and See (2009).

The second prediction is instead characterized by a more stringent condition. Indeed, decompose the variance of profits,

$$\sigma^2(\pi_i) = \sigma^2(s(q)) + \sigma^2(c_i(q)) - 2\rho_{s(q),c_i(q)}\sigma(s(q))\,\sigma(c_i(q)), \tag{3.10}$$

where $\rho_{s(q),c_i(q)}$ is the correlation coefficient between sales and costs. Then, the variance of profits is decreasing in the variance of costs $\partial\sigma^2(\pi_i)/\partial\sigma^2(c_i(q)) < 0$, such that in turn it is increasing in operating leverage following from prediction 1A, if and only if

$$\rho_{s(q),c_i(q)}\frac{\sigma(s(q))}{\sigma(c_i(q))} > 1, \tag{3.11}$$

which follows from computing the derivative. That is, prediction 1A is valid whenever the standard deviation of sales is sufficiently higher than that of costs and/or their correlation is sufficiently high. Suppose, instead, that it is not. For instance, assume a zero correlation between sales and costs: then a decrease in costs' variance naturally generates a decrease in cash flows' variance. In fact, the ratio of the two standard deviations is usually larger than one, because of costs are stickier, and the correlation is positive and quite large, so that condition (3.11) should hold for the majority of firms – as indeed it is the case.

Given the assumptions on $F(\cdot)$ and on prediction 1a, increasing ω_i results in a clockwise rotation of the distribution function $G(\cdot;\omega_i)$, such that it becomes more "spread-out." As in Johnson and Myatt (2006), $G(\cdot;\omega_i)$ is increasing in ω_i for $\pi_i < \bar{\pi}$ while decreasing in ω_i for $\pi_i > \bar{\pi}$, where $\bar{\pi}$ is the rotation point, at which profits identical for all firms and equal to profits at expected mean quantity $\bar{q}$. When this holds for all ω_i, then $\{G(\cdot;\omega_i)\}$ is ordered by a sequence of rotations and any two cumulative distribution function belonging to family $G(\cdot;\omega_i)$ must cross only once. Of course, this must be seen as a theoretical

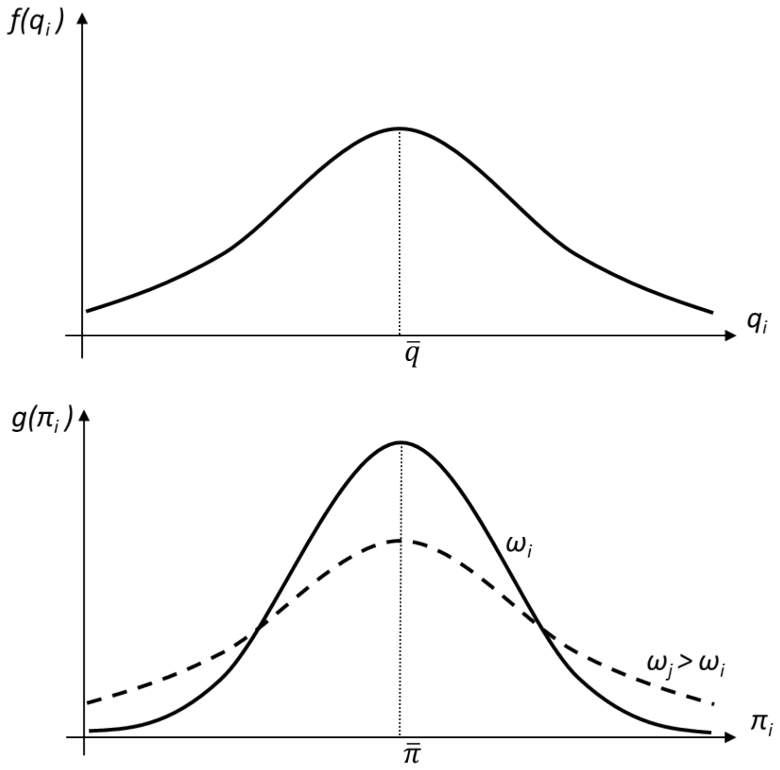


Figure 3.4: Probability density functions: quantity q_i and profits π_i.

depiction rather than a description of reality, especially in the cross-section, but it's still worth for the intuition.

Figure 3.4 shows the probability density functions of quantity, equal for all firms, and of profits, which instead is more or less peaked depending on operating leverage, with $\omega_j > \omega_i$. Figure 3.5 compares two cumulative distribution functions of profits, showing the rotation property. The intuition is that firms with higher operating leverage are more likely to experience larger swings in profits, either positive or negative, exactly because their cost function is made up mainly of fixed costs, which are by definition insensitive to variations in quantity. Hence, their profits are riskier and follow a more "spread-out" distribution function.

3.2.3 Cash holdings decision

Now that operating leverage has been linked to cash flow volatility, we can move to the cash holdings decision, using a simple trade-off model. From now on, for simplicity, I only keep the index i for operating leverage. There are three periods, $t = 0, 1, 2$, and the inter-temporal discount factor is assumed to be one. There is a risk-neutral firm who owns an asset that generates cash flows in the last two periods and there is no capital accumulation.

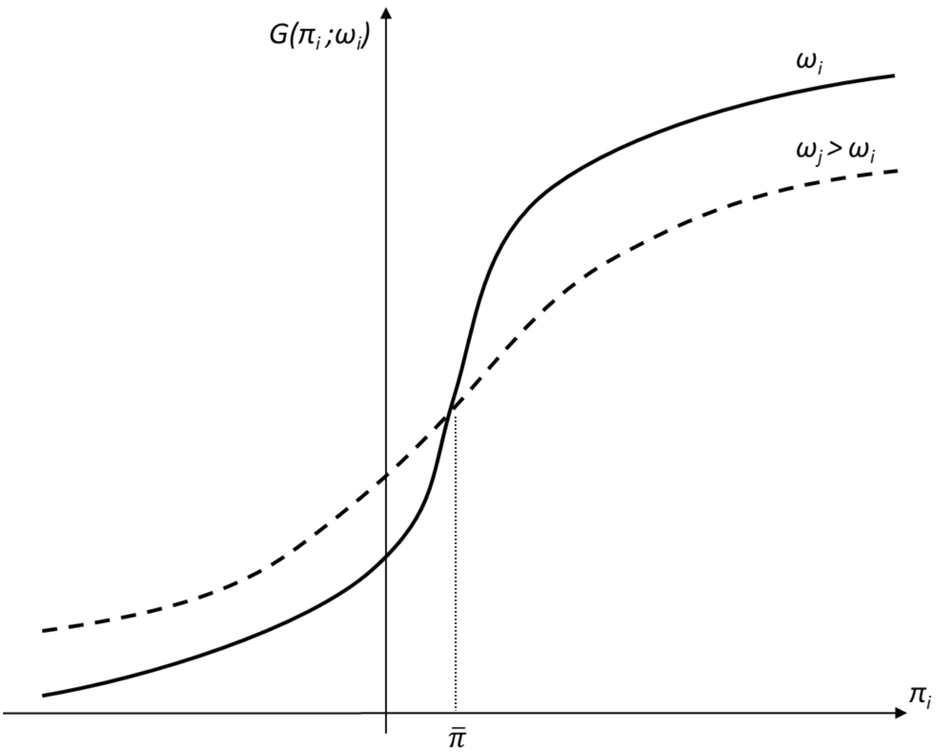


Figure 3.5: Rotation property of the cumulative distribution function.

In the first period, $t = 0$, the firm has to decide how to allocate its initial wealth $W > 0$ between a liquid and an illiquid asset. The illiquid asset is a bond, b, that pays a net return $r > 0$ in $t = 2$ but cannot be sold in $t = 1$. The liquid asset is cash, m, that is available for liquidation in both periods but pays no interest.

In the intermediate period, $t = 1$, the firm receives a random cash flow, which is distributed according to

$$\pi \sim G(\cdot; \omega_i),$$

where π denotes the firm's short-term profits, as in equation (3.7). There are two cases of interest: either the firm has a positive cash balance, $\pi + m \geq 0$, which allows it to continue to the next period, or the firm has a negative cash balance, $\pi + m < 0$, which requires the firm to raise external funds in order to continue operations. Raising external funds has a net cost κ per unit of funds raised. This captures the presence of frictions in financial markets that makes raising external funds costly; this may be due to the presence of asymmetric information, for instance, or many others explanation given in the literature. Also, for the sake of simplicity, assume that default is infinitely costly, so that the firm always raises external funds, if needed, but just to the point of covering its cash shortfall.

In the final period, $t = 2$, the firm receives the payoff on its illiquid asset, $(1 + r)\, b$, plus a certain cash flow, $\Pi > 0$, which can be interpreted as the long-term value of the firm. In fact, this assumption is not strictly necessary in what follows, since we already ruled out default by assumption; however, for the interpretation of the model, we could replace that assumption by saying that Π is sufficiently large to always make worthwhile to raise external funds and survive to the final period.

Therefore, the firm's ex ante gross payoff is:

$$\begin{cases} m + (1+r)\,b + \pi + \Pi & \text{if} : \pi + m \geq 0 \\ m + (1+r)\,b + \pi + \Pi + \kappa\,(\pi + m) & \text{if} : \pi + m < 0 \end{cases}$$

where $\pi^* + m = 0$ defines the threshold π^*, which is the level of short-term profits such that the cash balance is zero. This naturally depends on the cash holdings decision: $\pi^* = -m$. The firm then maximizes its expected payoff,

$$\begin{aligned} \max_{m} \quad & m + (1+r)\,b + \pi + \Pi + \int_{-\infty}^{\pi^*} \kappa\,(\pi + m)\, dG\,(\pi; \omega_i) \\ \text{sub.} \quad & W = m + b \\ & \pi^* = -m. \end{aligned} \tag{3.12}$$

Notice that the cost κ is proportional to the cash shortfall, $\pi + m$, and is paid only when profits are low enough, $\pi < \pi^*$, such that it is effectively a cost, even if it enters the maximand with a plus. The first-order condition, using the Leibniz integral rule, reads as

$$-r + \int_{-\infty}^{\pi^*} \kappa dG\,(\pi; \omega_i) + \kappa\,(\pi^* + m)\, g\,(\pi^*; \omega_i)\, \frac{\partial \pi^*}{\partial m} \;\; = \;\; 0, \tag{3.13}$$

which equates the marginal cost of holding the liquid assets, i.e. the opportunity cost r, with the marginal benefit of cash, i.e. decreasing the probability of having to raise costly external funds (and the amount thereof). The first-order condition simplifies to

$$m^* \;\; = \;\; -G^{-1}\,({}^{r}\!/\!_{\kappa})\,, \tag{3.14}$$

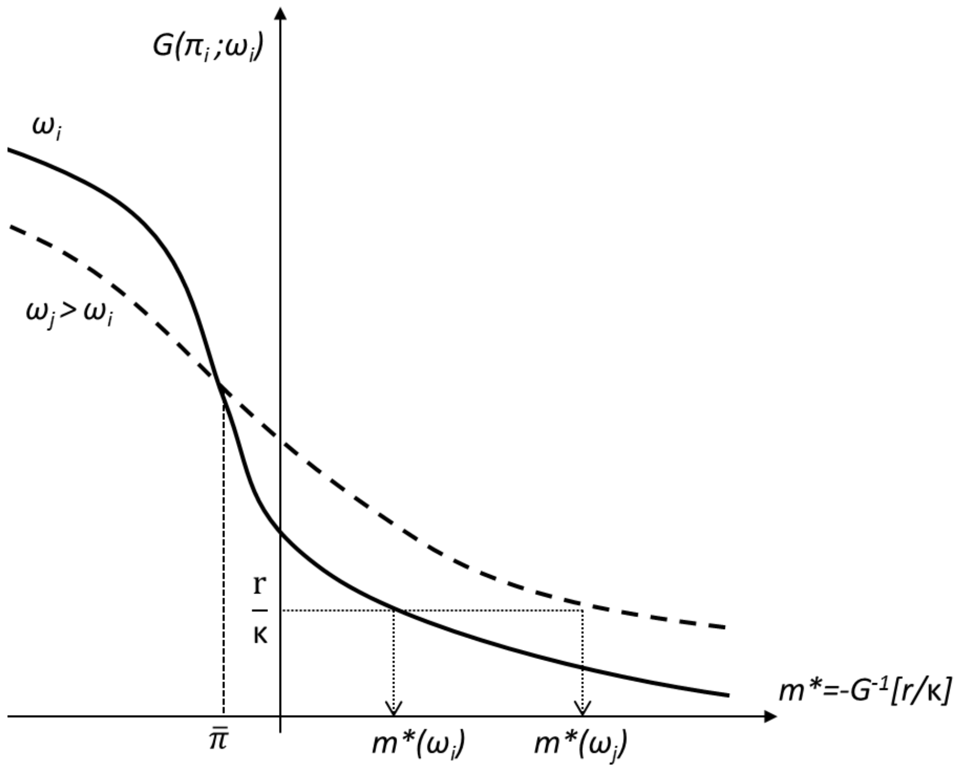
while the second-order condition always holds: $-\kappa g\,(-m^*) < 0$.

We can interpret equation (3.14), which gives the optimal level of cash holdings, with the aid of figure 3.6. The horizontal axis is reversed, so that we can directly view the inverse $G^{-1}\,(\cdot)$ as the optimal level of cash holdings, with the minus sign already accounted for, as in equation (3.14). There are two cumulative distribution functions associated with two different levels of operating leverage $\omega_j > \omega_i$. Notice that the ratio r/κ as well as the expected cash flow in the intermediate period $\bar{\pi}$ must be sufficiently low for the firm to be willing to hold cash, otherwise the optimal choice would be $m^* = 0$ or even negative, since the firm just expects to cover any liquidity shock with the cash accruing in the intermediate period or to pay any issuance cost. Then, it immediately follows that, for any given low enough ratio r/κ,

PREDICTION 2A. Cash holdings m^* are increasing in operating leverage,

$$\frac{\partial m^*}{\partial \omega_i} \;\; > \;\; 0. \tag{3.15}$$

Figure 3.6: Optimal cash holdings with $\bar{\pi} > 0$.



Furthermore, operating leverage plays a fundamental role in channeling the relationship between cash holdings and the cost/benefit of liquidity. Indeed, increasing the ratio r/κ does not unconditionally imply a lower level of optimal cash holdings, and viceversa, unless we assume that operating leverage is independently distributed of r and κ; this is in fact a strong assumption, since operating leverage characterizes the riskiness of a firm, which may well be linked to the opportunity cost of liquidity and/or the costs of external funds. Indeed, the model yields the following conditional prediction,

PREDICTION 2B. For any given degree of operating leverage, cash holdings m^* are increasing in the cost κ of raising external funds and decreasing in the cost r of holding liquidity,

$$\frac{\partial m^*}{\partial \kappa} > 0, \qquad \frac{\partial m^*}{\partial r} < 0. \tag{3.16}$$

3.3 Operating leverage in the data

This section describes how to obtain an empirical measure of operating leverage and then investigates its relationship with cash holdings and the model's predictions. As firms may hoard liquidity because of a precautionary motive, readers as well should be cautious in interpreting the following results, since the most important variable in the analysis is unavoidably difficult to measure.

3.3.1 Sample

Data comes from Compustat, which includes all the publicly listed firms in U.S. stock markets, from 1960 to 2015. First, I exclude financial firms (SIC 6000-6799) and regulated utilities (SIC 4900-4999), who may have peculiar cash management policies. Second, I exclude observations that have unreported or negative values of sales, unreported values or less than \$50 thousands of total assets, negative values of capital expenditures and of common/ordinary equity, and observations whose growth rate of sales exceeds 500%. Third, I exclude firms with gaps in their reported values of sales and of operating expenditures. Finally, I winsorize all variables at one and ninety-nine percentiles.

The remaining sample includes $21,751$ firms over 56 years, for a total of $251,715$ observations with a median number of observations per firm of eight; I refer to it as the "benchmark sample." In fact, its size is going to be smaller in practice, as not all variables can be obtained for all observations. In general, any variable is either in real terms, adjusted for inflation using the CPI index from BLS, with 1982-84 U.S. dollars, or a ratio, often over total assets (item `at` in Compustat). Cash holdings are defined as the cash/assets ratio (items `che` over `at` in Compustat), where cash includes cash and liquid marketable securities[2]; this is one of the most common measures used in the literature; see e.g. Bates et al. (2009).

3.3.2 Estimation of operating leverage

Operating leverage characterizes the elasticity of earnings with respect to sales. I assume it to be firm-specific and time-invariant. Operationally, I estimate it as the complement to one of the elasticity of operating costs with respect to sales. This "inverse" approach, which looks at costs rather than earnings, avoids the issues of handling negative values (of earnings) and changes in mark-ups and profit margins. Given that the elasticity of any function $f(x)$ with respect to x is defined as $\varepsilon = \partial \ln f(x) / \partial \ln x$, it is straightforward to get the elasticity of costs with respect to sales as the coefficient in the following regression:

$$\ln (rxopr_{i,t}) = \alpha_i + \varepsilon_i \ln (rsale_{i,t}) + \nu_{i,t}. \tag{3.17}$$

Variables $rxopr_{i,t}$ and $rsale_{i,t}$ are inflation-adjusted operating costs and sales; items `xopr` and `sale` in Compustat. Therefore, for each firm, operating leverage is obtained as

$$\omega_i = 1 - \varepsilon_i, \tag{3.18}$$

which is increasing in the ratio of fixed costs. A major inconvenience is the use of sales instead of quantity sold: indeed, firms often vary their product mix, which may account for much of any change in sales, rather than changes in quantities sold. However, I am not aware of any easy solution to this issue.

[2]This item represents cash and all securities readily transferable to cash as listed in the Current Asset section. This item includes, but is not limited to: Cash in escrow, unless legally restricted, in which case it is included in Current Assets - Other; Good faith and clearing house deposits for brokerage firms; Government and other marketable securities, including stocks and bonds, listed as short-term; Letters of credit; Margin deposits on commodity futures contracts; Time, demand and certificates of deposit; The total of a bank's currency and coin, plus its reserves with the Federal Reserve Bank and balances with other banks; Restricted cash.

Descriptive statistics. In theory, operating leverage is not restricted to the unit interval $[0, 1]$, as instead the share of fixed over total costs is constrained. In fact, by definition (3.5), operating leverage can also be defined as one minus the ratio of the marginal cost to average cost,

$$\omega_i \quad = \quad 1 - \frac{MC_i\left(\bar{q}\right)}{AC_i\left(\bar{q}\right)}, \tag{3.19}$$

which in principle can also be negative, e.g. when $MC_i\left(\bar{q}\right) > AC_i\left(\bar{q}\right)$. Indeed, negative operating leverage is associated to negative economies of scale, in which the average cost is increasing and smaller than the marginal cost. For instance, Lambrecht et al. (2016) argue that this also happens when a firm switches from internal production to concurrent sourcing, i.e. when both internal production and outsourcing occur.

In practice, the estimated measure is in line with the theoretical benchmark: about three quarters of all the estimated values fall into this unit interval, while the remaining values lie just below the zero threshold. I also winsorize it at the P1 and P99 percentiles. Summary statistics are reported in the following table.

Table 3.1: Estimated operating leverage, summary statistics.

Variable	Obs	Mean	Std. Dev.	P1	P5	P25	P50	P75	P95	P99
oplev	181220	.06	.23	-.5	-.17	-.03	.01	.09	.51	1.16

3.3.3 Operating leverage and cash holdings

The structure of the data allows for panel data analysis. Consider the following model:

$$m_{i,t} \quad = \quad c_i + \delta_t + \beta' \mathbf{x_{i,t}} + \gamma\omega_i + \varepsilon_{i,t} \tag{3.20}$$

where c_i denotes the individual time-invariant heterogeneity and δ_t is a set of time dummies. The dependent variable is cash holdings $m_{i,t}$, defined as the ratio of cash and short-term investment over total assets, for each firm-year observation. The aim is to consistently estimate γ, the coefficient on operating leverage ω_i. Finally, the set of control variables $\mathbf{x_{i,t}}$ is detailed in Appendix C.1; they are all commonly found in the literature.

To obtain consistent estimates in a random-effects specification, we need to assume that the unobserved firm heterogeneity c_i is uncorrelated with the included regressors, $\mathbf{x_{i,t}}$ and ω_i, i.e. the mean independence assumption

$$E\left[c_i \mid \omega_i, x_{i,1}, x_{i,2}, \ldots\right] \quad = \quad \alpha. \tag{3.21}$$

It is difficult to believe that the unobserved firm-specific constant terms c_i are randomly distributed across cross-sectional units, with mean α, and are not systematically related with the other observable regressors, $\mathbf{x_{i,t}}$ and ω_i. But moving to a fixed-effects specification, which would allow to drop assumption (3.21), is not feasible since we are estimating a coefficient on a time-invariant variable. Furthermore, notice also that the independent variable ω_i is subject to measurement error, which usually leads to an inconsistent estimate of γ, with an attenuation bias toward zero: this in fact makes the following analysis more robust, since, if anything, we would be measuring a lower bound.

In the following regressions, I always use robust estimation of the standard errors, which allows for intra-firm correlation, relaxing the usual requirement that the observations be independent. I present basic evidence of a positive relation between operating leverage and cash holdings in subsection 3.3.3, with a robustness analysis in subsection 3.3.3. Then, in subsections 3.3.3 and 3.3.3, I discuss its role in the secular increase of the cash-to-assets ratio, while subsection 3.3.3 concludes with an industry analysis.

Random effects model. Table 3.2 reports the estimated coefficients of a random effects specification. The estimated coefficient γ on operating leverage ω_i is positive and significant in all specifications: all columns include year dummies, the second column includes age and size, the third introduces a variety of control variables, which reduces the size of the sample by a half, while column four adds sales volatility. Among the covariates, operating leverage is often negatively correlated (but never more than -0.25) with the exception of the market-to-book ratio, R&D expenditures and sales volatility, which are positively correlated (0.17, 0.26 and 0.29).

As regard the control variables, there is a negative and significant relationship between cash holdings and: age, size (measured as the log of real assets), capital and acquisition expenditures, net working capital, and financial leverage. On the other hand, there is a positive relationship with: net cash flow, market-to-book ratio, the dividend-payer dummy, R&D expenditures, and sales volatility. Overall, all have the expected signs.

Robustness. Tables 5 and 3.4 use different measures of operating leverage. In addition to my preferred measure, obtained as described in section 3.3.2, I include four other measures of operating leverage that are similar to the ones used in the literature.

First, for each firm, consider the simple growth rate of sales and costs and then run a regression between them to obtain the elasticity of the costs growth rate; this in turn delivers operating leverage, as the complement to one. Implicitly, we are assuming a random walk behavior of sales and costs and consider only innovations to estimate operating leverage. This in column two, as Op. Lev. (Growth-RW).

Second, we can obtain a more refined estimation by detrending the time-series of sales and cost with an HP filter at annual frequency. Then, running the following regression

$$\mu_{i,t}^{rxopr} = \varepsilon_i^g \cdot \mu_{i,t}^{rsale} + \nu_{i,t}^g$$

where $\mu_{i,t}^{xopr}$ and $\mu_{i,t}^{rsale}$ are the innovations, defined as the cyclical component divided by the lagged value (which is indeed very similar to a growth rate), delivers an estimate of operating leverage; this is similar to Kahl et al. (2013), who instead estimate innovations as compounded annual growth rates. This in column three, as Op. Lev. (Growth-HP).

Third, we can use the logarithms of sales and costs, as in this article, but their deviations around a trend instead of their levels. In particular, I again use an HP filter to detrend the series (of the logs) and then estimate the elasticity on the (log) innovations;

Table 3.2: Random effects model.

	(1)	(2)	(3)	(4)
Op. Leverage	0.17***	0.12***	0.14***	0.13***
	(25.16)	(18.60)	(11.74)	(10.94)
Years since IPO		-0.0034***	-0.0016***	-0.0015***
		(-26.74)	(-12.53)	(-11.69)
Ln(total assets)		-0.013***	-0.0048***	-0.0042***
		(-13.44)	(-4.56)	(-4.07)
Op. Cash flow			-0.012*	-0.0099
			(-2.17)	(-1.81)
Net cash flow			0.049***	0.052***
			(5.51)	(5.72)
Net working capital			-0.28***	-0.28***
			(-32.78)	(-32.73)
Capital exp.			-0.31***	-0.31***
			(-27.12)	(-26.91)
Acquisition exp.			-0.17***	-0.17***
			(-22.90)	(-23.13)
Dividend payer (if =1)			0.0038	0.0049*
			(1.86)	(2.37)
Book leverage			-0.26***	-0.26***
			(-36.79)	(-37.15)
Market-to-book			0.012***	0.012***
			(12.91)	(12.81)
R&D exp.			0.070*	0.075**
			(2.47)	(2.65)
Sales volatility				0.061***
				(7.89)
Observations	181164	181164	80977	80977

t statistics in parentheses

Note: dependent variable is cash-to-asset ratio (che/at). Time FE are included.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

García-Feijóo and Jorgensen (2010) use instead a simple linear trend in time, for each firm. This in column four, as Op. Lev. (Log-HP).

Fourth, some authors have taken a different route, avoiding the estimation of an elasticity and instead using variables from the balance sheet. For instance, Novy-Marx (2010) approximated operating leverage as selling, general, and administrative expenses (`xsga`) plus cost of goods sold (`cogs`) divided by total assets (`at`). This in column five, as Op. Lev. (Balance sheet). However, this measure is much different from the others, suggesting that such shortcut might be misleading.

Overall, results are very similar, even surprisingly so. The only exception is the last measure, from balance sheet data, which instead gives a negative coefficient. I believe it to be a less reliable measure than the others, however. I also tried to use a fixed-effects instead of a random-effects model; most of the estimated coefficients are in fact barely affected[3], suggesting that the random-effect specification is not a bad approximation.

Table 3.3: Operating leverage, different measures.

Variable	Obs	Mean	Std. Dev.	P5	P25	P50	P75	P95
oplev	181220	.06	.23	-.17	-.03	.01	.09	.51
oplev_rw	177899	.13	.29	-.18	-.01	.06	.19	.71
oplev_gr	177899	.13	.32	-.23	-.01	.07	.22	.77
oplev_cycl	172789	.13	.27	-.18	-.01	.07	.21	.65
oplev_bs	168830	1.24	.89	.2	.65	1.07	1.57	2.93

Finally, table 3.5 adopts a different approach: it considers the decomposition of the estimated measure of operating leverage into an upward and a downward component, which are estimated by taking into account only observations with increases or decreases in sales, respectively. They both show up as significant, with similar magnitudes.

Operating leverage over time. This subsection looks at variation over time of the cross-sectional distribution of operating leverage. Figure 3.7 reports the evolution of the average, the median, and the lower and upper quartiles. There is an evident upward trend in all the aggregate measures. On average, firms today are more "operating levered" than in the previous decades, i.e. with a relatively more fixed cost structure, and there is also more variation in the cross-section.

Notice that such increase is due only to a change in the sample of firms, since the estimation procedure assumed the measure of operating leverage to be time-invariant for each firm. On the other hand, the increase in cash holdings can be due both to a change in the sample of firms and to a change in the cash holdings decision of each firm. To argue that an increase in average operating leverage is driving the increase in average

[3]Results available upon request.

Table 3.4: Robustness: different measures of ω_i.

	(1)	(2)	(3)	(4)	(5)
Op. Leverage	0.13***				
	(10.94)				
Op. Lev. (Growth-RW)		0.12***			
		(14.21)			
Op. Lev. (Growth-HP)			0.11***		
			(15.52)		
Op. Lev. (Log-HP)				0.12***	
				(14.37)	
Op. Lev. (Balance sheet)					-0.047***
					(-21.56)
Control variables	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes
Observations	80977	80977	80977	79555	75932

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.5: Robustness: upward and downward ω_i.

	(1)	(2)	(3)
Op. Leverage	0.13***		
	(10.94)		
Op. Lev. (Upward)		0.10***	
		(14.80)	
Op. Lev. (Downward)			0.10***
			(14.51)
Control variables	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes
Observations	80977	80945	80959

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

cash holdings, it is therefore necessary to investigate whether the change in cash holdings behavior is mainly due to a change in the sample of firms, rather than a change in firm-specific behavior. This indeed seems to be the case. Figures 3.8 and 3.9 plot average cash holdings and operating leverage by different cohorts. That is, the first cohort comprises all firms that were listed from 1970 to 1979, the second those from 1980 to 1989, and so forth. Older firms have consistently lower cash holdings than younger firms, over their entire lifespans – and also lower operating leverage. This remains true also when considering that newly-listed firms may hold larger cash balances due to the cash raised through the IPO – but this effect should vanish after five years or so. Indeed, the bulk of the increase in cash holdings seems to come from the entry of new firms, consistent with a sample-composition story, in line with the increase in average operating leverage.

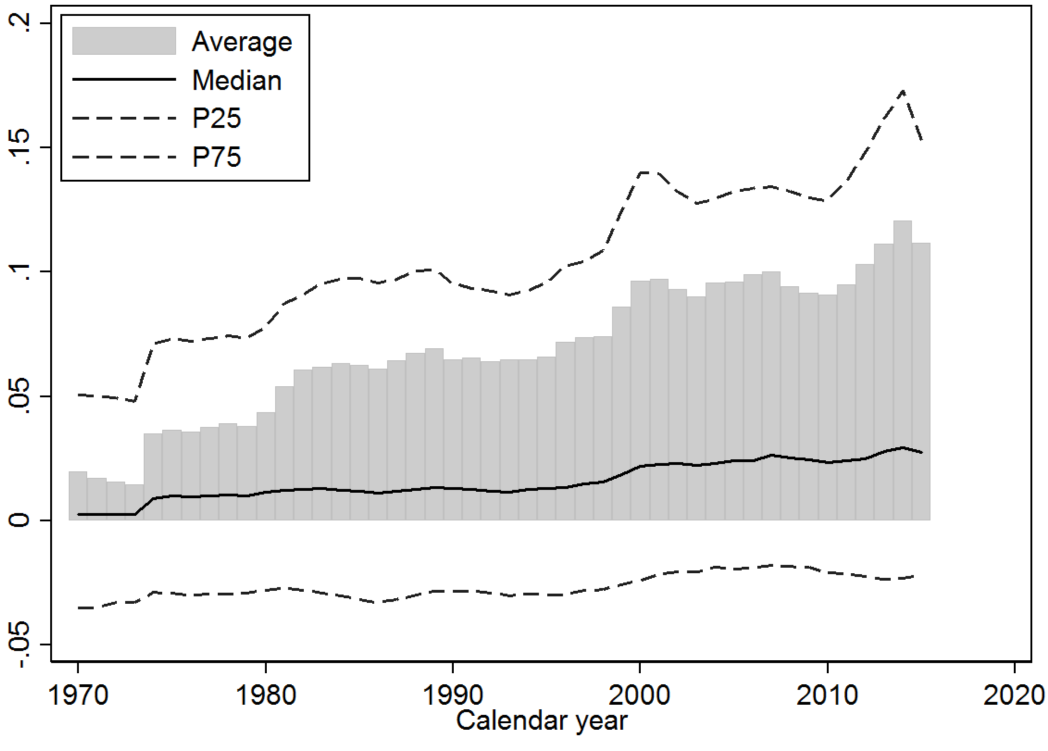


Figure 3.7: Operating leverage over time.

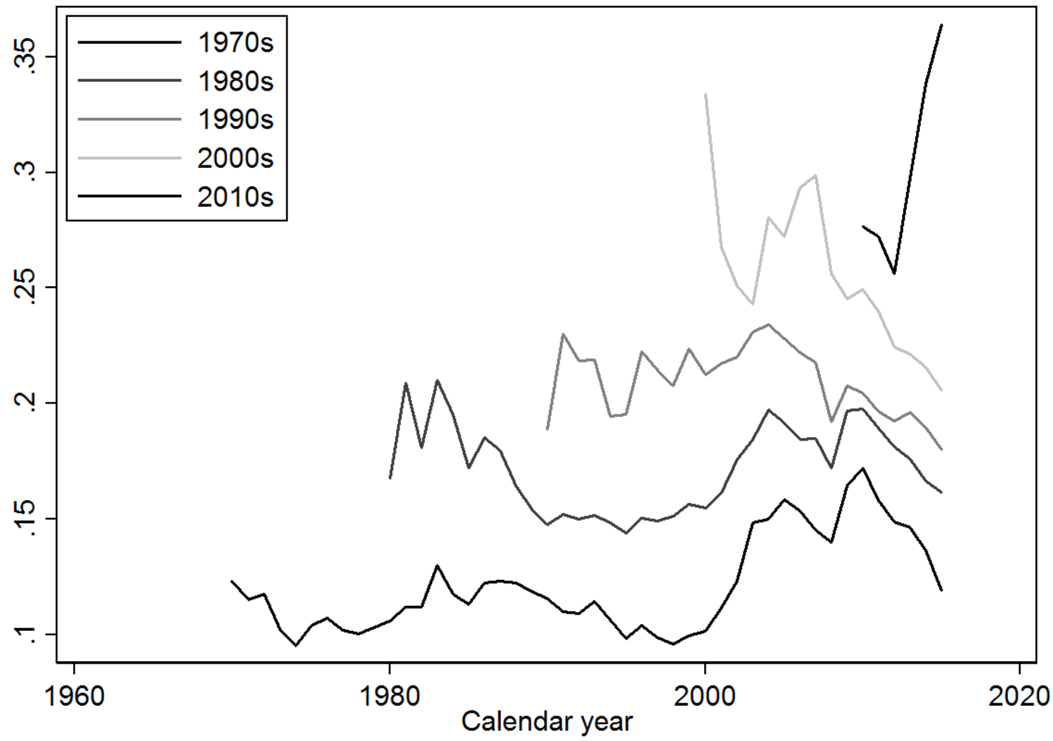


Figure 3.8: Cash holdings by different cohorts.

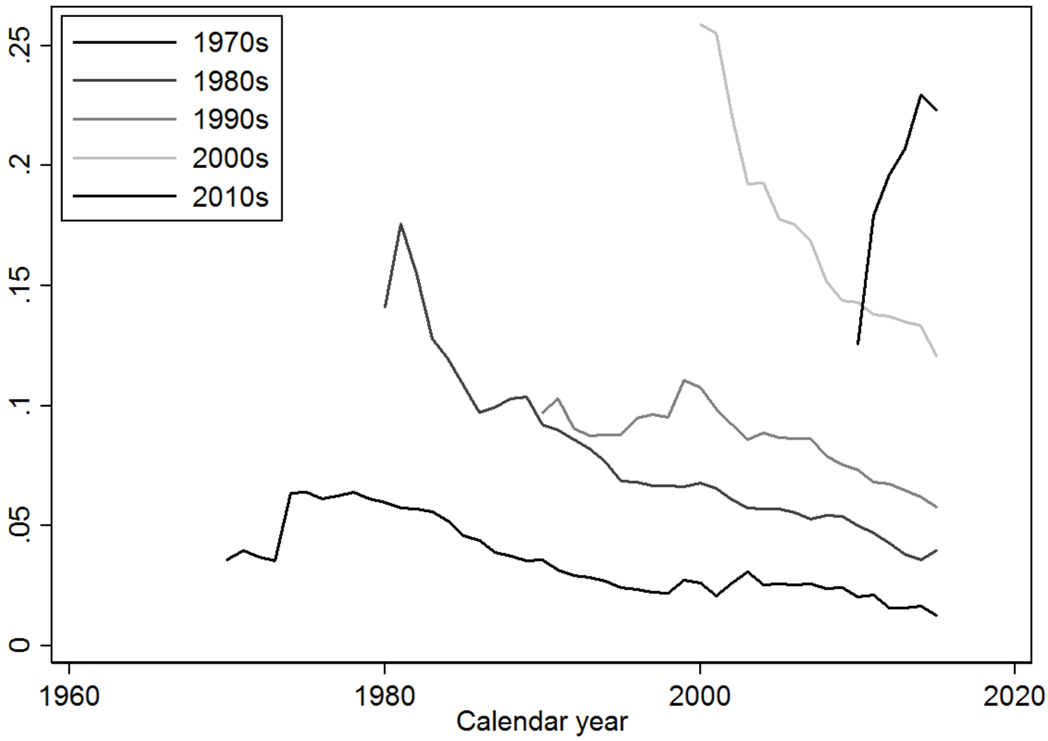


Figure 3.9: Operating leverage by different cohorts.

Explaining the secular increase in cash holdings. Given the estimated coefficients, we can try to assess the contribution of the various factors in the increase in cash holdings. During the 1970s, cash holdings were on average 9.3% of total assets, then increased to 22.2% in the period 2010-2015. In the same periods, average operating leverage increased from 0.03 to 0.11. Therefore, the increase in operating leverage would be associated to an increase of $(0.11 - 0.03) \cdot 0.1335 = 1.0\%$ in cash holdings, which is about 7.9% of the total increase in cash holdings. While this may not seem large enough, it is important to put it in a relative perspective against other variables. Table 3.6 does exactly so.

The most important factor, by far, seems to be the large reduction in working capital, from 20.5% to 3.5% of total assets, which account for 36.6% of the change in cash holdings. This is related to the technological and management improvements in supply chains and inventory management. The second most important factors are the increase in operating leverage, in book-to-market ratio, and the decrease in book leverage; they explain 7.9%, 8.2% and 12.8% of the change in cash holdings, respectively. All the other factors either explain a negligible amount of the total variation, e.g. R&D expenditures and sales volatility with 2.1% and 1.6%, or support instead a decrease in cash holdings. Overall, while the increase in cash holdings still remains puzzling, the increase in operating leverage seems to have been an important driving force in such secular change, at least comparable to other potential explanations already pointed out in the literature.

Table 3.6: Explained increase of cash holdings.

Variable	Average		Estimated coeff.	Explained variation in cash-to-assets	
	(1970s)	*(2010s)*		*(abs.)*	*(%)*
Op. Leverage	0.03	0.11	0.1335	1.0 %	7.9 %
Years since IPO	8.39	16.32	-0.0015	-1.2 %	-9.2 %
Ln(total assets)	-0.38	0.76	-0.0042	-0.5 %	-3.7 %
Op. Cash flow	5.9 %	0.5 %	-0.0099	0.1 %	0.4 %
Net cash flow	9.0 %	-3.4 %	0.0516	-0.6 %	-5.0 %
Net working capital	20.5 %	3.5 %	-0.2779	4.7 %	36.6 %
Capital exp.	7.9 %	5.3 %	-0.3084	0.8 %	6.2 %
Acquisition exp.	0.6 %	2.2 %	-0.1681	-0.3 %	-2.1 %
Dividend payer	0.63	0.41	0.0049	-0.1 %	-0.8 %
Book Leverage	0.26	0.19	-0.2588	1.7 %	12.8 %
Market-to-book	1.28	2.19	0.0117	1.1 %	8.2 %
R&D exp.	1.3 %	4.8 %	0.0750	0.3 %	2.1 %
Sales volatility	0.15	0.19	0.0606	0.2 %	1.6 %

Moreover, we can assess the forecasting performance of operating leverage in predicting cash holdings, in an out-of-sample exercise. First, I estimate the model over the first 40% of observations, i.e. the sub-sample that ends in 1994 included, and then generate predictions for the following years. Differently from section 3.3.3, I employ a time trend rather time fixed-effects, by necessity. Figure 3.10 plots the actual evolution of average cash holdings against the prediction using the full set of control variables, to show the overall match of the full model with the data: as already pointed out in the literature, it is difficult to predict the whole upward trend in cash holding, still so. Second, figure 3.11 performs a horse-race between variables: operating leverage, sales volatility, and research and development expenditures. Each of them is used to obtain a prediction for cash holdings, together with age, the logarithm of real assets, and a time trend as additional variables, to add a basic control of the sample composition. The performance of the prediction obtained with operating leverage is remarkably good when compared to the other two predictions. Moreover, it is also similar to predictions obtained with capital expenditures and net working capital (not shown; available upon request). This again suggests that operating leverage is an important factor driving this secular increase, at least comparable to other important factors pointed out in the literature.

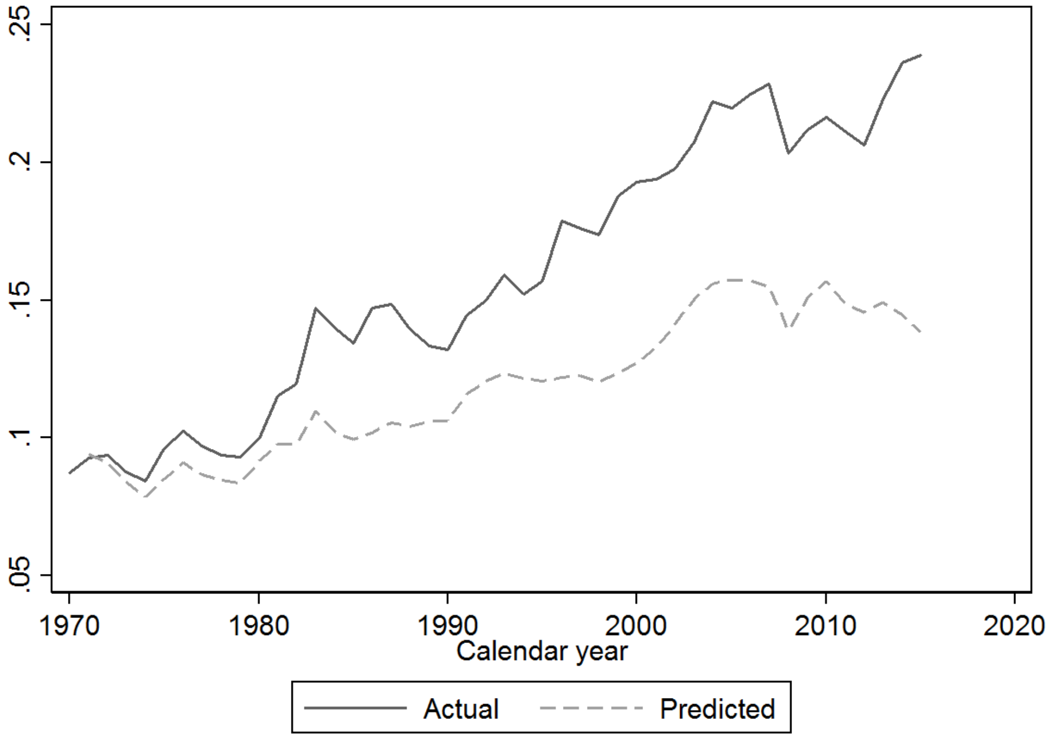


Figure 3.10: Cash holdings: actual vs. model's prediction.

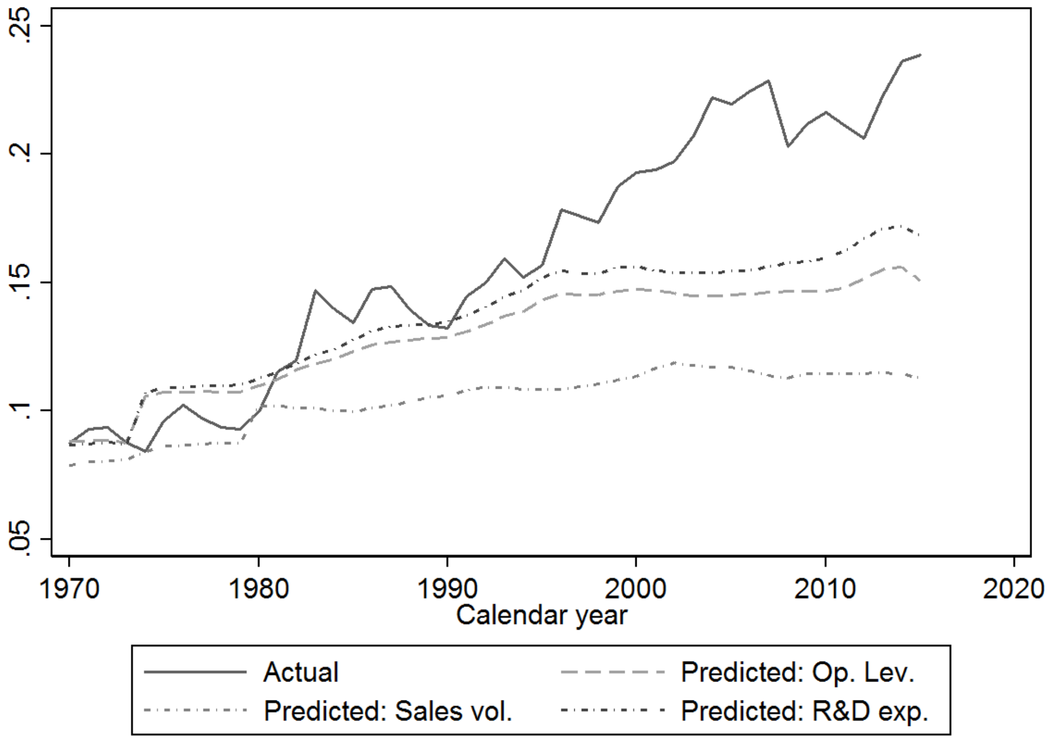


Figure 3.11: Cash holdings, out-of sample prediction: operating leverage vs. sales volatility vs. R&D expenditures. Additional control variables are time, firm's age and size.

Industry analysis. Finally, it is also of interest to map the firm-level measure of costs flexibility at the industry-level. Tables 3.8 and 3.9 detail the top and bottom industries within two common classification systems, the 2-digits SIC and the Fama-French 48 industries classification. Remember that not all industries are in the sample, since I eliminated financials and utilities[4]. See Kahle and Walkling (1996) for a general discussion about industry classifications.

In a purely descriptive perspective, the lowest rankings are mainly occupied by firms who operate in transportation or retail industries, while the highest rankings by firms who operate in more capital-intensive industries, such as mining, agriculture or pharmaceutical industry. The rankings broadly confirms what one could naively think about the degree of costs flexibility across different industries - which is reassuring.

[4]I also dropped 2-digits SIC industry 89, "Services, not elsewhere classified," since it had only two firms for a total of just three observations. It would have made the top spot, with an estimated operating leverage of above one!

Table 3.8: Fama-French 48 industries.

	mean op. leverage	description
1	.296	Precious Metals
2	.284	Pharmaceutical Products
3	.159	Medical Equipment
4	.146	Non-Metallic and Ind
5	.132	Petroleum and Natural Gas
...	...	...
39	0.016	Transportation
40	0.006	Retail
41	0.002	Communication
42	-0.000	Business Supplies
43	-0.002	Tobacco Products

3.3.4 Testing the model's predictions

This final section aims at testing the model's predictions. First, whether operating cash flow volatility is increasing in operating leverage, while costs volatility is not. Second, whether and how operating leverage channels the effects on cash holdings of the costs and benefits of liquidity.

Operating leverage: cash flow and costs volatilities. Does operating leverage increases cash flow volatility? This is, in fact, the central assumption behind the cash holdings model presented in section 3.2. First of all, we should consider only residual cash flow volatility, after controlling for the level of sales volatility, since the two might be mechanically related. In addition to employing sales volatility as a control variable, I also run for each firm the following regression,

$$\sigma_{i,t}\left(ebitda\right) \quad = \quad \alpha_i + \sigma_{i,t}\left(sales\right) + \varepsilon_{i,t}^{\sigma(ebitda)}, \tag{3.22}$$

where α_i is a firm-specific dummy and $\sigma_{i,t}\left(ebitda\right)$ and $\sigma_{i,t}\left(sales\right)$ are cash flow and sales volatilities, respectively. This, the residual $\varepsilon_{i,t}^{\sigma(ebitda)}$ should capture the residual cash flow volatility, net of sales volatility and also firm fixed effects.

Second, we should also check the assumption behind prediction 1B: that the correlation between sales and costs is sufficiently high; see equation (3.11). In fact, in the data, condition (3.11) holds for almost 80% of the observations, with only a minority of firms that do not comply. I obtain covariances and correlations from the variance decomposition of cash flow, i.e. equation (3.10), using the estimated variance of sales, costs and cash flow; in levels, not growth rates, otherwise equation (3.10) does not apply.

Cash flow is measured as the difference between sales (item `sale`) and operating costs (item `xopr`), which corresponds to earnings before interest, taxes, depreciation and amortization (item `ebitda` or equivalently `oibdp`), adjusted for inflation. It is the measure of cash flow that is mostly related to production activities.

Table 3.10 reports the results of three regressions, repeated twice: first for the whole sample and second for the restricted sample in which condition (3.11) holds. Column

Table 3.9: SIC 2-digits industries.

	mean op. leverage	2-digit SIC	description
1	0.385	86	Membership Organizations
2	0.268	10	Metal Mining
3	0.169	13	Oil and Gas Extraction
4	0.168	28	Chemical and Allied Products
5	0.153	99	Nonclassifiable Establishments
6	0.135	8	Forestry
7	0.124	1	Agricultural Production - Crops
8	0.113	78	Motion Pictures
9	0.112	38	Mesr/Anlyz/Cntrl Instrmnts; Photo/Med/Opt Gds; Watchs/Clocks
10	0.107	12	Coal Mining
...	...	...	...
57	-0.011	75	Automotive Repair, Services, & Parking
58	-0.012	42	Motor Freight Transportation
59	-0.012	41	Local, Suburban Transit & Interurban Hgwy Passenger Transport
60	-0.015	55	Automotive Dealers and Gasoline Service Stations
61	-0.015	72	Personal Services
62	-0.017	47	Transportation Services
63	-0.024	45	Transportation by Air
64	-0.030	76	Miscellaneous Repair Services
65	-0.034	29	Petroleum Refining and Related Industries
66	-0.213	9	Fishing, Hunting and Trapping

one (four) reports the regression of operating cash flow volatility on operating leverage. Column two (five) adds sales volatility as a control. Finally, column three (six) displays the estimated coefficients of a regression of residual cash flow volatility on operating leverage,

$$\varepsilon_{i,t}^{\sigma(ebitda)} = \alpha + \beta\omega_i + \nu_{i,t}. \tag{3.23}$$

The coefficient on ω_i is always positive, but is significant (and larger) only in the restricted sample. This indeed supports prediction 1B: operating cash flow volatility is increasing in operating leverage.

Furthermore, figures 3.12 and 3.13 plot the empirical probability density and cumulative distribution functions, respectively, of residual cash flow volatility for firms with below or above the median value of operating leverage. Both figures show how the distribution of residual cash flow volatility is indeed more spread out for the firms with larger operating leverage – in line with the theoretical model.

Next we move to prediction 1A: is operating leverage negatively related to operating costs volatility? In fact, we should expect a positive answer even without running the regressions: the higher the degree of fixed costs and the lower the volatility of costs, almost by definition. But table 3.11 does the check, using the same three types of regression already employed above: the estimated coefficient on ω_i is significantly negative, but only when properly controlling for sales volatility. This leave us with an interesting implication: operating leverage is positively related with sales volatility. That is, riskier businesses (in terms of sales) seem to go hand in hand with riskier firms (in terms of costs structure); this has also been noted in Banker et al. (2013).

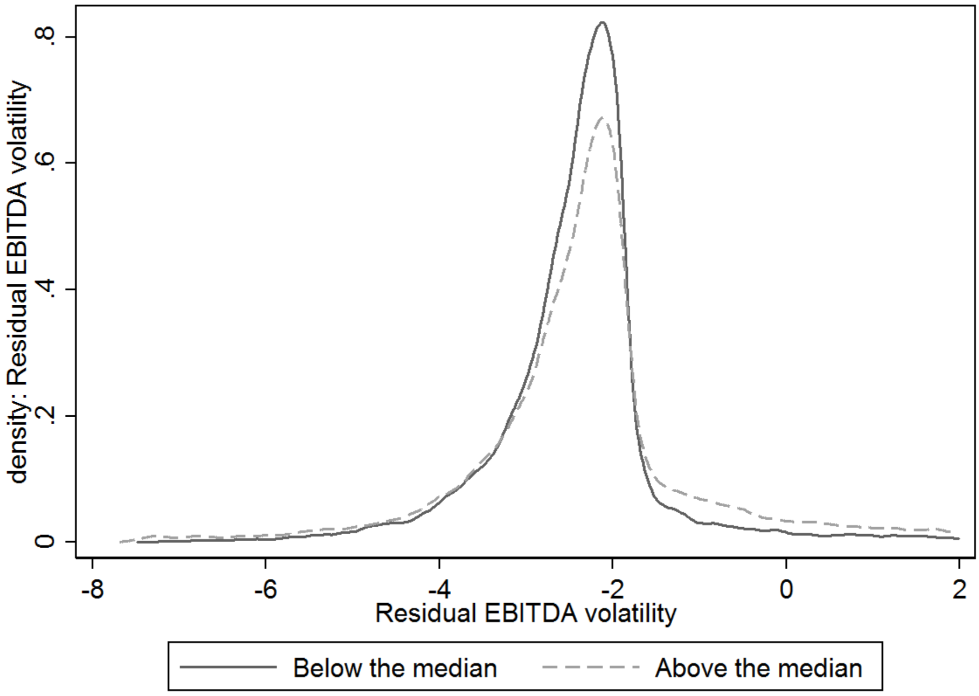


Figure 3.12: Probability density function: residual cash flow volatility $\varepsilon_{i,t}^{\sigma(ocf)}$.

Table 3.10: Cash flow volatility and operating leverage.

	(1)	(2)	(3)	(4)	(5)	(6)
Op. Leverage	5.27	4.09	4.54	10.8*	9.87*	10.5*
	(1.75)	(1.45)	(1.36)	(2.52)	(2.44)	(2.27)
Sales volatility		9.72***			10.8***	
		(3.51)			(3.36)	
Constant	3.93***	2.00**	0.58	3.09***	0.98	-0.25
	(9.52)	(3.28)	(1.42)	(10.32)	(1.52)	(-0.87)
Observations	103641	102961	102961	80240	79887	79887

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

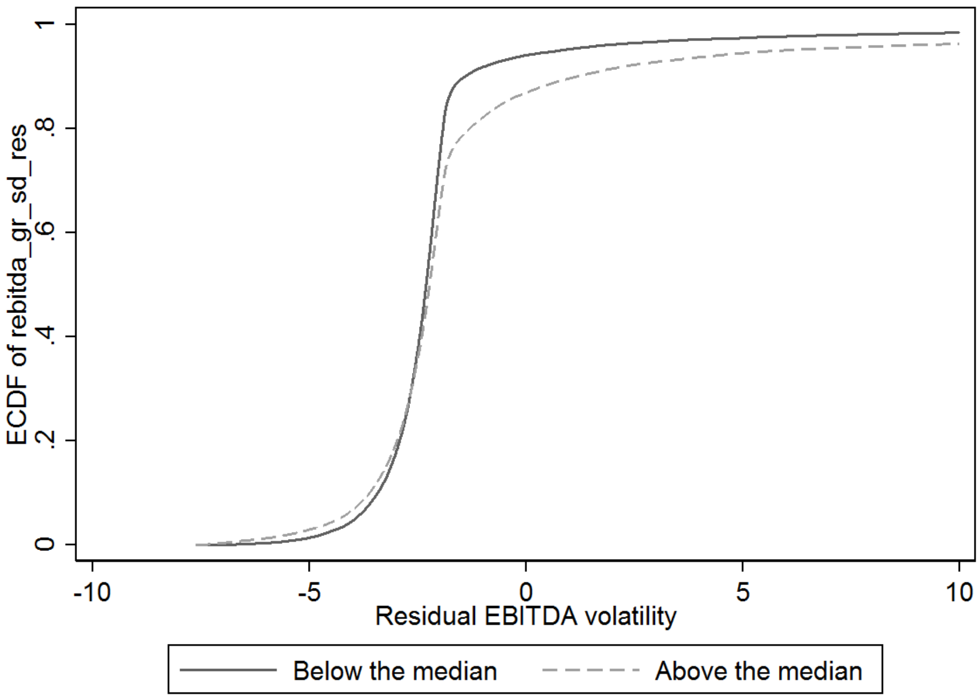


Figure 3.13: Cumulative distribution function: residual cash flow volatility $\varepsilon_{i,t}^{\sigma(ocf)}$.

Interaction with costs and benefits of liquidity. Prediction 2A has in fact already been confirmed: cash holdings are indeed positively correlated with operating leverage. The second part states instead that, for any given degree of operating leverage, cash holdings are positively related to the cost of raising external funds while negatively related

Table 3.11: Costs volatility and operating leverage.

	(1)	(2)	(3)
Op. Leverage	0.13***	-0.12***	-0.12***
	(15.08)	(-14.75)	(-15.01)
Sales volatility		0.87***	
		(129.50)	
Constant	0.19***	0.021***	0.0076***
	(134.50)	(15.90)	(14.67)
Observations	104336	103632	103632

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

to the cost of holding liquidity. The empirical challenge is to find valid proxies for these two costs.

I use two proxies for the cost of raising external funds κ. First, the ratio of interest and related expenses over total debt: item `xint` divided by `(dltt+dlc)`. This should give a broad but direct measure of how external financing is expensive for any firm, the only drawback being that not all firms do actually have debt outstanding. Second, the total payout ratio, measured as the sum of dividends paid and stock repurchased less stock issued; items `(dvt+prstkc-sstk)` divided by `at`. This is a commonly-used proxy of credit constraints: the larger the payouts, the less a firm is financially constrained. I also tried with firm size as a proxy for credit constraints, either as the log of real sales or the log of employees, with similar results.

I use two proxies as well for the cost of holding liquidity r. First, the ratio of capital expenditures over total assets; item `capx` divided by `at`. This should be proportional to the firm's need of cash, either for investing purposes or to maintain the capital stock. Second, the growth rate of sales, computed as the compounded annual growth rate (CAGR) over three years around each time period; item `sale` inflation-adjusted. This should capture how much a firm is growing and (presumably) using cash to sustain the growth. I also tried with the market-to-book ratio as a proxy for investing opportunities with similar results.

Tables 3.12 and 3.13 report the results of regressions that interact those four proxies with the estimated degree of operating leverage; non interacted variables are always included in the regressions, together with the group of control variables and time and firm dummies. All variables and interaction terms are winsorized at the 1st and 99th percentiles. The coefficients have all the expected sign, in accordance with prediction 2B; positive on the interaction term with interest expenses, while negative on the interaction terms with payout ratio, capital expenditures, and real sales growth – even if not all of them are statistically significant at the usual levels.

Table 3.12: Interaction with κ (positive).

	(1)	(2)
Op. Leverage	0.11***	0.11***
	(8.00)	(9.31)
Interest Expenses	0.0077*	
	(2.05)	
Op. Lev. * Int. Exp.	0.028	
	(0.57)	
Payout ratio		-0.11***
		(-10.80)
Op. Lev. * Payout ratio		-0.042
		(-0.95)
Observations	72161	76450

t statistics in parentheses

Note: dependent variable is cash-to-assets (che/at). Time FE are included.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.13: Interaction with r (negative).

	(1)	(2)
Op. Leverage	0.15***	0.14***
	(10.39)	(10.49)
Op. Lev. * Capex	-0.29**	
	(-3.04)	
Capital exp.	-0.29***	-0.31***
	(-24.91)	(-26.61)
Real sales CAGR		-0.013**
		(-2.78)
Op. Lev. * Real sale CAGR		-0.10**
		(-3.09)
Observations	80977	74067

t statistics in parentheses

Note: dependent variable is cash-to-assets (che/at). Time FE are included.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3.4 Conclusions

The extent to which firms hold cash as a precautionary motive depends also on operating leverage, which denotes a firm's capacity to adjust its costs to sales shocks. In particular, a higher degree of operating leverage leads to higher cash holdings, as the firm is subject to larger swings in cash flows following any given shock in sales.

Over the last decades, U.S. publicly listed firms almost doubled their average cash holdings. At the same time, the average degree of operating leverage also doubled. The link between the two seems robust, with the optimal cash holdings model's predictions finding supportive evidence in the data. Moreover, the empirical exercise carried out in this article suggests that about 10% of the increase in cash holdings can be associated to the increase in operating leverage, which is at least as the percentage attributable to other known factors in the literature, such as sales volatility or R&D expenditures. Even though much remains to be explained, the role of operating leverage presents a novel explanation of the long-term increase in cash holdings and also points out an interesting pattern. Indeed, one important question that remains to be answered is why operating leverage has increased. One potential explanation is a technological story, e.g. the increasing adoption of automation processes implies a larger share of fixed costs; another can be a business story, e.g. the market environment induced firms to take on greater risks and choose costs structure that are relatively less flexible. In fact, evidence even suggests that riskier businesses (in terms of sales) are positively related to riskier firms (in terms of costs structure).

To conclude, even if the theoretical setup and its implications are quite straightforward, the empirical evidence here presented cannot be seen as conclusive, given the objective difficulties in measuring operating leverage. In particular, further research can be done to better gauge the costs flexibility of firms. In fact, the costs structure may affect decisions other than cash holdings, such as capital expenditures, which in turn may affect the cost structure in an endogenous way. That is, new investments or acquisitions may change sensibly a firm's costs structure over time, which in fact is a possibility that I ruled out in the present article.

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Appendix A

Operating leverage and the decline in business dynamism

A.1 Control variables

The list of control variables employed in this article is detailed in table A.1 below. Most of them are commonly found in the corporate finance literature; e.g. Bates et al. (2009). Item `cpi` is the consumer price index, in 1982-84 U.S. dollars, from the Bureau of Labor Statistics, which is used to obtain inflation-adjusted series.

Table A.1: Control variables.

Variable:	*Description:*	*XPF name:*
Years since IPO	`NA`	`NA`
Log total assets	Inflation-adjusted values	`log(at/cpi)`
Capital exp.	`NA`	`capx/at`
R&D exp.	(Set to zero if missing)	`xrd/at`
Acquisition exp.	`NA`	`aqc/at`
Net working capital	(Net of cash)	`(wcap-che)/at`
Cash-to-assests	`NA`	`che/at`
Dividend payer (if=1)	(Dummy variable)	`=1` if `dvt`>`0`
Book leverage	`NA`	`(dltt+dlc)/at`
Market-to-Book	Book value of assets - book value of equity + market value of equity	`(at-ceq+csho*prcc_f)/at`
Sales volatility	Rolling SD of growth rate	[See equations (1.7) and (1.8)]
Op. Cash flow	Operating cash flow	`(oibpd-txt-xint-(nwc-L.nwc))/at`
Net cash flow	Net income + depreciation	`(ib+dp)/at`

A.2 Industry-level operating leverage

Given the inherently inaccuracy of any estimate of operating leverage at the firm level, in this section I exploit the panel structure to obtain a more accurate measure. The assumption we need to make is that operating leverage is the same for all the firms in the same industry: it is, in fact, a quite strong assumption, but nevertheless it is interesting to investigate the issue in this direction. For each industry j, I run the following panel regression:

$$\Delta c_{i,j,t} = \alpha_{j,0} + \beta_{j,0}\Delta s_{i,j,t} + \gamma_j \left(s_{i,j,t-1} - c_{i,j,t-1}\right) + \nu_{i,j,t} \tag{A.1}$$

where $i \in j$ denotes firms belonging to that industry. That is, obtain an estimate of operating leverage at the industry level: $1 - \hat{\beta}_{j,0} \to \omega_j$. Table A.2 reports summary statistics, while figure show the variation over time of the (across-industries) average operating leverage. The secular increase is still there, if anything more reinforced.

Table A.2: Summary statistics: operating leverage at industry-level.

Variable	Obs	Mean	Std. Dev.	P10	P25	P50	P75	P90
sic2	184454	.19	.14	.04	.09	.18	.23	.33
sic3	184454	.17	.15	.03	.07	.14	.24	.35
sic4	184447	.17	.15	.02	.06	.13	.25	.35
naics3	161004	.2	.14	.04	.1	.17	.26	.37
naics4	160573	.19	.16	.03	.08	.16	.26	.37
naics6	156833	.18	.17	0	.05	.13	.28	.37

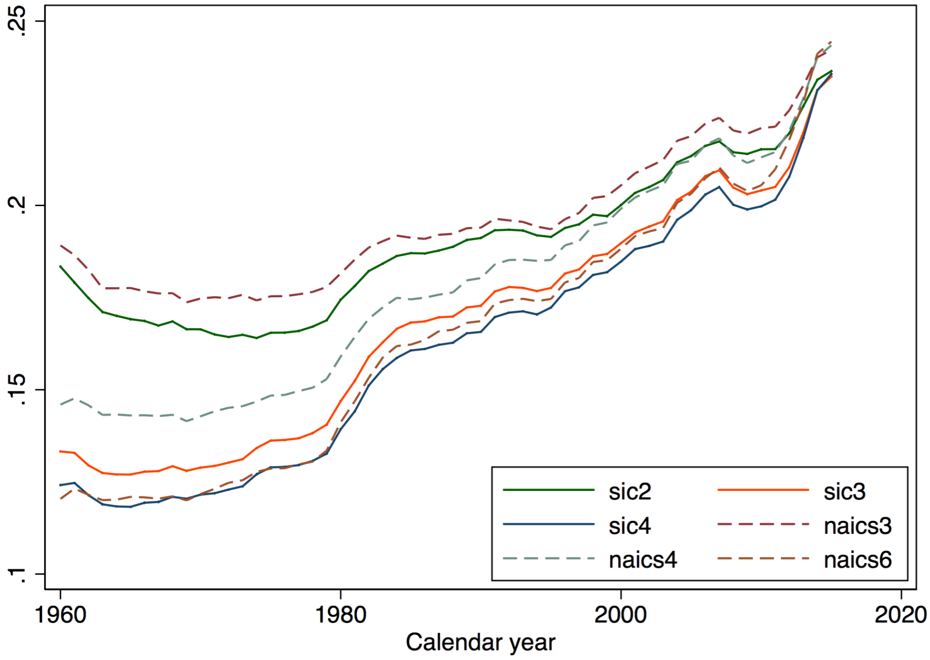
But how costly is the assumption of constant operating leverage within each industry? Though impossible to answer, we can have a look at the variation within industries of the firm-level measure; see figure A.2, here using the Fama-French 48 industries classification. There is actually a lot of variation within any industry – how much this is due to measurement error we cannot say. Yet, it is apparent that some industries have higher values of operating leverage. In particular, the three highest upper quartiles are in the Pharmaceutical Products, Precious Metals, and Petroleum and Natural Gas industries. Henceforth, the assumption we are making may not be too farfetched.

A.3 Other possible causes of the secular increase

Are there other possible determinants of the secular increase in operating leverage? In this subsection, I look after other potential explanations. I focus on the following hypotheses:

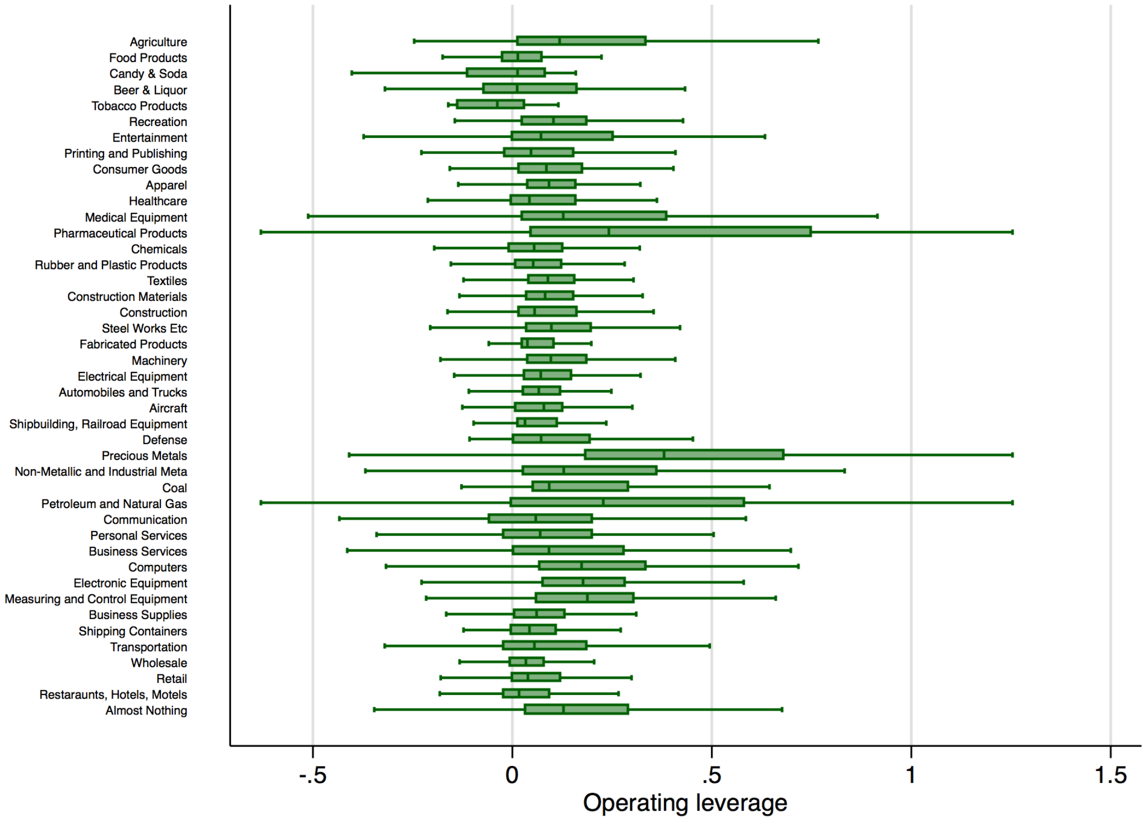
1. an increase in firms usage of automation technologies and industrial robots;
2. an increase in firm's markup correlation with sales;
3. an increase in outsourcing/offshoring.

Figure A.1: Average industry-level operating leverage.



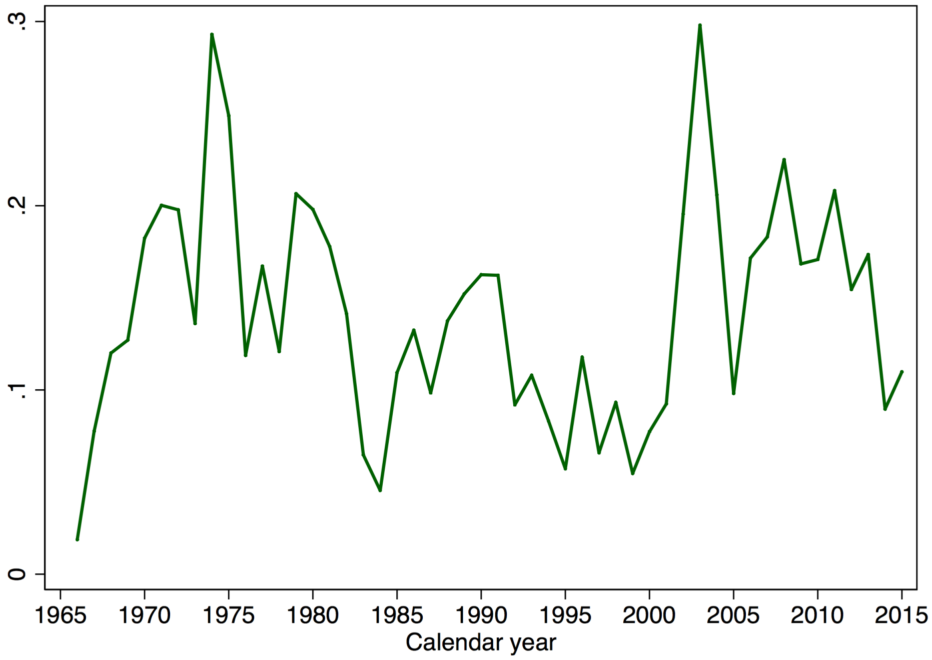
Note: the set of industries are defined by two most common classification systems: Standard Industry Classification (SIC) and North American Industry Classification System (NAICS). The number following the classification system denotes the disaggregation level, i.e. the number of digits. The number of distinct industries in each classification is 66 for sic2, 247 for sic3, 395 for sic4, 108 for naics3, 385 for naics4, and 1235 for naics6.

Figure A.2: Operating leverage: box-plot over Fama-French 48 industries.



Note: the filled line report the interquartile range, with the middle bar denoting the median; the solid line reports instead the lower (upper) adjacent value, which is defined as the observation that is above (below) the 25 (75) percentile minus (plus) 3/2 times the interquartile range.

Figure A.3: Cross-sectional correlation: PCM - sales growth rate.



The first cause seems very relevant. Indeed, the story might go, an automation-intensive plant might trade-off a lower marginal costs of production with a higher fixed cost (e.g. maintenance, set up, ...). However, there is a major empirical difficulty in assessing this story: the lack of data at the firm-level. There is now an increasing number of articles that focus on the spread of automation and robots, but at most they focus at the industry level; see Graetz and Michaels (2016, 2017) and Acemoglu and Restrepo (2017) in particular, which use data from the International Federation of Robotics (IFR). Henceforth, it remains an open question. All we can say is that: robot usage might well be related to R&D-intensity at the firm-level, but capital expenditures (which might proxy for investment in automation) are not correlated anymore with operating leverage once we control for industries dummies. Nevertheless, this explanation is certainly connected to the rising importance of innovation-intensive firms, i.e. the two ideas can very well overlap and be complementary.

The second cause is more a general concern: a positive correlation between sales and markups can induce a bias in the estimate of operating leverage. Indeed, if sales increase just because the markup has increased but costs have remained constant (i.e. a variation in prices without a variation in quantities), then we would measure a certain degree of rigidity in costs. In fact, I am not worried about the existence of this correlation: after all, this mechanism does fit into a broad definition of operating leverage. The concern is whether this correlation, if any, has changed over time. Figure A.3 reports the (cross-sectional) average correlation coefficient between the price-costs margin and the sales growth rate; the former is defined as $pcm = (sale - xopr)/xopr$, while the latter as the growth rate in equation (1.8). This statistic appears quite volatile, but there is no apparent secular trend: an increasing correlation between sales and markup does not seem a driving force of the secular increase in operating leverage.

Table A.3: Different estimation methodologies.

name		*description*
$\omega_{\ln}$	ln	$= 1 - \frac{\mathrm{d}\log(costs)}{\mathrm{d}\log(sales)}$
$\omega_{\mathrm{d}\ln}$	d_ln	$= 1 - \frac{\mathrm{d}\log(\Delta costs)}{\mathrm{d}\log(\Delta sales)}$
ω_{ebitda}	E	$= \frac{\mathrm{d}\log(ebit)}{\mathrm{d}\log(sales)}$
$\omega_{ebitda\|adj}$	E_adj.	see García-Feijóo and Jorgensen (2010)
$\omega_{\log\|HP}$	hp	log-sales and log-costs are detrended using an HP filter
ω_{rol}	rol	five-years rolling estimate

The third cause, i.e. the increase in outsourcing/offshoring is a very interesting issue. Operating leverage depends on the elasticity of operating costs, which include any operating expenditure (regardless of whether it is outsourced or not). Hence, a firm that outsources many of its expenditures items might obtain a greater flexibility and a lower level of operating leverage – or maybe not. In fact, it is not at all obvious that outsourcing makes an expenditure more flexible: for instance, outsourcing may require a contract that prescribes very specific delivery and payment obligations, which makes costs to be actually more rigid. Hence, the outcome really depends on the institutional/organizational/legal environment in which the firm operates – and I sincerely do not have any prior on this. Again, we need better data at the firm level, leaving it as another open issue and venue of research.

A.4 Operating leverage: robustness

This section describes alternative methodologies for the estimation of operating leverage. Table A.3 summarizes them.

First, the measure of operating leverage $\omega_{\ln}$ is obtained using the plain definition of costs elasticity, i.e. estimating the following regression:

$$y_t = \beta_0 + \beta_1 x_t + \nu_t \tag{A.2}$$

so that $\beta_1 \to 1 - \omega_{\ln}$. The problem with this definition is the potential non-stationarity of the two variables.

Second, the measure $\omega_{\mathrm{d}\ln}$ is instead the definition of cost elasticity applied to first differences, i.e. estimating the following:

$$\Delta y_t = \beta_0 + \beta_1 \Delta x_t + \nu_t \tag{A.3}$$

which in fact is miss-specified if the two variables are cointegrated, i.e. lags are missing, cf. with equation (1.3).

Third, the measure ω_{ebitda} is obtained by using the operating income before depreciation and amortization[1] instead of operating costs as dependent variable, i.e. estimating

[1] Item *oibdp* is the difference between sales (item *sales*) and operating costs (item *xopr*). It is also equal to item *ebitda*, i.e. earnings before interests, taxes, depreciation and amortization.

the following:

$$\underbrace{(x_t - y_t)}_{ebitda_t} \;=\; \beta_0 + \beta_1 x_t + \nu_t \tag{A.4}$$

so that $\beta_1 \to \omega_{ebitda}$. The problem is about negative values, which are not defined for logarithms and are about 15% of the total observations. Hence, we can improve upon this measure, as much of the literature have done, following García-Feijóo and Jorgensen (2010)[2]: using $\ln(1 + ebitda)$ if $ebitda \geq 0$ or $-\ln(1 - ebitda)$ if $ebitda < 0$ and then performing the regression on the detrended series, using a linear time trend. This delivers $\omega_{ebitda|adj}$.

It is possible to use other detrending methods. For instance, Kahl et al. (2013) use a compounded annual growth rate (CAGR) over a four-years period to distinguish innovations in the series. Here, to be more general, I apply a Hodrick-Prescott filter to obtain the cyclical components[3] μ_t^y and μ_t^x and then I perform the following regression:

$$\mu_t^{costs} = \beta_0 + \beta_1 \mu_t^{sales} + \nu_t \tag{A.5}$$

which gives $\beta_1 \to 1 - \omega_{\log|HP}$.

Finally, the measure ω_{rol} is the rolling-estimate, which comes from the same specification as in (1.3) but over a rolling time-window of five years.

Table A.4 presents the summary statistics of all these estimates, while table A.5 reports the cross-correlation matrix; values are winsorized at P1-P99 to eliminate the influence of big outliers on the average. Finally, figure A.4 reports the evolution of these measures averages over time. My preferred measure is SR, which comes from the short-run costs elasticity in the dynamic equation (1.4). In fact, all the measures obtained by looking at costs show a similar behavior; only the simple log estimate show a large difference in levels, but not in trends. However, the measures obtained by looking at earnings (i.e. ebitda) show a different pattern, with large differences in levels and quite constant over time. The concern that I have, especially with the adjusted measure $\omega_{ebitda|adj}$, is the arbitrariness in assuming a linear time trend to detrend the series, which might deliver badly-behaved residuals.

A.5 Simulation: operating leverage estimation

In order to assess the validity of the estimation procedure discussed in subsection 1.2.3 and to compare it with other estimation methodologies discussed in the literature (further details are in Appendix A.4), I use simulated data. First, I compare the performance of

[2] In fact, García-Feijóo and Jorgensen (2010) use *ebit*, not *ebitda*, but I choose the latter because I prefer to be as close as possible to the firm's production structure.

[3] which are percentage innovations. That is, given $x_t = x_t^{cycl} + x_t^{trend}$, they are defined as : $\mu_t^x = \frac{x_t^{cycl}}{x_{t-1}}$.

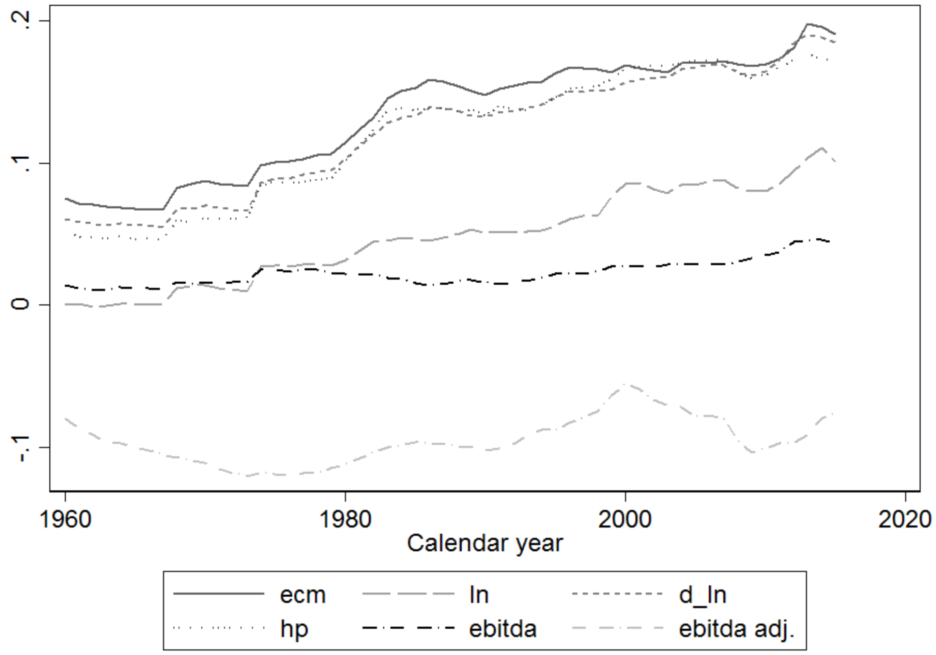
Table A.4: Summary statistics: different estimates of operating leverage.

Variable	Obs	Mean	Std. Dev.	P5	P25	P50	P75	P95
Operating Leverage	177632	.14	.27	-.14	.01	.08	.22	.69
Rolling Op. Leverage	113798	.14	.3	-.24	-.01	.08	.25	.74
Op. Leverage SR	177632	.16	.31	-.19	0	.08	.24	.9
Op. Lev. (ln)	181275	.05	.24	-.2	-.03	.01	.09	.5
Op. Lev. (d_ln)	177632	.13	.27	-.16	0	.07	.2	.67
Op. Lev. (ebitda)	171274	.02	.16	-.16	-.03	0	.05	.27
Op. Lev. (ebitda adj.)	177163	-.09	.23	-.42	-.14	-.08	-.03	.2
Op. Lev. (ebitda std.)	177163	.24	.38	-.05	.02	.1	.34	1.01
Op. Lev. (HP-filtered)	177930	.13	.32	-.23	-.01	.07	.22	.77
Op. Lev. (balance sheet)	168911	1.24	.89	.2	.65	1.07	1.57	2.93

Table A.5: Cross-correlation table for operating leverage estimates.

Variables	ecm	rol	adl	ln	d_ln	ebitda	ebitda_adj	ebitda_std	hp	bs
ecm	1.00									
rol	0.55	1.00								
adl	0.73	0.50	1.00							
ln	0.43	0.20	0.48	1.00						
d_ln	0.79	0.49	0.68	0.55	1.00					
ebitda	0.15	0.11	0.18	0.51	0.21	1.00				
ebitda_adj	0.17	0.08	0.16	0.16	0.20	-0.06	1.00			
ebitda_std	0.07	0.03	0.02	-0.06	0.09	0.13	0.12	1.00		
hp	0.64	0.42	0.62	0.49	0.78	0.23	0.21	0.07	1.00	
bs	-0.17	-0.14	-0.16	-0.08	-0.18	-0.07	0.21	-0.15	-0.14	1.00

Figure A.4: Robustness. The secular increase in operating leverage: 1970–2015.



the ECM with other methodologies over different data generating processes, but using the same sample. Second, I assess the accuracy of the estimate over different samples, but only for the ECM.

Consider a sample of $i = 1, \ldots, 5000$ firms with $t = 10$ years of observations each. Operating leverage is set to be constant for each firm and its value is i.i.d across firms from a uniform[4] distribution: $\omega_i \sim U[0, 1]$. That is, I try to be as agnostic as possible about its value. Sales $S_{i,t}$ can follow different random processes, which are specified in table A.6, while operating costs are directly related to sales as following:

$$C_{i,t} = \omega_i \bar{S}_i + (1 - \omega_i)(1 - \mu_{i,t}) S_{i,t} + \varepsilon_{i,t}$$

where the fixed cost is equal to average sales over the whole period, $\bar{S}_i = \frac{1}{10} \sum_{\tau=1}^{10} S_{i,\tau}$, while variable costs are equal to sales less the markup $\mu_{i,t}$, which is a random variable as well, which can take values specified in table A.6. Finally, $\varepsilon_{i,t} \sim N(0, 100)$ is an i.i.d error term, to introduce some disturbance between sales and costs, otherwise they would be perfectly collinear. Then, given these series for sales, costs, and in turn also earnings, I estimate operating leverage using five different methodologies, whose acronyms are in squared brackets: (i) the elasticity of earnings on sales [E], (ii) the elasticity of adjusted earnings on sales [E_adj], (iii) the elasticities of costs on sales in first differences [dln], (iv) the more general dynamic ADL specification [ADL], and (v) the error correction model [ECM], which is my preferred procedure. The second procedure corresponds to what seems to be the standard in the literature: first, obtain residuals for both sales

[4] I also set operating leverage to be constant across firms, $\omega_i = \omega = 0.2$, or to be drawn from other distributions, such as the beta distribution, $\omega_i \sim B(2, 5)$. The latter allows to be more in line with the empirical data, since the beta distribution $B(a, b)$ is bounded between zero and one and has mean $a/(a + b)$. Nonetheless, results are very similar; available upon request.

Table A.6: Data generating processes: sales and markup.

	process	*acronym*	*description*
$S_{i,t}$	$\sim N(1000, 100)$	Norm	normally distributed
	$\sim S_{i,t-1} + N(0, 100)$	Rw	random walk
	$\sim S_{i,t-1} + N(100, 100)$	Rwt	random walk with trend
	$\sim 350 + 0.65S_{i,t-1} + N(0, 100)$	AR.65	AR(1) with $\rho = 0.65$ (25P of sample)
	$\sim 50 + 0.95S_{i,t-1} + N(0, 100)$	AR.95	AR(1) with $\rho = 0.95$ (75P of sample)
$\mu_{i,t}$	$= 0.1$	Cons	constant (about 50P of sample)
	$\sim U(0.03, 0.25)$	Unif	uniformly distributed, between 25P-75P
	$\sim B(3, 7)$	Beta	beta distributed, with mean 0.3
	$\sim 0.1 + \gamma_{i,t}$	Cor	correlated with the related sales process, where $\gamma_{i,t}$ is sales growth rate

and earnings from OLS regressions with a time trend and the initial value, then, obtain the earnings elasticity from an OLS regression using the residuals; see García-Feijóo and Jorgensen (2010) for a detailed explanation.

Table A.7 reports the results of the estimation: the average estimated value for operating leverage, which we know to be 0.5, and the average mean squared error[5]. That is, for each firm, I compare the true value of operating leverage, which is itself a random variable, with the estimated value from each model and then I take the average over the whole sample. Given the number of different data generating processes, we can assess the robustness of the different estimation procedures. Overall, the ECM results to be the more accurate procedure, with the smaller average MSE.

As a second step, I assess how accurate is the ECM estimation when varying the number of years available for the estimation. Here, I assume that sales follow an AR(1) process with an autoregressive coefficient of 0.75, while the error in the costs function is now serially correlated with its lag with a coefficient of 0.5. The markup is 0.1 and operating leverage is 0.2. The sample is made of 40 groups, each with a corresponding number of years of data, from 5 to 45, with 2000 firms for each group. That is, the first group contains firms with only five years data, the second with six years, and so on. Table A.8 reports some summary statistics of the estimated value of operating leverage across the different groups of firms. Five years of data only does not guarantee much accuracy, but adding just one more year improves significantly the accuracy. With ten years of data we already have a pretty accurate estimate, whereas increasing further the sample size does not deliver anymore great improvements; with forty years of data, the interquartile rage is still .11-.24, while the true value is .2, so that it is obviously too much to ask for a very precise figure for any single firm with real-world data availability. However, the major interest is in the distribution, so that we do not have to worry much about the single estimates, as long as we are getting the big picture right. If anything, the ECM with this data specification delivers a little downward bias; considering also the presence of such measurement error, any empirical correlation is already a significant finding.

[5]The mean squared error is defined as $MSE(\hat{\omega}) = \frac{1}{n}\sum_{i=1}^{n}(\hat{\omega}_i - \omega_i)^2$. It is a classic efficiency measure of an estimator, indicating how far the estimates is from the true value.

Table A.7: Simulated data: estimated operating leverage and MSE.

		Op. Leverage					MSE				
sales	markup	E	E_adj	dln	ADL	ECM	E	E_adj	dln	ADL	ECM
Norm	Cons	0.3	0.24	0.52	0.52	0.46	0.17	0.18	0.01	0.01	0.01
Rw	Cons	0.28	-0.06	0.53	0.52	0.49	0.18	0.42	0.02	0.02	0.02
Rwt	Cons	0.22	-0.06	0.54	0.52	0.5	0.2	0.06	0.02	0.01	0.02
AR.65	Cons	0.3	-0.04	0.52	0.52	0.47	0.18	0.36	0.01	0.01	0.02
AR.95	Cons	0.29	-0.04	0.52	0.52	0.48	0.18	0.33	0.02	0.01	0.02
Norm	Unif	0.33	0.31	0.53	0.53	0.43	0.2	0.22	0.05	0.05	0.04
Rw	Unif	0.31	-0.02	0.54	0.53	0.47	0.2	0.45	0.08	0.07	0.07
Rwt	Unif	0.25	0.1	0.54	0.52	0.44	0.19	0.14	0.13	0.11	0.13
AR.65	Unif	0.33	-0.04	0.53	0.53	0.45	0.2	0.39	0.06	0.06	0.05
AR.95	Unif	0.31	-0.07	0.53	0.52	0.45	0.21	0.46	0.08	0.07	0.06
Norm	Beta	0.48	0.44	0.56	0.56	0.41	0.38	0.38	0.27	0.28	0.15
Rw	Beta	0.46	-0.23	0.57	0.56	0.45	0.35	0.69	0.45	0.39	0.28
Rwt	Beta	0.4	-0.21	0.56	0.56	0.38	0.21	0.66	0.8	0.68	0.63
AR.65	Beta	0.49	-0.17	0.56	0.56	0.44	0.4	0.72	0.38	0.33	0.21
AR.95	Beta	0.48	-0.25	0.56	0.55	0.44	0.41	1	0.43	0.42	0.28
Norm	Cor	0.49	0.3	1.28	1.06	0.98	0.34	0.27	0.85	0.42	0.35
Rw	Cor	0.34	-0.09	1.12	1.05	0.99	0.26	0.41	0.55	0.42	0.36
Rwt	Cor	0.29	-0.08	1.18	1.1	1.06	0.19	0.22	0.68	0.5	0.45
AR.65	Cor	0.39	-0.04	1.15	1.06	0.97	0.27	0.33	0.61	0.42	0.34
AR.95	Cor	0.35	-0.06	1.12	1.06	0.98	0.26	0.44	0.55	0.42	0.35
average		0.35	0.00	0.70	0.67	0.59	0.25	0.41	0.30	0.24	0.19

Table A.8: Simulation data: accuracy over different time spans.

group	mean	SD	25P	50P	75P	MSE
5	0.136	1.414	-0.116	0.175	0.442	2.003
6	0.155	0.557	-0.067	0.154	0.370	0.312
7	0.155	0.345	-0.032	0.155	0.330	0.121
8	0.154	0.284	-0.018	0.158	0.320	0.083
9	0.155	0.260	0.010	0.157	0.308	0.070
10	0.162	0.234	0.021	0.166	0.296	0.056
11	0.164	0.218	0.034	0.162	0.295	0.049
12	0.169	0.193	0.048	0.170	0.293	0.038
13	0.159	0.182	0.045	0.157	0.273	0.035
14	0.170	0.175	0.060	0.180	0.277	0.031
15	0.165	0.167	0.060	0.165	0.266	0.029
16	0.167	0.158	0.063	0.169	0.274	0.026
17	0.168	0.150	0.073	0.162	0.265	0.024
18	0.167	0.147	0.071	0.162	0.254	0.023
19	0.168	0.142	0.075	0.167	0.260	0.021
20	0.171	0.141	0.080	0.171	0.263	0.021
21	0.172	0.131	0.088	0.176	0.256	0.018
22	0.177	0.133	0.085	0.171	0.267	0.018
23	0.167	0.134	0.085	0.168	0.257	0.019
24	0.168	0.122	0.091	0.168	0.246	0.016
25	0.170	0.120	0.086	0.172	0.251	0.015
26	0.173	0.119	0.094	0.173	0.251	0.015
27	0.174	0.118	0.097	0.174	0.255	0.015
28	0.171	0.114	0.095	0.170	0.249	0.014
29	0.170	0.109	0.101	0.168	0.243	0.013
30	0.172	0.111	0.100	0.174	0.246	0.013
31	0.175	0.108	0.101	0.175	0.246	0.012
32	0.174	0.106	0.100	0.173	0.245	0.012
33	0.173	0.104	0.102	0.173	0.240	0.011
34	0.173	0.101	0.108	0.171	0.239	0.011
35	0.171	0.100	0.104	0.170	0.239	0.011
36	0.173	0.100	0.105	0.171	0.237	0.011
37	0.176	0.098	0.112	0.177	0.242	0.010
38	0.173	0.097	0.108	0.175	0.239	0.010
39	0.177	0.091	0.115	0.174	0.239	0.009
40	0.173	0.093	0.108	0.172	0.235	0.009
41	0.172	0.091	0.111	0.171	0.229	0.009
42	0.171	0.091	0.109	0.170	0.231	0.009
43	0.172	0.089	0.113	0.173	0.228	0.009
44	0.175	0.092	0.112	0.175	0.240	0.009
45	0.173	0.085	0.116	0.175	0.231	0.008
average	0.168	0.181	0.072	0.169	0.265	0.079

Appendix B

The corporate saving glut

B.1 Sample and control variables

Data comes from Compustat, which includes all the publicly listed firms in U.S. stock markets, from 1960 to 2015. First, I exclude financial firms (SIC 6000-6799) and regulated utilities (SIC 4900-4999), who may have peculiar cash management policies. Second, I exclude observations that have unreported or negative values of sales, unreported values or less than $50 thousands of total assets, negative values of capital expenditures and of common/ordinary equity, and observations whose growth rate of sales exceeds 500%. Third, I exclude firms with gaps in their reported values of sales and of operating expenditures. Finally, I winsorize all variables at one and ninety-nine percentiles. In general, any variable is either in real terms, adjusted for inflation using the CPI index from BLS, with 1982-84 U.S. dollars, or a ratio, often over total assets (item `at` in Compustat).

The list of control variables employed in this article is detailed in table B.1 below. Most of them are commonly found in the cash holdings literature; e.g. Bates et al. (2009). Item `cpi` is the consumer price index, in 1982-84 U.S. dollars, from the Bureau of Labor Statistics, which is used to obtain inflation-adjusted series.

Table B.1: Control variables.

Variable:	*Description:*	*XPF name:*
Years since IPO	`NA`	`NA`
Log total assets	`NA`	`log(at/cpi)`
OCF	Operating cash flow	`(ebitda-txt-xint-(nwc-L.nwc))/at`
NCF	Net cash flow	`(ni+dp)/at`
NWC	Net working capital (net of cash)	`(wcap-che)/at`
Capital exp.	`NA`	`capx/at`
R&D exp.	(Set `=0` if missing)	`xrd/at`
Acquisition exp.	`NA`	`aqc/at`
Dividend payer	(Dummy variable)	`=1` if `dvt>0`
Book leverage	`NA`	`(dltt+dlc)/at`
Market-to-Book	Book value of assets - book value of equity + market value of equity	`(at-ceq+csho*prcc_f)/at`
Sales volatility	Rolling S.D. of growth rate	[See equations (B.1) and (B.2)]

Volatility of variable $x_{i,t}$ is defined at the firm-level as the ten-years rolling standard deviation of the growth rate of $x_{i,t}$,

$$\sigma_{i,t}(x) = \left[\frac{1}{10}\sum_{\tau=0}^{9}\left(\gamma_{i,t-\tau}-\bar{\gamma}_{i,t}\right)^2\right]^{\frac{1}{2}} \tag{B.1}$$

where $\bar{\gamma}_{i,t} = \frac{1}{10}\sum_{\tau=0}^{9}\gamma_{i,t-\tau}$ is the average growth rate over the previous ten-years. In particular, the growth rate of variable $x_{i,t}$ is defined as

$$\gamma_{i,t} = \frac{x_{i,t}-x_{i,t-1}}{\left(x_{i,t}+x_{i,t-1}\right)/2}. \tag{B.2}$$

Notice that this measure is backward-looking. Yet, using a centered or forward-looking measure does not materially change the results of the paper. Finally, for operating leverage, see Saibene (2015).

B.2 Net lending/borrowing: empirical distribution

Figure (B.1) confronts the distribution of the net lending/borrowing measure (computed over total assets) of years 1975 vs. 2015. Overall, the distribution is skewed to the left, as there are firms that are heavy borrowers (as much as 150% of their assets, yearly) but there are not firms that are lending more than 50% of their assets. These are quite a reasonable boundaries. Moreover, most of the firms are concentrated around the 0% threshold. What changed in forty years?

First, there are actually more firms that are borrowing, as the left-tail of the distribution increased. Second, however, there is a lower mass of firms that are at the 0% level of just below, while slightly more firms – or at least as much – that are lending. Notwithstanding, it must be the case that larger firms are now on the right-side of the distribution, while they used to be on the left-side.

B.3 Net financial asset (NFA)

Armenter and Hnatkovska (2014) point out that listed firms in the U.S. are now net creditors, on average, rather than net debtors. They argue that taxes played a role in this transformation: the tax advantage of debt can actually drive firms accumulate financial assets, with tax reforms from the 1980s that reduced the relative cost of equity. They focus on the net financial assets position (NFA), which is a stock, both at the aggregate and at the firm-level. More precisely, NFA is measured as

$$\text{nfa} = (\text{che}+\text{aco}+\text{rect})-(\text{dlc}+\text{dltt}+\text{lco}+\text{ap}), \tag{B.3}$$

which is the difference between cash and short term investment (che), total other current assets (aco), accounts receivable (rect), and current debt (dlc), long-term debt (dltt), other current liabilities, accounts payable (ap). Approximately, this is equal to cash and liquid assets less outstanding debts.

Figure B.1: Net lending/borrowing: distribution of firms.

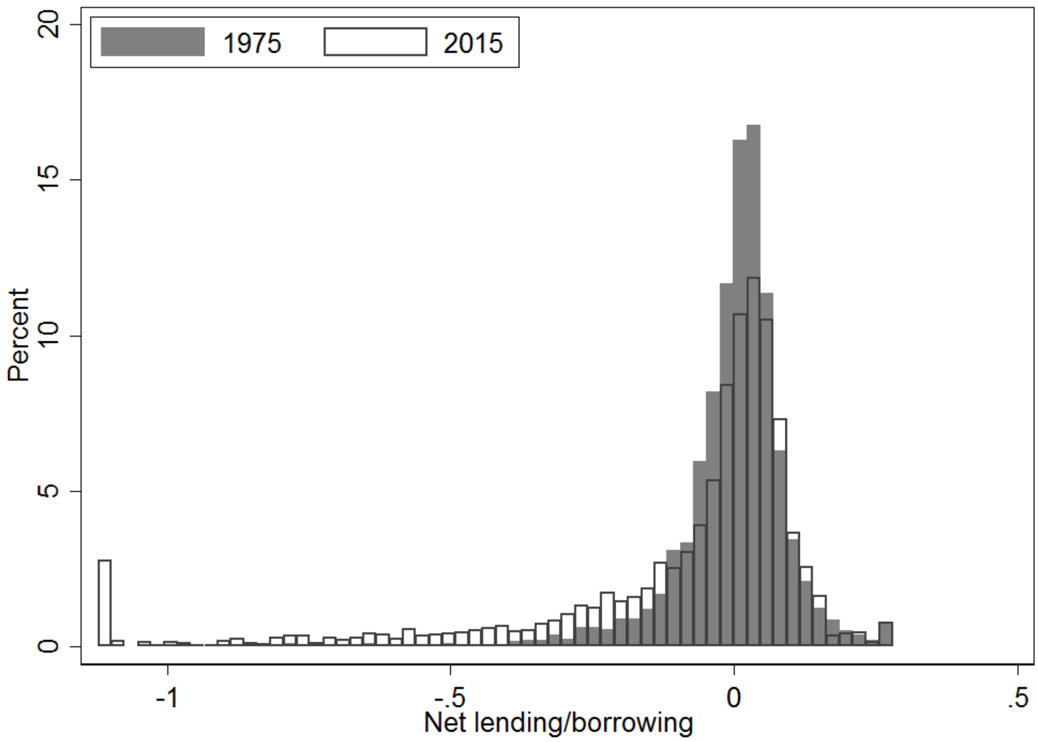
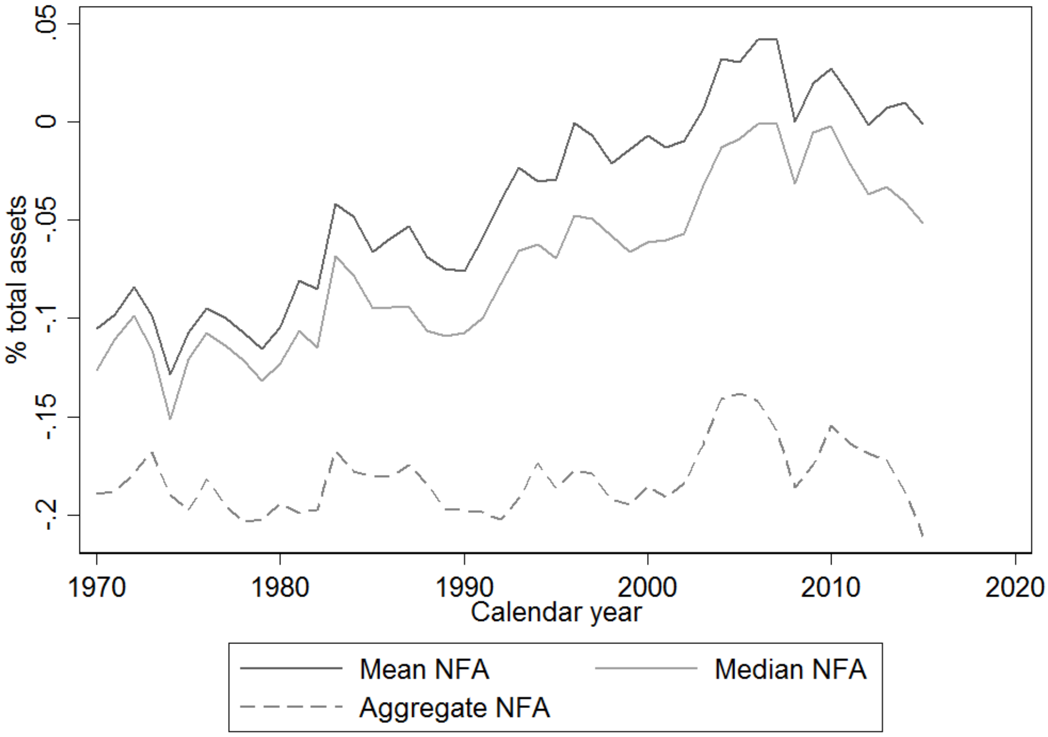


Figure B.2 shows the pattern of the NFA position, scaled by total assets. The average firm is almost a net lender, while the median already is. On the other hand, the aggregate position of the corporate sector is still that of a net debtor, at about 20% of total assets. This means that small firms are driving the increase in the mean/median values. Indeed, it is known that smaller, newer, and R&D intensive firms are accumulating large amounts of cash while at the same time issuing very little debt – on the other hand, larger firms, albeit they increased their cash holdings as well, are still financially leveraged.

To conclude, what remains to be clarified is why the NFA position of large firms (and at an aggregate level) show no apparent increasing trend, with the corporate sector as a stable net borrower, while the net lending/borrowing position would imply at least an increasing trend of the NFA. The answer must lie in the accounting: large firms have indeed started to lend rather than to borrow, but at the same time the managed to keep their NFA position quite balanced – perhaps by accumulating assets not included in the NFA measure.

Figure B.2: NFA to total assets: mean, median, and aggregate. 1970-2014.



Appendix C

Cash holdings and operating leverage

C.1 Control variables

The list of control variables employed in this article is detailed in table C.1 below. Most of them are commonly found in the cash holdings literature; e.g. Bates et al. (2009). Item `cpi` is the consumer price index, in 1982-84 U.S. dollars, from the Bureau of Labor Statistics, which is used to obtain inflation-adjusted series.

Table C.1: Control variables.

Variable:	*Description:*	*XPF name:*
Years from IPO	`NA`	`NA`
Ln(total assets)	Inflation-adjusted values	`log(at/cpi)`
Op. Cash flow	Operating cash flow	`(oibpd-txt-xint-(nwc-L.nwc))/at`
Net cash flow	Net income + depreciation	`(ib+dp)/at`
Net working capital	(Net of cash)	`(wcap-che)/at`
Capital exp.	`NA`	`capx/at`
Acquisition exp.	`NA`	`aqc/at`
Dividend payer	(Dummy variable)	`=1` if `dvt`>`0`
Book leverage	`NA`	`(dltt+dlc)/at`
Market-to-Book	Book value of assets - book value of equity + market value of equity	`(at-ceq+csho*prcc_f)/at`
R&D exp.	(Set `=0` if missing)	`xrd/at`
Sales volatility	Rolling S.D. of growth rate	[See equations (C.1) and (C.2)]

Volatility of variable $x_{i,t}$ is defined at the firm-level as the ten-years rolling standard deviation of the growth rate of $x_{i,t}$,

$$\sigma_{i,t}(x) = \left[\frac{1}{10}\sum_{\tau=0}^{9}\left(\gamma_{i,t-\tau}-\bar{\gamma}_{i,t}\right)^2\right]^{\frac{1}{2}} \tag{C.1}$$

where $\bar{\gamma}_{i,t} = \frac{1}{10}\sum_{\tau=0}^{9}\gamma_{i,t-\tau}$ is the average growth rate over the previous ten-years. In particular, the growth rate of variable $x_{i,t}$ is defined as

$$\gamma_{i,t} = \frac{x_{i,t} - x_{i,t-1}}{\left(x_{i,t} + x_{i,t-1}\right)/2}. \tag{C.2}$$

Notice that this measure is backward-looking. Yet, using a centered or forward-looking measure does not materially change the results of the paper.