Investment Slumps during Financial Crises: The Role of Credit Constraints

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Abstract

How much do credit constraints contribute to investment slumps during financial crises? For the Greek crisis that erupted in 2010, we find that tightened credit constraints contributed to about half of the observed collapse in investment rates. The remainder is explained by diminished demand and productivity firms faced. We use a novel firm-level dataset of manufacturing firms and show that standard dynamic investment models abstracting from credit constraints cannot reproduce the observed investment dynamics. Enhanced with borrowing constraints subject to an aggregate shock to eligible collateral, such models can account for the observed collapse in investment rates.

JEL classification: D22, D25, E22, E27, G01, G32, L60

Keywords: financial crises, investment slumps, leverage, Greek crisis, Greece, firm heterogeneity

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1 Introduction

The focus of this paper revolves upon answering the following question: How much do credit constraints contribute to investment slumps during financial crises? A large body of research demonstrates that financial crises are associated with substantial and persistent drops in investment (Schularick and Taylor, 2012[1]) and another body of work finds that credit constraints negatively affect real investment during financial crises (Campello, Graham, and Harvey, 2010). While the literature provides evidence that credit constraints negatively affect real investment, the quantitative importance of this effect through the lens of empirical models is not yet fully established. Notable exceptions of papers developinging and estimating empirical models of credit constraints include Whited (1992), Hennessy and Whited (2007), Khan and Thomas (2013) and Catherine, Chaney, Huang, Sraer, and Thesmar (2018). We contribute to this literature by quantifying the impact of credit constraints on real investment. One of the innovative features of our approach is the use a dynamic investment model with collateral constraints and firm heterogeneity applied to a novel firm-level dataset of Greek manufacturers spanning the years before and during a major financial crisis in an advanced economy: the Greek crisis that erupted in 2010.

Because the observed debt is an equilibrium quantity, it is determined by both demand and supply factors. Therefore, a quantitative study aiming at measuring the real economic impact of credit conditions needs to distinguish between these two.[2] Our empirical setting allows to control for demand shocks by focusing on manufacturing firms which have access to the European common market. Since some of these manufacturers do not rely solely on domestic sales, they maintain investment opportunities even during the crisis, generating ample cross-sectional variation of firm-level demand, which we control for at the firm level.[3] Additionally, given that the origin of the Greek financial crisis is mostly associated with the sovereign debt crisis, which is arguably exogenous to the manufacturing sector, and given the small size of the Greek economy, the collapse of the domestic banking sector is unlikely

[1] Schularick and Taylor (2012) report that in fourteen advanced economies post-World-War-II, real investment was on average 26% below trend five years after the outbreak of a financial crisis compared to normal years.

[2] Demand shocks manifest as lack of investment opportunities (Mian, Rao, and Sufi, 2013; Mian and Sufi, 2014) while supply shocks may work through the collateral channel (Chaney, Sraer, and Thesmar, 2012).

[3] In our data the sales growth distribution of firms with access to external markets, i.e. exporters, before and during the crisis look quite similar.

to affect manufacturers' export demand.

We find that tightened credit constraints associated with the banking crisis contributed to approximately half of the observed collapse in investment rates while the remainder is explained by the diminished demand and productivity firms face. To arrive at this answer, we use a confidential, census-type dataset of Greek manufacturing firms from 2002 to 2014 and characterize the relationship between firm investment, sales growth, and balance-sheet features. We find that, while the variation in investment opportunities, captured by sales growth, does not fully account for the observed decline in investment during the crisis, financial characteristics related to potential borrowing constraints have important explanatory power. Using our heterogeneous-firm dynamic model to analyze the data we show that the banking crisis in Greece, interacted with the high corporate debt accumulated over the preceding credit-boom period, explains 45% of the observed drop in average investment rates.

Our dynamic investment model is similar to Hennessy and Whited (2007), Khan and Thomas (2013) and Catherine et al. (2018) as it includes firm heterogeneity, capital adjustment costs, and a credit constraint in the form of a collateral constraint.[4] Like Hennessy and Whited (2007), our model is a partial equilibrium one but our focus is on the time series evolution of credit conditions like Khan and Thomas (2013). In order to emphasize the transitional dynamics of investment during the financial crisis, we use the cross-sectional distribution of observed leverage at the beginning of the crisis as a starting point for the counterfactual experiments. The structural model allows us to calculate firm investment under counterfactual scenarios exhibiting different intensities of the credit supply shock.

We focus on the Greek crisis that erupted in 2010 which perhaps is the most extreme crisis an advanced economy has experienced in the post-World-War-II period (see Figure 1). It involved a sudden stop of external financing, sovereign default, and near-collapse of the entire banking system.[5] Investment collapsed.[6] In 2014, five years into the crisis, real business fixed investment stood at less than half the average level attained during the eight years before the crisis. Leverage sharply dropped by 40% from 2010 to 2014.[7] These unique

[4]Other quantitative models with firm heterogeneity, capital adjustment costs, and credit constraints are Hennessy and Whited (2005) and DeAngelo et al. (2011).

[5]Gourinchas et al. (2017) provide a vivid account of these events.

[6]See Figure G1 in the Appendix G for a time series of aggregate investment.

[7]This is true across quantiles of the leverage distribution for manufacturing firms when conditioning on positive values. Leverage is measured as long-term debt over capital.

features of the Greek crisis, coupled with the detailed information in our firm-level data, provide a novel and particularly suitable setting for disentangling the importance of credit supply and collateral constraints in the observed investment collapse.

Our empirical method consists of three steps. First, we provide reduced-form evidence that the observed collapse in firm investment is related to the credit conditions facing firms. Even controlling for investment opportunities, firm investment dramatically fell during the years 2010 to 2014, compared with the preceding years. Specifically, the mean investment rate fell by 5.5 percentage points, and mean investment fell by 55 percent.[8] To examine the role of credit conditions, we use two proxies for financial constraints: the leverage ratio and a sector-level indicator for dependence on external finance (following Rajan and Zingales, 1998). We measure these prior to the onset of the crisis in order to address concerns about endogeneity. We find that firms operating in sectors that depended more on external finance displayed significantly lower investment rates during the crisis than firms in other sectors, controlling for investment opportunities. Additionally, we find that firms that entered the crisis with leverage in the highest tercile of the distribution, undertook 9% lower investment than did other firms, controlling for investment opportunities.[9] This evidence is consistent with a causal effect of a negative supply shock to external finance.

Second, we demonstrate that a workhorse investment model that abstracts from financing constraints can account for only half of the observed collapse in firm investment during the Greek crisis. We estimate a standard dynamic model of firm investment like in Cooper and Haltiwanger (2006) and Asker et al. (2014a) using the simulated method of moments (SMM). Firms face both convex and non-convex adjustment costs, but no financial frictions. This structure allows for a decomposition of the firm problem into a sequence of two parts: a static one to determine optimal profit and a dynamic one to determine optimal investment, thereby simplifying estimation.

We estimate the firm profit function and the profitability process for the entire manufacturing and for individual sectors. We use a non-linear generalized method of moments (GMM) estimator employing the Ackerberg et al. (2015) moments augmented by a selection correction moment. The latter is estimated from a first-stage sample selection model, like in

[8] The latter holds true for positive investment observations, as we take a logarithmic transformation that drops observations with non-positive values.

[9] Again, this refers to positive investment observations, as we take a logarithmic transformation that drops observations with non-positive values.

Olley and Pakes (1996), and corrects for firm selection due to exit and the sampling design of our dataset, which includes only firms with more than ten employees.

In estimating the dynamic part, we aim to contrast the pre-crisis and during-crisis periods. Thus, we estimate capital adjustment cost parameters and stochastic processes for firm profitability governing the pre-crisis period from 2002 to 2007. We then use initial conditions for capital and profitability observed in the beginning of the crisis and assess whether the estimated model can replicate the observed investment dynamics during the crisis. Following Asker et al. (2014a), we choose the following moments to match in the SMM estimation: the cross-sectional standard deviation of the investment rate, the proportion of firms choosing not to invest, and the proportion of firms undertaking an investment spike, whether positive or negative. The estimation is carried out both at the sectoral and at the whole manufacturing levels. We find that the estimated models match the chosen data moments very closely and that the structural estimates of convex and non-convex adjustment costs are in the range found in the literature. This model does a poor job of explaining the observed drop in firm investment rate during the crisis, accounting for less than half of it. An important observation is that the model performs particularly badly in sectors in which the average profitability rose during the crisis, yet investment collapsed. This observation, paired with the documented reduced-form evidence for financing constraints, leads us to consider a dynamic model with borrowing constraints.

Third, we address the inadequacy of the standard investment model to capture the observed investment dynamics. To that effect, we develop and solve an extension that accommodates for borrowing constraints affecting firm investment such that the potential impact of the banking crisis can be quantified. We adopt the firm decision setup in Khan and Thomas (2013) and allow firms to accumulate debt in order to finance investment. Firms may borrow up to a collateral constraint, as motivated by Kiyotaki and Moore (1997) and Jermann and Quadrini (2012). We allow for an aggregate financial shock to the maximum amount of debt a firm can raise against its collateral. In the case of the Greek economy, this shock reduces the maximum amount of eligible collateral and is indicative of the restriction in credit due to the systemic banking crisis. We differ from Khan and Thomas (2013) in allowing for both convex and non-convex capital adjustment costs and an endogenous exit by firms that attempt to issue non-positive dividends.

The dynamic model works as follows. An aggregate financial shock hits the economy and tightens the collateral requirement for borrowing. If there was overaccumulation of corporate debt during the preceding boom period, the aggregate shock would force some firms closer to their collateral constraint. This would raise the effective discount applied to the shadow value of capital and lead some firms to reduce investment, including some firms with good investment opportunities. The model captures the fact that certain sectors and firms reduce their levels of investment despite obtaining good profitability realizations. These firms are forced to deleverage from previous high debt levels.

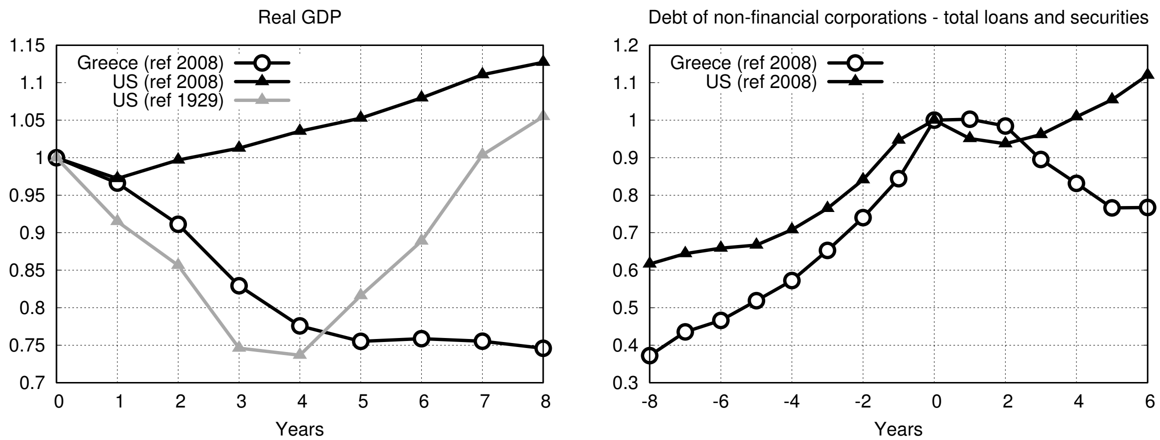
We simulate the response of firm investment during the Greek crisis. Firm leverage, defined as long-term debt over capital, fell 40% from 2010 to 2014 in our dataset.[10] This fall indicates that credit supply contracted. Our model, which is calibrated to reflect the observed credit tightening, demonstrates how credit constraints can have a substantial effect on firm investment decisions. We use the observed distributions of firm investment, capital, leverage, and profitability at the beginning of the crisis and the structural estimates of adjustment cost parameters from the second step described above. The aggregate tightening of the collateral constraint resulting from the banking crisis is calibrated to match the observed drop in the median leverage ratio during the crisis compared to the preceding period. Quantitatively, the model is able to reproduce the drop in firm investment rates in manufacturing. We show that the banking crisis in Greece interacted with the high corporate debt accumulated over the preceding credit-boom period to produce about half of the observed drop in average investment rates. The rest of the drop is accounted for by changes in firm investment opportunities. Nested models, where borrowing constraints are absent or exist but the economy has not been subjected to a banking crisis, fail to replicate the firm investment behavior observed in the data.

Several aspects of the Greek crisis make the crisis a particularly good laboratory to quantify the effect of credit constraints on firm investment. First, because of the doom loop between the sovereign and banks, Greece suffered a systemic banking crisis in which all domestic banks were subjected to similar levels of distress.[11] The shock originated from sovereign debt, was truly aggregate, and was not tied to a particular sector of the economy. Thus, it is likely to have affected, even if differentially, all firms in the economy. This means that the shock to the credit supply was exogenous to manufacturing firms and largely

[10] This is true across all quantiles of the distribution involving positive leverage.

[11] For a discussion of the doom, or diabolic, loop, see Brunnermeier and Oehmke (2013).

Figure 1: The Greek crisis



Sources: FRED (Federal Reserve Bank of St. Louis), Eurostat, and OECD. Total debt in the right panel refers to bank loans and securities of non-financial corporations from the System of National Accounts measured in current prices.

independent from the firm's house bank. Second, Greek firms are completely dependent on banks for debt finance and in particular on domestic banks (with very few exceptions).[12] This ensures that the state of the Greek banking system alone adequately portrays conditions of credit supply. Finally, conforming to a common pattern documented by Schularick and Taylor (2012), the collapse in economic activity during the Greek crisis was preceded by a splurge in which credit to the private economy rose by 137% in the years 2002–2009, followed by a fall of 26% during 2010–2014. This is likely to have rendered many firms vulnerable to financial shocks. The near-collapse of the banking sector during the Greek crisis represents a tremendous negative shock to the supply of external finance for non-financial firms.

Connection to the literature. Our paper is related to several strands of the literature. A voluminous literature investigates the impact of credit conditions on the macroeconomy. We relate most closely to papers looking at the real impact of financial dislocation during large crises. In a seminal paper, Bernanke (1983) demonstrated that dire credit conditions played an important role in propagating the Great Depression in the United States. More recently, several studies have brought historical data to the analysis of the nature and consequences of large crises and other rare events. Examples are Reinhart and Rogoff (2009), Barro (2009),

[12] Kalemli-Ozcan et al. (2018) find that in their dataset of Greek firms, 99.9% of Greek firms report having relationships with Greek banks only.

Almunia et al. (2010), and Schularick and Taylor (2012). Some papers study the real effects of the credit squeeze during the recent financial crisis in the United States and in Europe. Examples are Acharya et al. (2018), Chodorow-Reich (2013), Duchin et al. (2010), Kahle and Stulz (2013), and Martin and Philippon (2017). More closely related to our paper, are those by Gopinath et al. (2017) and Gourinchas et al. (2017). Gopinath et al. (2017) demonstrate the important role of debt accumulation during boom years in the investment and productivity declines observed during a crisis. Gourinchas et al. (2017) focus on the Greek crisis. Using aggregate data, they find that much of the drop in investment can be accounted for by high debt accumulated during the boom period. Also relevant is the work of Benmelech et al. (2017) showing that the credit supply channel had an important contribution for the contraction of employment during the US Great Depression.

Our paper is also related to the literature that analyzes financial fragility induced by collateral constraints (see Bernanke et al., 1999 for a framework and early survey). Particularly relevant papers are those of Nolan and Thoenissen (2009), Jermann and Quadrini (2012), Khan and Thomas (2013), Gilchrist et al. (2014), Buera and Moll (2015), Catherine et al. (2018), and Ottonello and Winberry (2018) that feature disturbances to collateral constraints faced by firms.

Two important related papers on firm investment with adjustment costs are Cooper and Haltiwanger (2006) and Asker et al. (2014a). We build on these and extend them in the estimation of firm profitability. Specifically, to estimate firm profitability, we use the Ackerberg et al. (2015) non-linear GMM, augmented by a term following Olley and Pakes (1996) that corrects for firm selection due to exits and sampling design.

Finally, our paper is related to the empirical literature on investment and debt. Two early examples are Whited (1992) and Bond and Meghir (1994). Both estimate an Euler equation for optimal capital accumulation in the presence of convex adjustment costs and find an empirical role for debt. More recently, Kalemli-Ozcan et al. (2018) find that high ex ante leverage negatively affected firm investment during the recent financial crisis in Europe. They control for investment opportunities using four-digit industry×country×year fixed effects and assume there are no idiosyncratic, firm-specific factors.

Our contribution to the literature takes a particular financial crisis – the Greek crisis, which erupted in 2010 – and uses it as a laboratory to quantify the impact of credit constraints on investment. We differ from past literature by employing a census-type, firm-level dataset and controlling for investment opportunities at the firm level, in order to separate out the role of balance-sheet health. In contrast to past studies, our dataset comprises all enterprises, except for micro-sized ones, in the economy under study. This makes it ideal for drawing inferences about aggregate investment dynamics. The dataset also contains firm balance-sheet information that allows to analyze the potential financial constraints on investment. Our methodological innovation is to use estimates of firm profitability, combining demand and productivity effects, in order to control for investment opportunities, and then use a dynamic model to analyze the impact of firm leverage and borrowing constraints on the unexplained portion of firm investment. In addition, we allow for firm heterogeneity in the production and demand functions.

2 Near-Collapse of the Banking System

Gourinchas et al. (2017) provide a very informative account of the unfolding of the Greek crisis. In summary, a combination of a sudden stop of external financing, default by the sovereign, and near-collapse of the whole banking system lead to the crisis. In this section, we will provide some more information about the extreme stress that the entire Greek banking system was subjected to during the crisis.

Fears of a sovereign default and possible abandoning of the euro widely spread during 2010 and persisted for several years thereafter. Depositors reacted by withdrawing their savings from banks. From December 2009, deposits declined from €238 billion to around €151 billion in June 2012 and to €126 billion by the end of 2017.[13] Although banks tried to replace the lost liquidity by borrowing from the European Central Bank, there was a substantial reduction in total credit to the private sector. Total credit to non-financial corporations fell from €124 billion in the end of 2009 to €92billion in the end of 2014. Twelve years before, in the end of 2002, it had stood at €52 billion.

The entire banking sector was infected with sovereign troubles through the infamous doom loop.[14] In February of 2012, the Greek sovereign defaulted on its debt, much of which was held by Greek banks. This was to be called "Private Sector Involvement" (PSI) and

[13]Data come from the Bank of Greece website and refer to domestic private sector deposits and repos in Greek banks.

[14]For a discussion of the doom, or diabolic, loop, see Brunnermeier and Oehmke (2013).

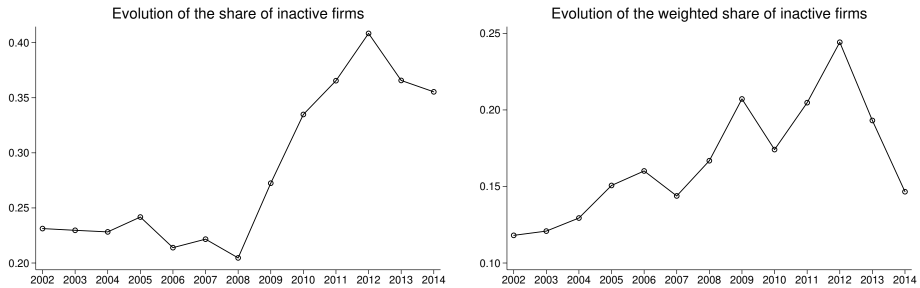
caused Greek banks to collectively lose about €38 billion, more than wiping out their total capital. Bank equity was actually negative. Through regulatory action, the banking system was consolidated into a very concentrated market structure. The four largest banks were recapitalized with funds borrowed from European countries and the International Monetary Fund (IMF), while most of the remaining banks went through the resolution process. The resolution and recapitalization processes were completed in July 2013. A second recapitalization took place in April and in May of 2014. The following year – 2015 – was an even more tumultuous one. The banking system was subjected to a long administrative bank holiday, the imposition of capital controls, and a third round of recapitalization.

The preceding summary conveys the elements of a sharp and prolonged banking crisis. It was systemic in nature, where all domestic banks were subjected to high levels of distress. This meant that the tightening of credit conditions to firms was largely independent of which was the firm's house bank. It seems warranted, therefore, to model this shock as an aggregate financial shock to firms. The severity of its bite to individual firms, however, might differ by balance-sheet health. We explore this in the rest of the paper.

3 Data

Our analysis of firm investment behavior during the Greek crisis is based on a sample of all manufacturing firms with at least 10 employees over the years 2002-2014. Production data come from the Annual Survey of Manufactures (EBE) and exports data come from the INTRASTAT and EXTRASTAT surveys, all administered by the Greek Statistical Agency ELSTAT. Our sample contains panel data for approximately 5,500 firms and covers a little less than half of manufacturing employment (see Table D1 in Appendix D). Until 2005 the survey was a census of firms with at least 10 employees, but, from 2006 onward, it is a census-type survey of plants above the 10-employee threshold accompanied by sampling weights. The unit of observation until 2007 was the plant, but, since 2008, the unit of observation has been the firm. To make the sample consistent across years, we add each available variable at the firm level for the years until 2007. For this paper we use information on total labor costs, gross output/revenue, expenditures on materials, gross investment, long-term liabilities, short-term liabilities, total balance-sheet assets, and the accounting depreciation flow. We use the depreciation flow to construct the capital stock of a firm at the year of

Figure 2: Share of investment-inactive firms before and during the crisis



Notes. A firm is considered inactive if its investment rate is less than 1%. Right-hand-side panel illustrates value-added weights. Sources: EBE and ELSTAT.

appearance in our sample and the investment flows to create the capital stock for subsequent years by the perpetual inventory method.[15] Aggregate series and sectoral deflators come from Eurostat's publicly available database.

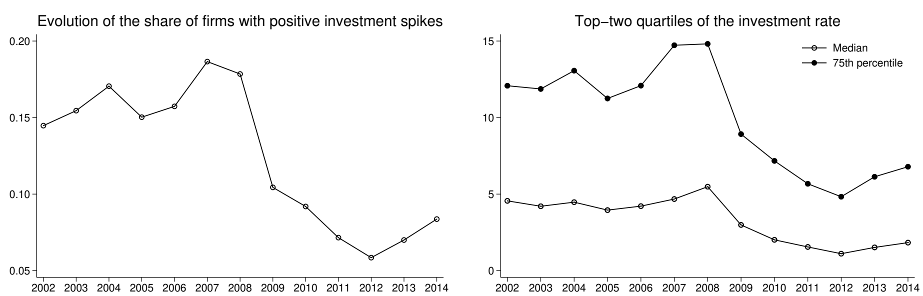
4 The Puzzle of the Investment Collapse and the Role of Credit Conditions: Reduced-Form Evidence

This section runs reduced form regressions, which are common in the literature, for the purpose of benchmarking our dataset and motivating our model specification. We find that the qualitative features of the data are broadly consistent with the existing literature and we establish three results: (1) fundamentals do not explain the investment collapse in manufacturing observed during the crisis; (2) firms in sectors with the highest external financial dependence exhibit the highest drop in investment; and (3) firms with the highest leverage at the beginning of the crisis invested less than did firms arriving at the crisis with low leverage. We arrive at these results by running investment regressions of the kind common in the reduced-form investment literature. Figures 2 and 3 show the manufacturing investment collapse at all margins. The left-hand-side panel of Figure 2 shows that the share of firms with an investment rate, I/K, less than 1% in absolute value soars to 40% from a pre-crisis level of about 20%. To explore the aggregate implications of microbehavior, the right panel of the same figure shows the same statistic, but with value-added weights. Still,

[15]For more details about the construction of the variables and the summary statistics, see Appendix D.

with value-added weights, the basic result that firms with an investment rate less than 1% doubled persists. Next, we turn to the intensive margin of firm investment behavior. The left-hand-side panel of Figure 3 shows the share of firms with a positive spike for any given year. Observations of positive investment spikes, defined as those with at least a 20% investment rate, dramatically dropped from 2008 onwards. Investment spikes are interesting, both because they are a feature of the nonlinearity of investment rate distributions (see Cooper and Haltiwanger, 2006 and Bachmann and Bayer, 2014) and because these observations are responsible for half of aggregate investment. The right-hand-side panel of Figure 3 depicts the evolution of the two-top quartiles of the investment rate distribution, thereby establishing that the investment rate dropped approximately by half across quantiles. Because the top investment-rate quartile is responsible for 71% of aggregate manufacturing investment, this graph confirms that micro investment patterns are consistent with the aggregate investment collapse we saw in Figure G1.

Figure 3: Share of firms with a positive investment spike before and during the crisis



Notes. Left-hand-side panel: An observation is considered a spike if the investment rate is above 20%. Spikes are responsible for 46% of aggregate investment. Right-hand-side panel: The top quartile is responsible for 71% of the aggregate investment. I/K is provided as a percentage. Sources: EBE and ELSTAT.

4.1 Reduced-Form Investment Specifications

The investment collapse after 2009 does not seem terribly surprising given that Greece was in a severe recession. To investigate whether the investment collapse merely reflects a worsening of investment opportunities and weak demand for firms' output, we explore the joint distribution of investment and its determinants. We consider investment in physical capital a dynamic decision. The dynamic nature of the decision to invest may be due to capital adjustment costs, time to build, and persistent firm-specific profitability shocks, all of which are ingredients of the model developed and estimated in Section 5. In such a model, a firm's optimal investment is determined by the current level of a firm's capital stock and firm-specific factors directly affecting the flow of profit. The investment literature considers current capital stock and firm-specific investment opportunities to be variables with explanatory power over investment and proxies for investment opportunities using either Tobin's q or sales growth.[16] Tobin's q is usually constructed as the ratio of a firm's market-to-book value of its assets. Because nearly all of the firms in our sample are not publicly traded, their market value is not observed, and, thus, proxying for investment opportunities using Tobin's q is not an option. Our preferred measure of firm profitability is the growth of log sales ($\Delta \log sales$). This measure can be constructed at the firm level at any sample year for any firm, whether public or private.

Let I^* denote the optimal investment for a firm with capital K and investment opportunities $\Delta \log sales$. G denotes the cumulative joint distribution of $I^*, K, \Delta \log sales$, $G(I^*, K, \Delta \log sales) \in [0, 1]$. The goal of this section is twofold. First, we explore whether the joint distribution of investment and its fundamental determinants K and $\Delta \log sales$ before the crisis (2002–2007) is very different from the distribution during the crisis (2010–2014). Second, we investigate if this difference can be attributed to firms' balance-sheet health and credit conditions. To these ends, we focus on analyzing the distribution of investment rate conditional on fundamentals $G_1(I^*/K|K, \Delta \log sales)$ and the distribution of the logarithm of investment $G_1(\log I^*|K, \Delta \log sales)$, which is also conditional on fundamentals.

In particular, we focus on models describing the most important features of these distributions: the mean, the median, and the top quintile of the investment rate; the mean log investment for firms with positive investment; the share of firms with nearly zero investment; the share of firms with an investment rate above 20%; and the share of firms with negative, zero, positive but less than 20%, and higher than 20% investment rates. We control for the fundamentals by using a complete second-degree polynomial in the conditioning variables:

$$\begin{aligned} \text{controls} = &\beta_k \log K + \beta_s \mathit{\Delta} \log sales + \\ &\beta_{ks} \log K \cdot \mathit{\Delta} \log sales + \beta_{kk} (\log K)^2 + \beta_{ss} (\mathit{\Delta} \log sales)^2 \end{aligned}$$

[16] See Asker et al. (2014b) for an example from the investment literature and Bond and Van Reenen (2007) for a survey of microeconometric models of investment.

We model discrete outcomes, such as inaction and positive spikes, using a logit model and the discrete outcome of negative, zero, positive but less than 20%, and higher than 20% investment rates using an ordered logit model.

4.2 The Puzzling Investment Collapse

The first results of this section are that (1) the joint distribution of investment and its fundamental determinants K and $\Delta \log sales$ before the crisis (2002–2007) is very different from the distribution during the crisis (2010–2014) and (2) this difference is not explained by the fundamental determinants of investment, namely capital and log sales growth. To quantify the differences in investment before and during the crisis, we run several investment models on a crisis dummy variable equal to one during the years 2010–2014, our set of controls, and sector fixed effects.

The results of all our specifications are presented in Table 1. The first four columns in the top panel present the mean and the selected quantiles of the investment rate distribution conditional on fundamentals and the crisis dummy variable. The mean, the median, and the top quintile of the investment rate all dropped by 4.9, 2.3, and 6.9 percentage points even if we condition on fundamentals. These are substantial drops considering that the pre-crisis levels of the mean, the median, and the top quintile of the investment rate distribution were 12%, 4%, and 16%. Thus, the drop roughly implies a 50% decline. To quantify the investment drop as a percentage, we ran a regression of the logarithm of investment on the left-hand side. The results, which are presented in the last column of Table 1, indicate that positive investment dropped on average by 52%.[17] This number implies that positive investment dropped by half, and this drop is not explained by fundamentals.

To further explore the change in the joint distribution of investment and fundamentals during the crisis, we focus on certain features, such as the probability of being inactive ($|I/K| \leq 1\%$) and the probability of experiencing a positive spike ($I/K > 20\%$), that the literature considers central. To parsimoniously summarize the whole investment rate distribution, we decompose the investment rate into few intervals, in particular, negative

[17] Kennedy (1981) showed that for a regression in which the dependent variable y is in logs, the transformation of a dummy variable estimated coefficient β using the formula $100 * e^{\hat{\beta}-.5\hat{\sigma}(\hat{\beta})^2-1}$ represents the effect of the dummy variable on y as a percentage. This transformation of the 2010–2014 dummy coefficient in the log investment regression maps the estimated value -0.74 to -52.2%.

Table 1: Fundamentals do not explain the investment collapse during the crisis

This table analyzes the investment and investment rate distributions conditional on fundamentals before and during the crisis. The very large coefficients β_c of the crisis dummy (the 2010–2014 dummy) in all models strongly suggest that the investment collapse in manufacturing cannot be explained by fundamentals.

Continuous-outcome models

Model	$E(y\|x)$	$Median(y\|x)$	$Quantile_{80}(y\|x)$	$E(y\|x)$
Dependent Var y	I/K	I/K	I/K	$\ln I$
2010–2014 dummy	-0.049	-0.023	-0.069	-0.74
$(= \beta_c)$	(0.0034)	(0.0011)	(0.0041)	(0.026)
$\log K$	-0.019	0.0025	-0.016	0.86
	(0.0017)	(0.00032)	(0.0012)	(0.0081)
$\Delta \log \text{sales}^{\dagger\dagger}$	0.078	0.029	0.10	0.88
	(0.0072)	(0.0019)	(0.0072)	(0.051)
$(\ln K)^2$	0.0040	-0.00012	0.0029	0.044
	(0.00073)	(0.00011)	(0.00043)	(0.0028)
$(\Delta \log \text{sales})^2$	0.0036	0.0084	0.038	-0.15
	(0.0077)	(0.0020)	(0.0078)	(0.050)
$\log K \times \Delta \ln \text{sales}$	-0.012	0.0038	-0.014	0.057
	(0.0061)	(0.0011)	(0.0042)	(0.032)
N	19,748	19,748	19,748	15,899
R^2 adjusted	0.044			0.51
Pseudo R^2		0.028	0.044	
Sector FEs	Yes	Yes	Yes	Yes

Discrete outcome models

Model	Inaction	Spike$^+$ I/K	Discretized $I/K^{\dagger}$
	$LogitProb(y=1\|x)$	$LogitProb(y=1\|x)$	$OrderedLogit(y=j\|x)$
Dependent var y	$\mathbb{1}\{\|I/K\| \leq .01\}$	$\mathbb{1}\{I/K > .2\}$	$j \in \{0,1,2,3\}^{\dagger}$
2010–2014 dummy	0.74	-0.83	-0.68
$(= \beta_c)$	(0.035)	(0.050)	(0.029)
$\exp(\beta_c)$[¶]	2.10	0.44	0.51
N	19,748	19,748	19,748
Pseudo R^2	0.062	0.057	0.034
Sector FEs	Yes	Yes	Yes
Controls[§]	Yes	Yes	Yes

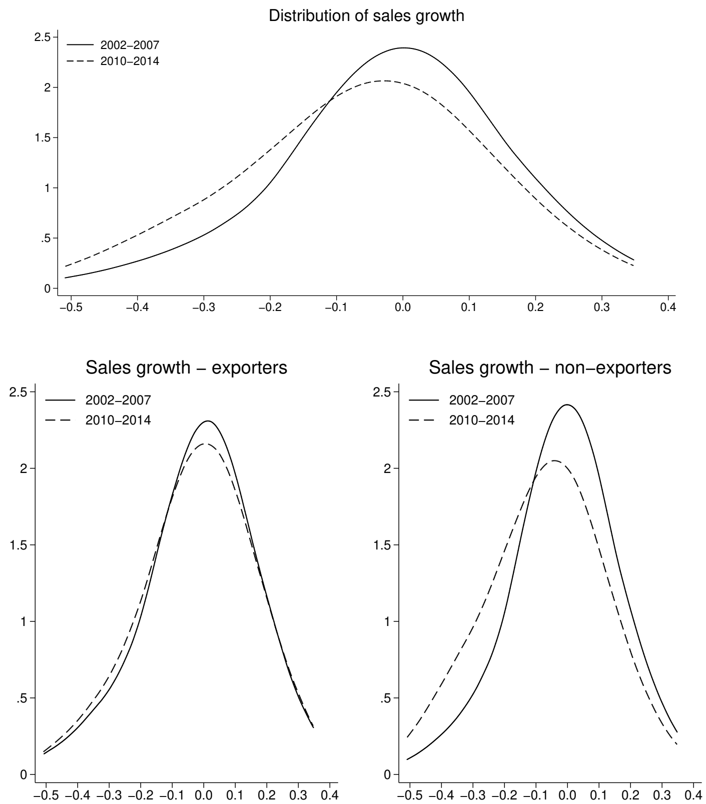
Heteroskedasticity-robust standard errors are in parentheses.
[‡]Kennedy (1981) showed that for a regression in which the dependent variable y is in logs, the transformation of a dummy variable estimated coefficient β using the formula $100 * e^{\hat{\beta} - .5\hat{\sigma}(\hat{\beta})^2 - 1}$ represents the effect of the dummy variable on y as a percentage. This transformation of the 2010–2014 dummy coefficient in the log investment regression maps the estimated value -0.74 to -52.2%.
[†] The investment rate is discretized by the following mapping $j\ I/K \mapsto \mathbb{N}$:
$j(I/K)$ is equal to 0 if $I/K \in (-\infty, -.01)$; 1 if $I/K \in (-\infty, -.01)$; 2 if $I/K \in (.01, .2]$; and 3 if $I/K \in (.2, \infty)$.
[¶]In the output of the discrete outcome models, the results are easier to interpret if they are displayed as proportional odds ratios by transforming the estimated coefficient β to $\exp(\beta)$. Thus, a reported number below unity reflects a negative coefficient. From the properties of the logit model, this implies that the exponentiated coefficient has the interpretation of a relative odds ratio. By odds, we refer to the odds for jumping to the immediately higher outcome: $\exp(\beta) = \frac{\text{Prob}(Y=y+1 \mid X=x+1)}{\text{Prob}(Y=y \mid X=x+1)} / \frac{\text{Prob}(Y=y+1 \mid X=x)}{\text{Prob}(Y=y \mid X=x)}$.
[††]Sales are deflated by the industry-specific producer price index. [§]The set of control variables consists of a complete second-degree polynomial in the two fundamentals: sales growth, $\Delta \ln$ sales, and capital, $\ln K$. The coefficients of the polynomial terms are not reported to economize on space but can be found in Appendix E.

investment, inaction, positive but less than 20% investment, and higher than 20% investment, and model the probability of each discrete interval as an ordered logit. The second panel of Table 1 presents the results of two logit estimators and one ordered logit estimator. The crisis dummy coefficient in the first column implies that during the crisis, the odds of being inactive versus active, $Prob(inactive)/Prob(active)$, are more than twice (2.1 times, to be precise) as large as the odds before the crisis, even though we condition on fundamentals. The crisis dummy coefficient in the second column implies that during the crisis, the odds of observing a positive investment spike are less than half as large as the odds before the crisis. The crisis dummy coefficient in the third column implies that during the crisis, the odds of jumping from one investment rate bin to one immediately higher is less than half as large as the odds before the crisis, conditional on fundamentals.

To see how the cross-sectional distribution of the proxy for investment opportunities before the crisis compares with the one during the crisis, Figure 4 depicts the sales growth distribution $\Delta \log sales$ before and during the crisis. The distribution has shifted toward the left and the dispersion seems to have increased. To be precise, during the crisis, the median dropped by 4 percentage points and the mean by 7, whereas the interquartile range shifted from 0.21 to 0.28, and the standard deviation from 0.26 to 0.31 (see the detailed statistics in Table D2 in the appendix). The drop in the average sales growth and median sales growth is consistent with a large crisis, and the increase in dispersion is consistent with pro-cyclical dispersion of gross output growth that has been documented in the literature (Bachmann and Bayer, 2014). Even though the transformation of the $\Delta \log sales$ distribution during the crisis is qualitatively consistent with other crisis episodes, the magnitude of these changes seems too small to account for a 50% collapse in investment.

Investment opportunities for exporting firms. The arguably small drop in sales growth in the manufacturing sector is not surprising, because Greece is a small open economy with unfettered access to the EU market, and the manufacturing sector's output is predominantly tradable. Therefore, although the domestic demand for firms' output may have plummeted, it is reasonable that the demand in the export market did not plummet as well. In fact, the bottom panel of Figure 4 provides evidence that the $\Delta \log sales$ distribution barely changed during the crisis for firms with exports in excess of 15% of their revenue. To be precise, the median $\Delta \log sales$ of these exporting firms fell only by 1 per-

Figure 4: Sales growth distributions before and during the crisis



Notes. The top and the bottom 5% of the whole sample is excluded. Growth is the one-year change of log gross output. Exporters are firms with exports at least 15% of their total revenue. Sources: ELSTAT.

centage point and the standard deviation of $\Delta \log sales$ increased by 20% (see the detailed statistics in Table D5 in the appendix). These numbers indicate that, even during the crisis years, there were plenty investment opportunities for these exporters which account for 20% of the observations and 37% of the total investment expenditure.

Undoubtedly, assessing the quantitative impact of the observed changes in fundamentals on investment requires formal quantitative analysis. In the rest of the paper, we carry out such analysis using both a reduced-form and a structural approach, and our results strongly suggest that fundamentals do not explain the investment collapse.

In sum, firm investment in manufacturing collapsed during the crisis, but this collapse does not appear to be explained by fundamentals. Our finding – that investment behavior, rather than solely fundamentals, changed during the crisis – is robust to a variety of specifications. The results are not sensitive to the definition of the pre-crisis and crisis periods. Tables F2 and F3 in Appendix F show a structural break in firm investment behavior somewhere between 2009 and 2010 and indicate that the period from 2002 to 2007 looks quite different than the period from 2010 to 2014. The results are also robust to weighting by firms' value-added share, indicating that the change in microbehavior may have aggregate implications (see Table F1 in Appendix F). We proceed by empirically investigating the change in credit conditions during the crisis and the effect that these changes might have had on firm investment when interacted with balance-sheet conditions.

4.3 The Role of External-Finance Dependence

Here, we present the second result of this section: the degree of firm dependence on external financing has predictive power over firm investment behavior during the crisis years. The stylized facts we present in this section are consistent with a story in which firms that entered the crisis with the largest external financing needs decreased their investment much more than did firms with similar fundamentals.

To explore whether external-finance dependence predicts investment behavior during the crisis, we construct an industry's technological demand for external financing using the methodology of Rajan and Zingales (1998).[18] Under the assumption that capital markets in the pre-crisis period are relatively frictionless, we can identify external financing needs at the industry level by calculating the following statistic: $Median\{\frac{Investment - VariableProfit}{Investment}\}$. To construct our sectoral index of external financial dependence RZ, we further transform this index by adding its minimum value plus unity and then taking the logarithm.

Our hypothesis is that a firm in an industry more dependent on external financing performs worse during the crisis than does a firm in an industry less dependent on external financing, after controlling for fundamentals. We test this hypothesis by running the same set of specifications used in Table 1 and augmenting them by an interaction term $RZ \times Dummy_{crisis}$. Table 2 presents the results from all the specifications. Because the units of the RZ index are not particularly helpful for interpreting our results, we further

[18] Rajan and Zingales (1998) attribute the heterogeneity in external financing needs across sectors to technological factors. In fact, they say "We assume that there is a technological reason why some industries depend more more on external finance than others. To the extent that the initial project scale gestation period, the cash harvest period, and the requirement for continuing investment differ substantially between industries, this is indeed possible."

Table 2: Investment and the degree of external financial dependence

In this table we explore the role of external-financing dependence in investment during the crisis. To do so, we construct an index of external-financial dependence, similar to that of Rajan and Zingales (1998), at the industry level using the pre-crisis microdata. The estimated coefficient of this index interacted with a crisis dummy variable in several investment regressions shows that firms in industries with higher dependence on external financing invested less than did similar firms in industries less dependent on external funds. These results suggest that credit conditions may have played a role in firms' investment decisions during the crisis.

Continuous-outcome models				
Model	$E(y\|x)$	$Median(y\|x)$	$Quantile_{80}(y\|x)$	$E(y\|x)$
Dependent var y	I/K	I/K	I/K	$\log I$
2010–2014 dummy×RZ‡	-0.010	-0.0054	-0.012	-0.061
	(0.0038)	(0.0011)	(0.0043)	(0.030)
2010–2014 dummy	-0.049	-0.024	-0.069	-0.73
	(0.0035)	(0.0011)	(0.0042)	(0.026)
N	19748	19748	19748	15899
R^2 adjusted	0.044			0.51
Pseudo R^2		0.028	0.045	
Sector FEs	Yes	Yes	Yes	Yes
Controls§	Yes	Yes	Yes	Yes

Discrete-outcome models			
Model	Inaction $LogitProb(y=1\|x)$	Spike$^+$ I/K $LogitProb(y=1\|x)$	Discretized $I/K^\dagger$ $OrderedLogit(y=j\|x)$
Dependent var y	$\mathbb{1}\{\|I/K\| \leq .01\}$	$\mathbb{1}\{I/K > .2\}$	$j \in \{0,1,2,3\}^\dagger$
2010–2014 dummy×RZ	0.072	-0.13	-0.093
$(=\beta_c)$	(0.033)	(0.054)	(0.029)
2010–2014 dummy	0.75	-0.81	-0.68
	(0.035)	(0.049)	(0.029)
$\exp(\beta_c)$¶	1.07	0.88	0.91
N	19,748	19,748	19,748
Pseudo R^2	0.062	0.058	0.035
Sector FEs	Yes	Yes	Yes
Controls§	Yes	Yes	Yes

Heteroskedasticity-robust standard errors are in parentheses.

‡RZ is the Rajan and Zingales (1998) external-finance dependence index calculated from the pre-crisis data at the sectoral level. We further transform this index by adding its minimum value plus unity and then taking the log. This variable is then normalized by subtracting the mean and dividing by the SD so that the units of the estimated coefficient are one SD of the RZ index.

† The investment rate is discretized by the following mapping $j\ I/K \mapsto \mathbb{N}$:
$j(I/K)$ is equal to 0 if $I/K \in (-\infty, -.01)$; 1 if $I/K \in (-\infty, -.01)$; 2 if $I/K \in (.01, .2]$; and 3 if $I/K \in (.2, \infty)$.

¶The results of the discrete outcome models are easier to interpret if they are displayed as proportional odds ratios by transforming each estimated coefficient β to $\exp(\beta)$. Thus, a reported number below unity reflects a negative coefficient. From the properties of the logit model, this implies that the exponentiated coefficient has the interpretation of a relative odds ratio. By odds, we refer to the odds for jumping to the immediately higher outcome: $\exp(\beta) = \frac{\text{Prob}(Y=y+1 \mid X=x+1)}{\text{Prob}(Y=y \mid X=x+1)} / \frac{\text{Prob}(Y=y+1 \mid X=x)}{\text{Prob}(Y=y \mid X=x)}$.

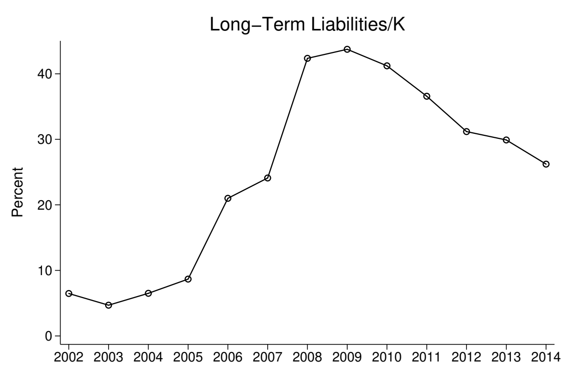
§The set of control variables consists of a complete second-degree polynomial in the two fundamentals: sales growth, $\Delta \ln$ sales, and capital, $\ln K$. The coefficients of the polynomial terms are not reported to economize on space but can be found in Appendix E.

transform the RZ index by subtracting the mean and dividing by its standard deviation. All coefficients of the term interacting the RZ with the crisis dummy are statistically significant and imply a negative correlation between external finance dependence and firm investment during the crisis controlling for fundamentals. In particular, firms in a sector with external financial needs 1 standard deviation above the average have a mean, a median, and a top quintile investment rate of 1, 0.5, and 1.2 percentage points lower than firms in the sector with average external financial dependence. To quantify the investment drop as a percentage, we ran a regression of the logarithm of investment on the left-hand side. The results, which are presented in the last column of Table 2, indicate that positive investment in sectors with external-finance dependence 1 standard deviation above the average is 6.1% lower than in the sector with average external finance needs.

4.4 The Role of Leverage

Here, we present the third result of this section: during the crisis, investment by firms entering the crisis with high leverage is substantially lower than is investment by firms entering the crisis with low leverage. The data patterns we present in this section are consistent with a story in which firms accumulate debt to grow prior to the crisis, and the banking crisis, which culminates in 2012, tightens firms' leverage constraints, and, as a result, highly leveraged firms do not invest in the face of investment opportunities during the crisis period.

Figure 5: The deleveraging episode



Notes. The figure illustrates the top tertile of the leverage distribution. Source: ELSTAT.

Figure 5 establishes the deleveraging episode. The figure depicts the evolution of the top tertile of the distribution of long-term liabilities over capital stock; we refer to this as "leverage". Leverage increased during the early 2000s and started to decrease sharply from 2010 onwards, with a cumulative drop of 40% by 2014.[19] Long-term liabilities over assets is our preferred measure of leverage for two reasons. First, it exhibits the largest drop during the crisis, compared with other measures of leverage, as is evident in Figure G2 in Appendix G. That figure shows that all measures of leverage – namely, long-term liabilities over capital, total liabilities over capital, and total liabilities over assets – drop during the crisis, but the ratio of long-term liabilities over capital drops twice as much as the measure with the second-largest drop. Second, as the reduced-form analysis will demonstrate, it has the strongest predictive power over investment.[20] The time-series properties of the top tertile of the leverage distribution reflect the evolution of the whole leverage distribution, as Figure G3 demonstrates. The figure focuses on percentiles above the median, because the median leverage is zero for most of the pre-crisis years.[21]

To quantify the effect of leverage on investment, we run investment regressions with the same explanatory variables used in the specifications in Table 1, but we add a dummy variable equal to one if a firm's leverage was in the top tertile of the leverage distribution during the years 2007–2009. Our identifying assumption is that pre-crisis leverage and pre-crisis investment are simultaneously determined, and current investment opportunities proxied for by sales growth are orthogonal to pre-crisis leverage. Table 3 presents the results of two specifications: an inaction logit and a loglinear investment regression. The top panel of the table estimates a different leverage coefficient for each crisis year. Notice that the leverage coefficient changes signs between 2011 and 2012 in both specifications, thereby establishing that pre-crisis leverage is negatively correlated with investment from the culmination of the

[19] For the drop as a percentage, see G2 in Appendix G.

[20] Almeida, Campello, Laranjeira, and Weisbenner (2011) use a novel 'maturing debt' empirical strategy to study the real effects of the 2007 credit crisis by exploiting the cross-sectional firm heterogeneity in the maturity of long-term debt. This empirical strategy that compares the firms with maturing debt in any given year with firms whose debt is not maturing the same year is also used by Benmelech et al. (2017) and Benmelech, Bergman, and Seru (2011). We follow a similar empirical strategy in the sense that we compare firms which are different regarding their reliance on long-term debt, but not exactly the same since we do not have information on the maturity dates of the long-term debt. Since we separate firms in terms of their long-term leverage before the beginning of the crisis we expect a large fraction of this debt to be maturing during the crisis years.

[21] See Table D3 in Appendix D.

Table 3: Firm-level leverage and investment behavior

In this table, we investigate the role of leverage in investment during the crisis. To do so, we construct a measure of leverage at the firm level and run investment regressions with this measure of leverage on the right-hand side of the regressions. We focus on models describing the most important features of the investment distribution: the mean log investment for firms with positive investment and the share of firms with nearly zero investment. There are two main results. First, pre-crisis leverage is positively correlated with investment before 2011–2012, and the correlation becomes negative afterward. The timing of the switch coincides with the culmination of banking crisis in 2012 and is ongoing. Second, focusing on the severe banking crisis years 2012–2014, we find that firms arriving at the recession with leverage in the top tertile of the leverage distribution invested 13% less than did similar firms with pre-crisis leverage in the bottom-two tertiles.

	Year-specific leverage coefficients	
Model	Inaction $Logit Prob(y = 1\|x)$	loglinear reg. $E(y\|x)$
Dependent var y	$\mathbb{1}\{\|I/K\| \leq .01\}$	$\log I$
	The High LT leverage dummy is interacted with yearly dummies[††]	
2010	-0.23 (0.12)	0.24 (0.090)
2011	-0.075 (0.11)	-0.040 (0.094)
2012	0.16 (0.11)	-0.17 (0.10)
2013	0.20 (0.11)	-0.094 (0.10)
2014	0.11 (0.11)	-0.15 (0.098)
N	8,131	6,385
Sector FEs	Yes	Yes
Year FEs	Yes	Yes
Controls[§]	Yes	Yes
	Restricting the sample to 2012–2014 (i.e., the severe banking crisis years)	
High LT leverage ($= \beta_c$)	0.15 (0.067)	-0.14 (0.059)
$\exp(\beta_c)$[¶]	1.17	
N	4,838	3,787
Sector FEs	Yes	Yes
Controls[§]	Yes	Yes

Heteroskedasticity-robust standard errors are in parentheses.

[††]This dummy variable equals one if the ratio of a firm's long-term liabilities over its capital stock is in the top tertile during the years 2007–2009 and zero otherwise.

[¶]The results of the discrete outcome models are easier to interpret if they are displayed as proportional odds ratios by transforming each estimated coefficient β to $\exp(\beta)$. Thus, a reported number below unity reflects a negative coefficient.

[§]The set of control variables consists of a complete second-degree polynomial in the two fundamentals: sales growth $\Delta \ln$ sales and capital $\ln K$. The coefficients of the polynomial terms are not reported to economize on space but can be found in Appendix E.

banking crisis in 2012 onwards. To quantify the effect of leverage during the banking crisis, we restrict our sample to the banking crisis years 2012–2014 and run the same specifications but allow for a single coefficient on leverage for all years. The results, which are presented in the bottom panel of Table 3, suggest that during the crisis, investment by firms with the highest pre-crisis leverage is 13% lower[22] and 17% more likely to be zero than is investment by firms with low pre-crisis leverage.

Table D4 in Appendix D shows the evolution of the long-term leverage (the ratio of long-term liabilities over capital) at the sectoral level. Although the level of leverage across sectors is heterogeneous, the time-series properties of leverage are similar. Median leverage increased in the late 2000s and then sharply dropped to zero, suggesting a strong deleveraging process in our period of analysis.

5 Analysis: An Empirical Dynamic Investment Model without Credit Constraints

In this section we completely specify a dynamic model of investment in order to estimate the relevant parameters aimed at capturing the key characteristics of Greek manufacturing firms for our period of analysis. We also show that fundamental variables that determine investment decisions (capital and profitability) cannot account for the investment collapse observed in the data.

5.1 A Stylized Investment Model with Firm Heterogeneity

Given the structure of the data available and our interest in investment dynamics, we set up a standard dynamic model of firm investment decisions that allows us to infer whether patterns of the data can be explained with typically used fundamental variables, such as productivity or demand shocks. The model generally follows from Cooper and Haltiwanger (2006) and Asker et al. (2014a). We assume that each firm maximizes variable profits every

[22] Kennedy (1981) showed that for a regression in which the dependent variable y is in logs, the transformation of a dummy variable estimated coefficient β using the formula $100 * e^{\hat{\beta} - .5\hat{\sigma}(\hat{\beta})^2 - 1}$ represents the effect of the dummy variable on y as a percentage. This transformation of the 2010–2014 dummy coefficient in the log investment regression maps the estimated value -0.14 to -12.8%.

period, while the investment problem takes into account a time-to-build lag before newly acquired capital becomes available for production. That is, capital for firm i on period $t+1$ is determined by the previous period level of capital and investment:

$$K_{it+1} = (1-\delta) K_{it} + I_{it}$$

with δ being the capital depreciation rate. The solution to the former problem generates a static variable maximum-profit function,[23] $\Pi(K,\omega)$, that depends on the current level of capital K and a profit shock ω, assumed to follow an $AR(1)$ process. Note that, conditional on positive capital, the variable profit, $\Pi(K,\omega)$, is also always positive. With this optimal profit function, the firm is then able to determine optimal capital investment for the next period, where the capital adjustment costs are of crucial importance. Note that this structure allows for a decomposition of the firm problem into a static part (optimal profit) and a dynamic part (investment).

Being a central part of our model, capital adjustment includes both convex and non-convex adjustments captured by the function $C(I_{it}, K_{it}, \omega_{it})$ that also allows for interactions of the cost with the current realization of the profitability shock. We assume that firms only incur these costs if investment is different from zero.

Given this specification, firm i's investment problem at time t can be represented with the following value function:

$$V(K_{it},\omega_{it}) = \max\left\{V^a(K_{it},\omega_{it}), V^i(K_{it},\omega_{it})\right\} \tag{1}$$

where V^a and V^i stand for the values of adjusting through non-zero investment and inaction with zero investment, respectively. These can be recursively represented with

$$V^a(K_{it},\omega_{it}) = \max_{I_{it}\neq 0}\left\{\Pi(K_{it},\omega_{it}) - C(I_{it},K_{it},\omega_{it}) + \beta E_{\omega_{it}}\left[V(I_{it}+(1-\delta)K_{it},\omega_{it+1})\right]\right\}$$

$$V^i(K_{it},\omega_{it}) = \Pi(K_{it},\omega_{it}) + \beta E_{\omega_{it}}\left[V((1-\delta)K_{it},\omega_{it+1})\right]$$

where ω_{it} follows an $AR(1)$ process specified below.

[23]Appendix H.1 provides a derivation of a particular optimal profit function.

5.1.1 Specification of Functional Forms in the Model

As mentioned above, the model structure allows for a decomposition of the firm problem into a static component and a dynamic component. The static component amounts to the solution of the optimal variable profit given some initial capital and profitability realization. For that optimal variable profit, we assume a following functional specified as

$$\Pi\left(K_{it},\omega_{it}\right)=\exp\left(\omega_{it}\right)K_{it}^{\beta_K} \tag{2}$$

where ω_{it} captures the probitability shock assumed to follow an $AR(1)$ process:

$$\omega_{it}=\mu_{\omega}\left(1-\rho\right)+\rho\omega_{it-1}+\nu_{it},\quad \nu_{it}\sim N\left(0,\sigma_{\nu}\right) \tag{3}$$

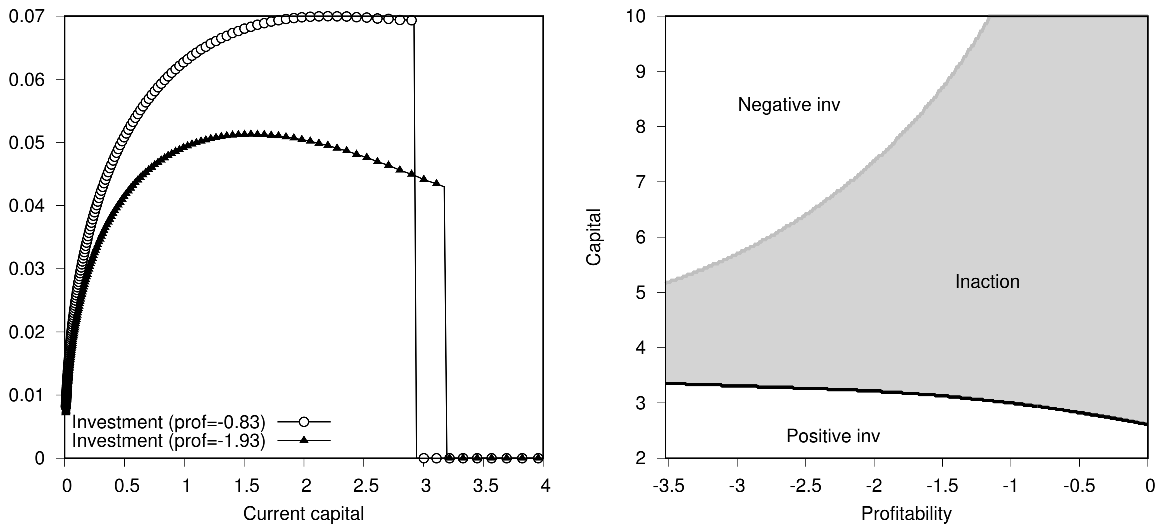
Given the profitability process and profit function, firms choose their investment decisions, where adjusting capital carries costs assumed to include both convex and non-convex components. These costs only emerge if the investment decision is different from zero. The particular functional form is defined as

$$C\left(I_{it},K_{it},\omega_{it}\right)=\begin{cases} I_{it}+F\cdot\Pi\left(K_{it},\omega_{it}\right)+\gamma\cdot K_{it}\cdot\left(\frac{I_{it}}{K_{it}}\right)^2 & if\ \ \frac{I_{it}}{K_{it}}>0\\ 0 & if\ \ \frac{I_{it}}{K_{it}}=0\\ I_{it}+F\cdot\Pi\left(K_{it},\omega_{it}\right) & if\ \ \frac{I_{it}}{K_{it}}<0 \end{cases} \tag{4}$$

where the asymmetry of this cost function allows firms to dispose of capital without having to incur large capital adjustment costs, while maintaining some capital irreversibility. Note that the presence of $F\cdot\Pi\left(K_{it},\omega_{it}\right)$ induces regions of inaction as the investment decision follows a (s,S)-type policy, as discussed in Caballero et al. (1995), and thereby helps to explain investment spikes and other important features of the data. This specification for the fixed adjustment cost captures a firm's opportunity cost in terms of variable profits. With any capital adjustment, a plant's profits fall by a F factor during the adjustment period, consistent with the evidence in Power (1998) and Sakellaris (2004).

Note that the above specification with a non-convex adjustment cost that is proportional to the level of variable profits implies that investment bursts are less costly during periods of low profitability. This should reduce the correlation between investment and profitability,

Figure 6: Inaction and investment policy functions implied by the model under different realizations of the profitability shock ω



Note. This figure uses parameter estimates for the *whole manufacturing* sector, which are summarized later in Tables 4 and 6.

but not to the extent of making it negative under a large autocorrelation of the profitability shock. Without the profitability shocks, a firm would only invest if current capital falls under a critical level. With profitability shocks, this level becomes profit dependent and thus allows the model to generate both inaction and investment spikes that are also correlated with the current profit shock realization, as shown in Figure 6.

With the specification summarized in (3) and (4), we can then estimate all relevant parameters associated with the standard investment model (1): four profitability parameters (β_K, ρ, σ_ν, μ_ω) and two capital adjustment costs parameters (F, γ).

5.2 Estimation

The estimation makes use of the data discussed in Section 3 in order to recover the parameters of interest for the dynamic investment model. Our estimation strategy takes into account the fact that the investment problem can be divided into a static part and a dynamic part. We use firms' optimality conditions to estimate the parameters of interest for the optimal profit function: the curvature of the profit function β_K, the mean of the profitability shock μ_ω, its persistence ρ, and the standard deviation of the underlying innovation σ_ν. We can then use these parameters to estimate the dynamic parameters associated with capital adjustment costs: the non-convex parameter F and the convex parameter γ. We perform this estimation separately for each sector and for the manufacturing sector as a whole using yearly observations.

5.2.1 Structural Estimation of Firm Profitability

To quantify the change in investment behavior through the lens of a model and investigate the quantitative importance of leverage, we develop and estimate a structural model of a firm's decision to invest.

Time is discrete, and the horizon is infinite. A firm's maximum profit function solely depends on physical capital and a profitability shock. Capital is quasi fixed in the sense that investment takes one period to become productive. Profitability is exogenous to the firm and first-order Markovian. The quasi-fixed nature of capital and the exogeneity of profit shocks imply that the parameters governing the maximum profit function and its evolution can be estimated independently of firms' investment decisions. Let i denote a firm and t denote time. The profit function and the evolution of profitability are specified as follows:

$$\log \Pi_{it} = \omega_{it} + \beta_K \log K_{it} \tag{5}$$

$$\omega_{it} = E\left(\omega_{it} | \omega_{it-1}\right) + \nu_{it} = \bar{\omega} + \rho\omega_{it-1} + \nu_{it} \tag{6}$$

$$\nu_{it} \sim N\left(0, \sigma_\nu\right) \tag{7}$$

where Π represents variable profits defined as sales minus expenditure on labor and materials, β_K is the curvature of the profit function, ω the profitability shock, ρ its persistence, and ν its innovation.

While an ordinary least squares (OLS) regression may seem like a natural estimator for the profit function coefficient β_K defined in (5), it has two potential issues. The first issue is the persistence of the profitability process in (6) that implies that large firms are likely to be more productive. This, in turn, induces a correlation between ω_{it} and K_{it} that will bias the estimate of β_K upward. A straightforward way of solving this problem is to use an alternative moment condition, namely that the innovations in profitability are orthogonal to past profits and current capital stock, which is quasi fixed. This estimator and its properties are clearly presented in Ackerberg et al. (2015) and the references therein. The second issue arises from firm selection due to exit and also the sampling design of our data, which include only firms above the ten-employee cutoff. We solve this issue by using as an instrument the predicted probability of a firm remaining in the sample estimated from a first-stage sample selection model like in Olley and Pakes (1996).[24]

Therefore, we estimate the parameters β_K, ρ with a non-linear GMM estimator using the Ackerberg et al. (2015) moments augmented by the predicted probability instrument like in Olley and Pakes (1996). The moment conditions are presented below.

$$E\left[\left(\log \Pi_{it} - \beta_K \log K_{it} - \rho\left(\log \Pi_{it-1} - \beta_k \log K_{it-1}\right) - \beta_P \hat{P}_{it} - \textstyle\sum_{t=1}^{T} d_t \beta_t\right) \otimes \begin{pmatrix} d_1 \\ \vdots \\ d_T \\ \log K_{it} \\ \log \Pi_{it-1} \\ \hat{P}_{it} \end{pmatrix}\right] = 0$$

After estimating β_K and ρ, we calculate firm-specific profitability shocks $\hat{\omega}_{it}$, and the constant of the process is estimated as the sample mean of $\hat{\omega}_{it} - \hat{\rho}\hat{\omega}_{it}$. The sample is reduced by trimming the top and the bottom 1% of the $\hat{\nu}_{it}$ distribution and $\hat{\sigma}_{\nu}$ is estimated as the sample standard deviation of the empirical $\hat{\sigma}_{\nu}$ distribution.

Table 4: Parameter estimates of the profit function and the profitability process

Sector	Estimates of model parameters				AR(1)-implied and data moments†			
	β_K	ρ	ω_0	σ_ν	Mean(ω)	$SD(\omega)$	$\frac{\omega_0}{(1-\rho)}$	$\frac{\sigma_\nu}{\sqrt{1-\rho^2}}$
Food and beverages	0.568	0.658	-0.212	0.649	-0.607	1.036	-0.622	0.862
Apparel and lather	0.232	0.698	-0.209	0.627	-0.389	1.185	-0.694	0.877
Paper	0.484	0.779	-0.146	0.482	-0.607	0.879	-0.661	0.768
Chemicals	0.538	0.705	-0.142	0.561	-0.407	0.985	-0.480	0.791
Plastic and rubber	0.484	0.618	-0.339	0.578	-0.818	0.915	-0.887	0.736
Non-metal minerals	0.610	0.556	-0.522	0.789	-1.035	1.034	-1.177	0.949
Metal products	0.471	0.541	-0.480	0.745	-0.891	0.981	-1.045	0.886
MachEq vehicles	0.526	0.681	-0.279	0.679	-0.712	1.019	-0.873	0.927
Whole manufacturing	0.476	0.679	-0.257	0.666	-0.544	1.079	-0.801	0.908

†The estimated parameters of the AR(1) profitability process imply a cross sectional mean of $\frac{\omega_0}{(1-\rho)}$ and a cross-sectional standard deviation of $\frac{\sigma_\nu}{\sqrt{1-\rho^2}}$. Our parameter estimates imply moments close to the moments calculated from the profitability estimates $\{\hat{\omega}_{it}\}$.

We estimate the model for the whole manufacturing sector and for disaggregation at the

[24] For details about the specification and estimation of the sample selection model see Appendix A.

individual two-digit sector level. The first serves as a parsimonious way to present results, and the second accommodates a larger degree of heterogeneity by allowing for sector-specific profit functions and profitability processes. The parameter estimates for the whole manufacturing sector and each sector separately are presented in Table 4. The parameters seem reasonable in the sense that the profit function curvature $\hat{\beta}_K$ for the whole manufacturing is a little lower than the Cooper and Haltiwanger (2006) estimate of 0.592. Persistence $\hat{\rho}$ is high (0.679) but far from 1, guaranteeing a finite variance of the ω distribution. Turning to the parameter estimates at the sectoral level, estimates for the curvature of the profit function display a significant degree of heterogeneity ranging from 0.12 to 0.83. Compared with other similar studies, Asker et al. (2014a) estimate numbers from 0.28 to 1. More importantly, all of our estimates for $\hat{\beta}_K$ are smaller than 1, implying decreasing returns to the scale of the profit function and therefore a well-defined optimal value of investment in the dynamic problem of the firm. Our set of estimates for the profitability process, are also similar to the previous studies mentioned and our persistence parameter is less than 1 in all sectors. This similarity to other studies implies a substantial degree of within-sector dispersion of profitability and substantial persistence and thus provides a potentially important link between profitability and investment decisions.

Finally, we also show in the last four columns in the table that our parsimonious $AR(1)$ specification for the profitability shock ω_{it} seems to describe well the cross-sectional distribution of the profit shock estimates, $\hat{\omega}_{it}$. The right panel of the table compares the cross-sectional moments of ω implied by the estimated parameters to the moments in the actual data. The moments are relatively close, suggesting that the AR(1) model of the profitability process does a good job in describing the cross-sectional properties of the ω distribution even though the estimator does not attempt matching it.

Table 5 presents profitability and investment moments by sector. Notably, across-sector heterogeneity in the profitability distribution from before to during the crisis is substantial. For instance, the average estimated firm profitability of the Food, Paper, and Chemicals sectors increased during the crisis. In contrast, there does not seem to be much heterogeneity in the investment collapse across sectors, a finding that is consistent with our reduced-form result that the investment collapse cannot be entirely explained by fundamentals.

Table 5: Profitability and investment moments before and during the crisis

Sector	Period	$SD(\omega)$	$SD(\nu)$	$Mean\,(\omega)$	$Mean(I/K)$	Inaction
Food and beverages	*Pre-crisis*	0.979	0.633	-0.716	0.124	0.179
	During crisis	1.058	0.647	**-0.581**	**0.073**	0.243
Apparel and lather	*Pre-crisis*	1.173	0.599	-0.316	0.081	0.313
	During crisis	1.145	0.638	-0.523	0.048	0.416
Paper	*Pre-crisis*	0.847	0.471	-0.711	0.093	0.246
	During crisis	0.882	0.497	**-0.551**	**0.070**	0.285
Chemicals	*Pre-crisis*	0.968	0.526	-0.560	0.131	0.098
	During crisis	0.955	0.564	**-0.335**	**0.077**	0.221
Plastic and rubber	*Pre-crisis*	0.847	0.557	-0.778	0.136	0.161
	During crisis	0.967	0.594	-0.883	0.079	0.247
Non-metal minerals	*Pre-crisis*	0.967	0.739	-0.948	0.130	0.181
	During crisis	1.116	0.857	-1.196	0.059	0.388
Metal products	*Pre-crisis*	0.847	0.651	-0.743	0.135	0.212
	During crisis	1.066	0.802	-1.075	0.059	0.371
MachEq vehicles	*Pre-crisis*	0.951	0.615	-0.627	0.127	0.229
	During crisis	1.072	0.744	-0.873	0.068	0.358
Whole manufacturing	*Pre-crisis*	1.032	0.626	-0.625	0.114	0.217
	During crisis	1.113	0.698	-0.742	0.066	0.316

5.2.2 Structural Estimation of Capital Adjustment Costs

Given that we focus on the crisis impact in the Greek economy, we estimate the set of parameters governing capital adjustment costs only for the pre-crisis period, while maintaining the same stochastic process for the firm profitability shock for the entire period in our sample. Allowing for additional degrees of the freedom in the profitability process would improve the fit of the model at the expense of rendering the parameters governing this process as "free" for no identifiable reason. The underlying assumption is that the sequence of negative (or positive) shocks faced by firms during the crisis period are interpreted by the relevant decision-makers as mean-reverting ones. We then assess if our estimated model can replicate the observed dynamics in the average investment rate during the crisis.

For the estimation of the capital adjustment costs parameters, we use simulated method of moments (SMM). In particular, the estimation method consists of the following steps. We first solve the dynamic investment model using an initial guess of the parameters: $\Theta = (F, \gamma)$. From this model, we extract policy functions used to generate a simulated version of the data for N firms, $\left\{\{\omega_{it+1}, k_{it+1}, i_{it}\}_{t=1}^{T}\right\}_{i=1}^{N}$, given a set of initial conditions that capture relevant state variables $\{\{\omega_{it=0}, k_{it=0}\}\}_{i=1}^{N}$. Then a set of simulated moments is constructed from the simulated data, $\Psi^s(\Theta)$, and finally compared with the same set of moments generated by the actual data Ψ. To estimate the parameters, we use the following distance criterion:

$$\mathcal{D}(\Theta) = \min_{\Theta} \left[\Psi - \Psi^s(\Theta)\right]^\intercal W^{-1} \left[\Psi - \Psi^s(\Theta)\right]$$

where W is an identity matrix.

To compute the model described in Equation (1), we rely on a standard value function iteration, using two-dimensional cubic b-spline approximations. We set the annual discount factor parameter to $\beta = 0.95$ and the depreciation rate to $\delta = 0.09$. This last parameter is in accordance with the implied average depreciation rate described in Appendix D. These calibrated parameters are assumed to be common across all sectors. As for the statistical moments used in the SMM procedure, we follow Asker et al. (2014a) and choose the following three: (1) frequency of investment inaction, $Prb\left(|I_{it}/K_{it}| \leq 0.01\right)$; (2) frequency of investment rate spikes larger than 20%, $Prb\left(|I_{it}/K_{it}| \geq 0.2\right)$; and (3) the standard deviation of the investment rate, $sdev\left(I_{it}/K_{it}\right)$. These statistics are matched with the corresponding moments of the model and simulated for the sample period using the initial conditions for K_{it} and ω_{it}, consistent with what we observe in the dataset.[25] Simulating the model based on initial conditions substantially improves the model's fit, because the simulation allows for optimal investment decisions from a set of firms not necessarily operating at an ergodic distribution.

As mentioned before, we aim to contrast firm investment dynamics during the two main periods of our analysis: *pre-crisis* (2002–2007) and *during crisis* (2010–2014). To do that, we use the profitability parameters estimates from Table 4 and restrict our sample to the *pre-crisis* period for the estimation of capital adjustment costs. We exclude the *during crisis* period from our estimation to assess how estimates of the capital adjustment cost associated with normal times can explain dynamics of the investment rate during a period of financial turbulence. The point of this exercise is to identify the main drivers that change firm behavior relative to investment. We implicitly assume that firms maintain the same expectations about future profits given their current profitability realization. In that sense, we evaluate whether both convex and non-convex capital adjustment costs, usually associated

[25]In Appendix B, we describe how we draw initial conditions that are consistent with our data. The method described should ease the replication of our results by an interested reader.

Table 6: Dynamic estimates of the capital adjustment cost parameters using the pre-crisis period (2002–2007) for the calibrated parameters: $\beta = .95$ and $\delta = .09$

Sector	Data moments†			Simul. moments			Estimates§		
	SD	Inact.	Spike	SD	Inact.	Spike	F	γ	*Dist*
Food and beverages	.25	.18	.16	.20	.18	.18	.03	12.22	.002
Apparel and leather	.29	.31	.14	.20	.32	.19	.02	14.78	.011
Paper	.19	.25	.15	.18	.25	.15	.02	20.67	.000
Chemicals	.23	.10	.18	.15	.10	.20	.01	9.67	.006
Plastic and rubber	.23	.16	.21	.22	.15	.21	.01	7.00	.000
Non-metal minerals	.28	.18	.18	.18	.18	.22	.04	5.33	.012
Metal products	.27	.21	.19	.22	.22	.21	.02	8.67	.002
MachEq vehicles	.27	.23	.19	.20	.22	.22	.06	16.56	.006
Whole manufacturing	.26	.22	.17	.22	.22	.20	.03	13.98	.002

† Our data moments include the firm-level standard deviation of the investment rate (SD), inaction measured as the proportion of firms with an absolute value of the investment rate smaller than 1% (inact), and the proportion of firms for which the absolute value of the investment rate is in excess of 20% (spike).
§ The estimates columns F, γ, and *Dist* refer to the non-convex adjustment cost of capital, the convex cost, and our distance criterium $\mathcal{D}(\Theta)$.

with deep technological parameters,[26] can explain investment dynamics in both periods.

To summarize the estimation procedure, for each sector, we match all the $sdev\left(I_{it_p}/K_{it_p}\right)$, $Prb\left(\left|I_{it_p}/K_{it_p}\right| \leq 0.05\right)$, and $Prb\left(\left|I_{it_p}/K_{it_p}\right| \geq 0.2\right)$ moments for the *pre-crisis* period $t_0 = \{2002, ..., 2007\}$, using 5000 initial conditions $\left\{\left\{\omega_{it_p}, k_{it_p}\right\}\right\}_{i=1}^{N}$ and a unique set of profit function estimates: $\hat{\beta}_K$, $\hat{\rho}$, $\hat{\sigma}$, and $\hat{\mu}$. Results of this estimation procedure can be found in Table 6 for all eight sectors available and the whole manufacturing sector.

The first six numerical columns of the table show both the data- and the model-generated moments. It is clear that the model is able to match the data moments, capturing, in particular, the relatively small standard deviation of the investment rate and the large proportions of both inaction and investment spikes. This performance generates small distance $\mathcal{D}(\Theta)$ outcomes of the estimation procedure with a maximum of 0.01 in the *Non-metal minerals* sector, an about 11-percentage-point average deviation from the data moments. Our procedure generates *pre-crisis* estimates for the non-convex cost of adjustment of $(mean, max, min) = (0.03, 0.06, 0.01)$, implying a 3% average loss of current variable profits when firms engage in either positive or negative investment, and estimates for the convex cost of investment of $(mean, max, min) = (12.2, 20.7, 5.3)$, implying a 24% increase in the

[26]These can be related to business disruptions incurred during installation of new capital equipments, slow learning of operating new capital, delivery lags and time to install, and lack of secondary markets for used capital.

marginal adjustment costs of capital for each 1-percentage-point increase in the investment rate.[27] Despite being large and heterogenous, our estimates are still within range of similar studies (e.g., Merz and Yashiv, 2007).

5.3 Explaining the Collapse in the Average Investment Rate

Given the estimates of the dynamic firm investment model described above, we now analyze the ability of the model to generate the investment collapse observed in the Greek economy during the years 2002–2014. This exercise is evaluated by simulating the model with the parameters estimated in the previous section and using the observed and/or estimated values for capital and the profitability shock, $\{\{\omega_{it}, k_{it}\}\}_{i=1}^{N}$, for both the *pre-crisis* period and the *during crisis* period. In particular, note that the model described in Equation (1) generates investment policy functions with a behavior similar to what is represented in Figure 6:

$$I_{it} = f^{Inv}\left(K_{it}, \omega_{it}; F, \gamma\right) \tag{8}$$

To analyze the predictive ability of the model regarding the evolution of the investment rate, we compute the following difference:

$$\Delta\left(\overline{I/K}\right) = E\left[\frac{f^{Inv}\left(K_{it_1}, \omega_{it_1}; F, \gamma\right)}{K_{it_1}}\right] - E\left[\frac{f^{Inv}\left(K_{it_0}, \omega_{it_0}; F, \gamma\right)}{K_{it_0}}\right] \tag{9}$$

where $t_{j=0,1}$ stands for the sample observations associated with the *pre-crisis* period, $t_0 = \{2002, ..., 2007\}$ and the *during crisis* period $t_1 = \{2010, ..., 2014\}$. It follows that the variable defined in (9) is intended to capture the investment collapse observed in the data, assuming *stability* of the adjustment cost parameters (F and γ). In other words, we use the estimates of the *pre-crisis* period to evaluate the *during crisis* prediction of the investment rate. The results of this exercise are summarized in Table 7.

Patent in Equation (8) is the fact that the investment policy depends on both the current level of capital and the current profit shock realization. It follows that a reduction in the investment rate can be accounted by the model either with a small realization of the prof-

[27] The particular interpretation of the parameter γ comes from the implied Euler equation associated with the problem (1), where $1 + 2\gamma I_{it}/K_{it} = \beta E_{\omega_{it}}\left[V_K\left(K_{it+1}, \omega_{it}\right)\right]$. If one considers the left-hand side of this equation of the marginal adjustment cost of capital, then increasing the investment rate by 1 percentage point should increase the shadow value by $0.01 \times 2\gamma$.

Table 7: Model predictions for the variation of the investment rate between the *pre-crisis* (2002–2007) and *during crisis* (2010–2014) periods

Sector	profit (Δ%)	Capital (Δ%)	Inv rate (Δpp)	
	Data	Data	Data	Simul.
Food and beverages	12.7	-17.1	-5.2	1.8
Apparel and leather	-14.9	1.0	-3.3	-0.4
Paper	14.8	-9.3	-2.3	3.7
Chemicals	21.0	10.0	-5.4	-2.1
Plastic and rubber	-10.3	11.0	-5.7	-4.4
Non-metal minerals	-24.8	9.5	-7.1	-2.6
Metal products	-37.6	-4.7	-7.6	-3.1
MachEq vehicles	-24.3	-31.4	-5.9	-2.1
Whole manufacturing	-12.3	-3.5	-4.9	-2.2
Mean abs error†				4.0
Root-mean-square error‡				4.3
Max abs error§				6.9

† The mean absolute error captures a general fit of the model's predictions and is computed as $meanAE = (1/\#S)\sum_{s\in S}\left|\Delta^{model}\left(\overline{I/K}_s\right) - \Delta^{data}\left(\overline{I/K}_s\right)\right|$, where S is the set of all sectors in the sample.

§‡ The max absolute error and the root-mean-square error are computed using the same differences between the model's prediction and the data we use for the mean absolute error.

itability shock or with a large accumulation of capital. The first two columns of the table precisely show that, on average, profitability decreased between the periods (-12%) at the same time that firms had a slight decrease in their capital stock (-3.5%). These dynamics imply a model prediction in which investment would fall between the two periods. It is, however, evident that the model is only able to capture qualitative, but not quantitative, dynamics of the investment rate. Note that the model is only able to account for about 45% of the observed fall in the investment rate. This suggests that a standard model of firm investment may be inadequate to explain investment dynamics during large crises.

Another indicator showing that inability is the relatively large values of the mean square error (MSE) measured. To understand this inadequacy, consider, for example, the *Food and Beverages* sector. There, we observe a substantial increase in the profitability and also a simultaneous collapse of the investment rate. Note, however, that the model actually predicts increases in the investment given the improvement of profitability conditions, coupled with the fact that capital adjustment costs are not very large. In general, the observed across-sector heterogeneity in profitability generates disparate predictions for the investment rate dynamics that are in strong contrast with the overall collapse in the investment rate that occurred in the *during crisis* period.

This lack of quantitative bite in the standard investment model, asks for the consideration of an alternative mechanism that can deliver a more or less uniform drop of the investment rate across sectors, while accounting for the observed heterogeneity in the firm profitability. Such a mechanism may be induced through a common (across-sector) financial crisis shock that prevents profitable firms from investing or even forces them to deleverage. This mechanism interacts with large previous accumulation of debts to generate a collapse of investment and seems particularly relevant during the Greek crisis. It is precisely these features that we formally analyze in an alternative model presented in the following section.

6 Analysis: An Empirical Dynamic Investment Model with Collateral Constraints

The inability of the model presented in the previous section to explain the firm-level dynamics of the investment rate suggests that other factors may have played an important role during the Greek crisis. Consistent with the large deleveraging observed both at the aggregate level and in the microdata, we introduce a variation of the previous model that can account for banking crises. This is done by adapting the model introduced by Khan and Thomas (2013) to include financial frictions and banking crises periods. Here, we allow firms to accumulate debt that can be used to finance investment up to a collateral constraint, as studied in detail by Kiyotaki and Moore (1997) and Jermann and Quadrini (2012). We allow for a financial shock to the minimum amount of collateral a firm has to pledge in order to borrow. A shock that reduces that minimum amount of collateral is used to capture the Greek economy's banking crisis that was contemporaneous with the collapse of investment. We differ from Khan and Thomas (2013) in allowing for both convex and non-convex capital adjustment costs and for endogenous exit by firms that find it unfeasible to pay non-negative dividends. Implicit in this last point is the fact that firms cannot use equity to sustain investment or debt repayment expenditures, thus implying that firms that overborrow may move closer to exit in this economy. Because we directly observe profitability conditions, which are then used to feed the model, we abstract from any general equilibrium considerations.

Formally, we model firms that distribute non-negative dividends, thus assuming away any equity injections from stockholders. In order to finance investment, firms can either use retained earnings net of past loan repayments or use new loans. That is, a firm i starting in period t with a profitability ω_{it}, capital K_{it}, and current debt B_{it} chooses a particular dividend payout of

$$D_{it} = \Pi\left(K_{it}, \omega_{it}\right) - C\left(I_{it} + (1-\delta)K_{it}, K_{it}, \omega_{it}\right) + qB_{it+1} - B_{it} \geq 0$$

where q is the price of debt, and the maximum amount of new debt is constrained by the maximum amount of collateralized capital:

$$B_{it+1} \leq \xi_t K_{it}$$

Here, the variable ξ_t is an aggregate banking shock with two potential outcomes – $\xi_t \equiv \{\xi^{low}, \xi^{high}\}$ (low and high) – and is governed by the following Markov chain:

$$\Pi^{\xi} = \begin{bmatrix} p^{high} & 1-p^{high} \\ 1-p^{low} & p^{low} \end{bmatrix}$$

Note that the relevant state space for a firm includes $s_{it} = \{K_{it}, B_{it}, \omega_{it}, \xi_t\}$. Also, given the nature of the capital adjustment cost, we define I_{it}^{d} as the level of investment that maximizes the proceeds of disposing capital as

$$I_{it}^{d} = \arg\max_{I} \left\{-C\left(I + (1-\delta)K_{it}, K_{it}, \omega_{it}\right)\right\}$$

We then assume that if a firm is unable to generate non-negative dividend payouts, it exits the market with a value given by

$$V^{x}\left(s_{it}\right) = -B_{it} \quad if \quad \Pi\left(K_{it}, \omega_{it}\right) - C\left(I_{it}^{d} + (1-\delta)K_{it}, K_{it}\right) + q\xi_t K_{it} - B_{it} < 0$$

thus implicitly defining a region of the state space characterized by firm exit

$$\Psi\left(s_{it}\right) \equiv \mathbf{1}\left\{\Pi\left(K_{it}, \omega_{it}\right) - C\left(I_{it}^{d} + (1-\delta)K_{it}, K_{it}\right) + q\xi_t K_{it} - B_{it} < 0\right\} \tag{10}$$

Exiting firms in our model are the ones that, due to an overaccumulation of debt, cannot sustain a positive dividend payment. Because we do not allow for equity inflows in this model, these firms are forced to exit the market, because they cannot generate further liquidity given that they are already borrowing at their limit. The role of Ψ in our model allows us to include firm observations with large amounts of debt that nevertheless face a tightening of credit conditions.

This implies that we can write the value of an incumbent firm with capital K_{it}, debt B_{it} (new debt has a price $q = \beta$), and profitability ω_{it} as

$$V\left(s_{it}\right)=\begin{cases} V^{0}\left(s_{it}\right) & if \quad \Psi\left(s_{it}\right)=1 \\ V^{x}\left(s_{it}\right) & if \quad \Psi\left(s_{it}\right)=0 \end{cases} \tag{11}$$

where V^0 represents the value of a non-exiting firm given by

$$V_0\left(s_{it}\right)=\max\left\{V^a\left(s_{it}\right),V^i\left(s_{it}\right)\right\}$$

and V^a stands for the value of adjusting capital:

$$V^a\left(s_{it}\right)=\max_{I_{it}\neq 0,B_{it+1},D_{it}}\left\{D_{it}+\beta E_{\omega_{it},\xi_t}\left[V\left(s_{it+1}\right)\right]\right\} \tag{12}$$

$$\begin{aligned} s.t.& \\ B_{it+1} &\leq \xi_t K_{it} \\ D_{it} &= \Pi\left(K_{it},\omega_{it}\right)-C\left(I_{it}+\left(1-\delta\right)K_{it},K_{it},\omega_{it}\right)+qB_{it+1}-B_{it} \\ D_{it} &\geq 0 \end{aligned}$$

while V^i stands for the value of investment inaction:

$$V^i\left(s_{it}\right)=\max_{B_{it+1},D_{it}}\left\{D_{it}+\beta E_{\omega_{it},\xi_t}\left[V\left(s_{it+1}\right)\right]\right\}$$

$$\begin{aligned} s.t.& \\ B_{it+1} &\leq \xi_t K_{it} \\ D_{it} &= \Pi\left(K_{it},\omega_{it}\right)+qB_{it+1}-B_{it} \\ D_{it} &\geq 0 \\ K_{it+1} &= (1-\delta)K_{it} \end{aligned}$$

As pointed by Khan and Thomas (2013), this problem allows for a reformulation that specifically focuses on constrained and unconstrained firms given financial needs for investment, thus simplifying the analysis and computation of the model. Constrained firms place a non-zero probability of entering a state in which the collateral constraint binds; otherwise, these firms are unconstrained. Appendix H.2 shows some further implications of the model.

6.1 Policy and Impulse Response Functions for Investment

To understand the new mechanisms introduced by a model of firm-level investment allowing for financial frictions, we study the policy and impulse response functions generated at the solution of the problem. As mentioned in the analysis of the model, the value of unconstrained firms in (20) is equivalent to the value of the standard investment model represented in Equation (1). For that reason, to study the main differences that accrue from augmenting that standard model to include financial frictions, we study the model outline above by calibrating it with the same profit and adjustment costs parameters that were estimated in Section 5.2.[28] As for the remaining parameters, we use the following calibration: $\{\xi_l = 0.2;\ \xi_h = 0.8;\ p_h = 0.977;\ p_l = 0.688;\ q = \beta\}$, which is explained in detail below.

Figure 7 compares three policy functions regarding investment:

1. Unconstrained firm's investment policy: this is implied by the value $W(s_t)$ equivalent to the standard investment model, which is outlined in Section 5.1 and represented by $I_{it}^{unconst} = f(K_{it}, \omega_{it})$.

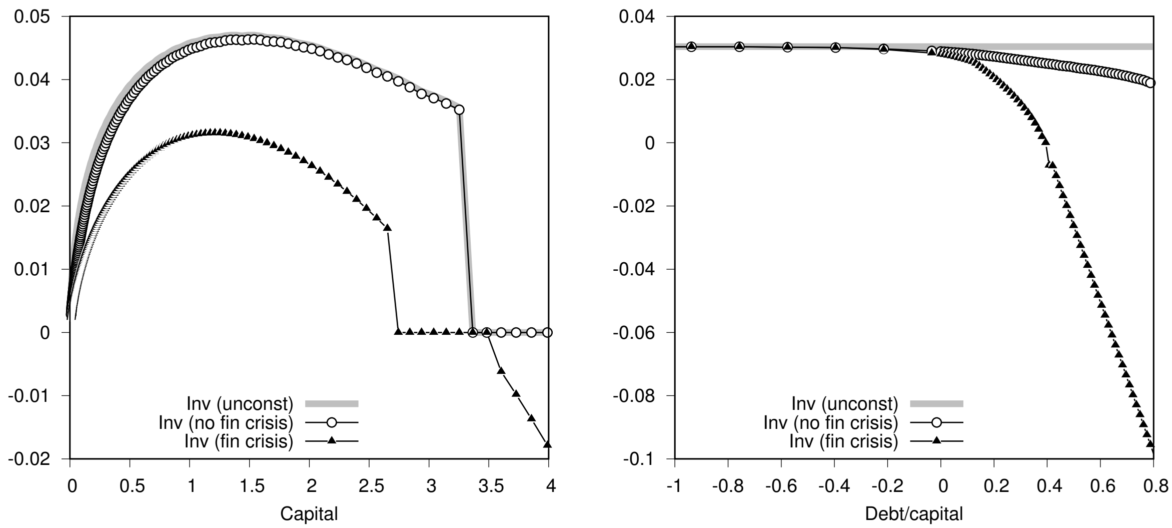
2. Collateral constrained firm's investment policy under no banking crisis: this is implied by the value $V(s_{it})$ whenever the credit constraint shock is loose $\xi_t = \xi^{high}$ and is represented by $I_{it}^{constr} = g\left(K_{it}, B_{it}, \omega_{it}, \xi_t = \xi^{high}\right)$.

3. Collateral constrained firm's investment policy under a banking crisis: this is implied by the value $V(s_{it})$ whenever the credit constraint shock is tight, $\xi_t = \xi^{low}$ and is represented by $I_{it}^{constr} = g\left(K_{it}, B_{it}, \omega_{it}, \xi_t = \xi^{low}\right)$.

From the figure, one infers the role of debt in the collateral constraint model as a potential inhibitor of investment. The left panel of the figure shows that the typical shape of the

[28] We use the calibration that resulted from the estimation of the *whole manufacturing* sector for the *pre-crisis* (2002–2007) period.

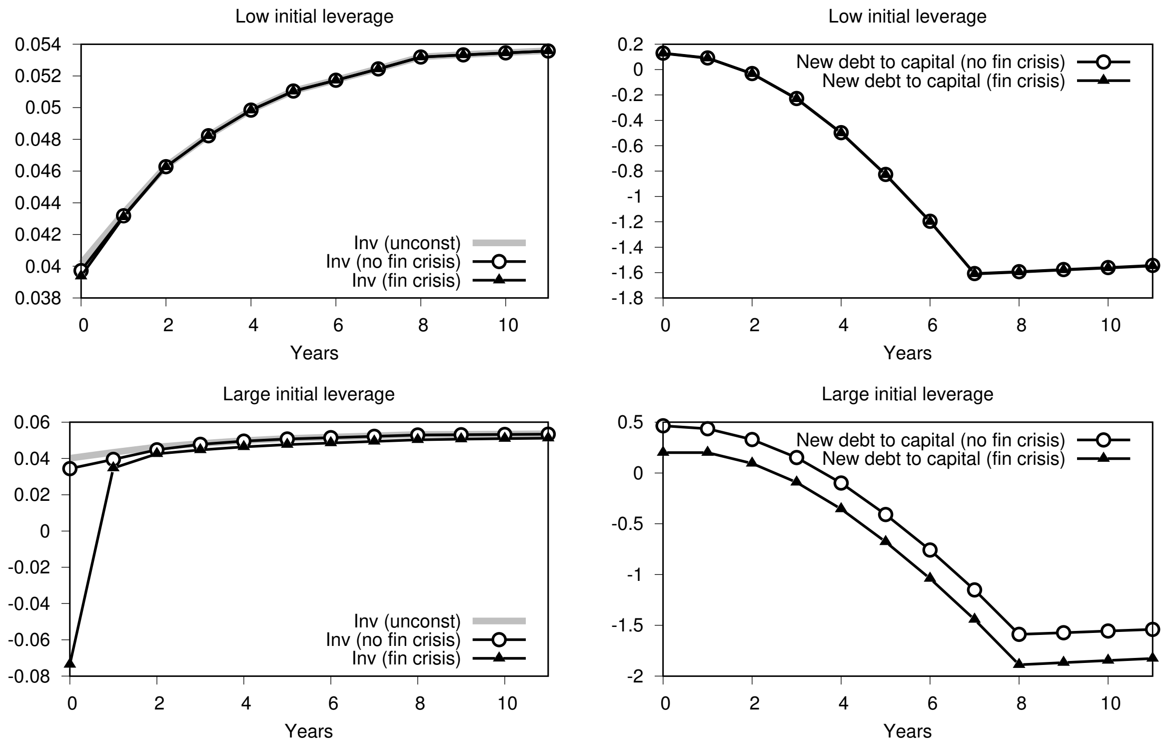
Figure 7: Investment policy functions for the collateral constraint model



Notes: The panel on the left fixes the leverage ratio to $D/K = 0.24$ and $\omega = -2.33$. The panel on the right uses $K = 0.29$ and $\omega = -2.33$. Negative values for D/K imply that the firm has financial savings. Calibration is based on the *whole manufacturing* sector and will be explained below.

investment policy function, which is characterized by inaction, is similar to that derived from the standard investment model (see Figure 6). Note, however, that under a financial crisis, that is, when the collateral constraint tightens, the level of investment reduces relative to the case in which the collateral constraint is loose. This reduces firms' access to the financial resources required to invest. In some cases, they even may be forced to deleverage, where additional resources to repay debts may come at the expense of investment. The right panel of the figure shows that when the initial burden of debt is larger, this adverse effect on investment is larger. Relative to unconstrained firms, when the investment level of constrained firms becomes lower, the initial debt is larger, and this effect is even worse if the economy is under a financial shock that forces firms to deleverage because of a tighter collateral constraint. Looking instead at impulse response functions implied by the model generates similar conclusions about the role of deleveraging in investment. Figure 8 plots these impulse response functions by generating a positive profitability shock on period 1 that then reverts to its mean. We look at implied investment for both unconstrained and constrained firms given different levels of initial debt (low and large, as described in the figure note). Also, to understand the role of tightening the collateral constraint, we plot the investment associated with $\xi = \left\{\xi^{low}, \xi^{high}\right\}$. The figure shows that the impact of debt

Figure 8: Investment impulse response functions from the collateral constraint model (initial negative profitability shock)



Notes: These impulse response functions result from inducing a negative shock in profitability, $\omega_{t=1} = -2.33$ (with unconditional mean $\omega = -.8$), for a firm with $K_{t=1} = .61$. Low and large initial leverage corresponds to $D/K = .10$ and $D/K = .45$, respectively. Calibration is based on the *whole manufacturing* sector and will be explained below.

on investment becomes more important when firms are closer to the collateral constraint. Focusing on the case in which the initial debt level is low, one observes that, because firms are comfortably far from their collateral constraint, an investment level identical to that of an unconstrained firm can be achieved, whether or not the environment associated with credit disbursement is tight.

This relatively benign role of credit conditions starts changing with larger levels of initial debt. The middle two panels of the figure show that a larger level of initial debt may force firms to deleverage when faced with tighter credit conditions. That is, while firms under no financial crisis can achieve levels of investment similar to those of unconstrained firms, under a financial crisis that tightens credit conditions, firms have to deleverage. Deleveraging implies reducing the amount of new debt relative to capital, to the maximum admissible ratio (in this case $\xi^{low} = 0.2$), where part of the debt service effort comes from lower investment. For an even larger initial debt, captured in the bottom two panels of the figure, the effect on investment is even more intense. Under that case, we even observe negative levels of investment for the environment with tight collateral constraints.

This analysis illustrates why a model with collateral constraints can improve the empirical observations associated with the collapse of the firm-level investment rate during the Greek depression. One one hand, an overaccumulation of corporate debt during a boom period may bring firms closer to their collateral constraint and thus make debt servicing more burdensome at the expense of investment. On the other hand, this investment effect is reinforced when high levels of debt are associated with a financial crisis that forces firms to deleverage. The model can also explain why certain sectors reduce their levels of investment despite observing good profitability realizations. These are precisely the firms that cannot expand on their current profitability conditions, because they are forced to deleverage away from their previous debts.

In the next section, we use a calibrated version of this model to investigate whether any of these channels relevantly explain the dynamics of the investment rate during the crisis period.

6.2 The Role of Credit in the Investment Collapse

To understand if the inclusion of credit conditions can improve the quantitative results associated with the collapse of the investment rate, we run numerical simulations of the model outlined above under a particular calibration. The two main sets of parameters that determine the model are those governing the capital adjustment costs and those associated with credit conditions. Regarding the former, we note that under a low-debt regime, the policy functions for investment of the collateral constrained model are very similar to those for a standard investment model, where there's no role for credit. Therefore, because we observe low leverage ratios for firms in the *pre-crisis* period,[29] we use the estimated parameters for the capital adjustment costs contained in Table 6 during the *pre-crisis* period for the calibration of the collateral constraint model.

For the credit conditions in our model, we have two main states of the world: tight

[29]The data observations for the mean leverage across sectors can be found in Tables D3 and D4.

Table 8: Calibration of the collateral constraint model for Greece

Parameters	Values	Comments
Profit function	From Table 4	Estimated from the entire period data
Profitability process	From Table 4	Estimated from the entire period data
Capital adjustment costs	From Table 6	Estimated from the *pre-crisis* period data
Credit conditions	$\xi^{high} = 0.8$	99th percentile leverage data in the *pre-crisis* period
	$\xi^{low} = 0.20$	Match median leverage drop in the data
	$p^{high} = 0.977$	Khan and Thomas 2013
	$p^{low} = 0.688$	Khan and Thomas 2013

credit conditions, ξ^{low}, and loose credit conditions, ξ^{high}. For the loose credit conditions, we impose that the maximum amount of debt a firm can borrow relative to capital cannot exceed 80%, which corresponds to the 99^{th} percentile of debt leverage observed in the sample for the *pre-crisis* period. For the tight credit conditions, we calibrate our model such that the fall in leverage ratios matches the observed median fall across all sectors. This yields $\xi^{low} = 0.2$, a relative change of ξ^{high}/ξ^{low}, similar to that used in Khan and Thomas (2013). The probabilities associated with each of these parameters are also taken from the same authors: $p^{high} = 0.977$ and $p^{low} = 0.688$, which were used by Khan and Thomas (2013) to study credit conditions during the 2007–2009 recession in the United States. This choice of parameters should be quite conservative, because the financial crisis was arguably larger in Greece. Table 8 summarizes the entire calibration.

Given this calibration, we then perform a numerical exercise similar to that in Section 5.3. Here, the objective is to evaluate whether a model with credit frictions can generate a collapse of the investment rate across sectors, despite the observed variability in profitability conditions. For this new model, the investment policy functions assume the following form:

$$I_{it} = g^{Inv}\left(K_{it}, B_{it}, \omega_{it}, \xi_t\right)$$

This implies that to simulate the investment reaction in the model, we need to impose initial conditions on all the state variables, namely, the current capital level, current debt, profitability, and the current collateral constraint current shock realization. The performance of the model is then assessed by computing the following differences across sectors:

$$\Delta\left(\overline{I/K}\right) = E\left[\frac{g^{Inv}\left(K_{it_1}, B_{it}, \omega_{it_1}, \xi_{t_1}\right)}{K_{it_1}}\right] - E\left[\frac{g^{Inv}\left(K_{it_0}, B_{it_0}, \omega_{it_0}, \xi_{t_0}\right)}{K_{it_0}}\right]$$

where, as before, t_0 stands for the observations associated with the *pre-crisis* period, $t_0 = \{2002, ..., 2007\}$ and t_1 for observations associated with the *during crisis* period, $t_1 = \{2010, ..., 2014\}$.

For initial conditions, we use the observed levels of capital and the estimated levels of profitability for both periods. As for debt initial conditions, we attempt to capture the main correlations between observed firm-level leverage with capital and profitability. To do so, we run auxiliary regressions, projecting for each sector the observed leverage ratio (measured as debt relative to capital) onto capital and profitability. We then use the predicted debt leverage given capital and profitability to assign the initial debt level per firm observation. This approach captures the leverage distribution observed in the data for each sector.

Finally, to evaluate the role of credit conditions in investment rate decisions, we assume that the *pre-crisis* period is associated with loose collateral constraints, $\xi_{t_0} = \xi^{high}$. For the *during crisis* realization of this shock, we compute the model predictions under a contraction of credit $\xi_{t_1} = \xi^{low}$ (associated with a banking crisis) and under no variation in this shock $\xi_{t_1} = \xi^{high}$ (associated with no banking crisis). Table 9 summarizes the results of these numerical exercises.

The results of this exercise point to the inclusion of credit conditions explaining, at least, part of the collapse in the investment rate. Focusing on the *whole manufacturing*, while the standard investment model can only explain an average fall of 2.2 percentage points of the investment rate across periods, the model with collateral constraints, allowing for a tightening of the credit conditions, can account for a fall of 4.7 percentage points, about 96% of the collapse in the investment rate. Note that tightening credit conditions reinforce the negative impact on investment, because many firms are then forced to immediately repay a larger amount of their past debts. This is evident in the table when we compare the "no banking crisis" with the "banking crisis" columns, where the fall from 4.7 percentage points to 2.8 percentage points in the investment rate can be accounted for by the negative shock on ξ.

Finally, allowing for collateral constraints and banking crises improves the fit of the model measured by the absolute and square errors. Relative to the "no leverage", the "no banking crisis" column shows no improvement of the model fit. However, allowing for the "banking crisis" delivers not only better predictions for the *whole manufacturing* but also better predictions for every other sector. In that sense, the inclusion of the banking shock can better capture the overall collapse in the investment rate observed across sector. This

Table 9: Model predictions for the variation in the investment rate between the *pre-crisis* (2002–2007) and *during crisis* (2010–2014) periods, using the collateral constraint model for a no banking crisis outcome ($\xi_{t_1} = \xi^{high}$) and a banking crisis outcome ($\xi_{t_1} = \xi^{low}$)

Sector	Data Inv rate (Δpp)	Simul.: Inv rate (Δpp) No lev[†]	No bank crisis	Bank crisis
Food and beverages	-5.2	1.8	1.8	-0.6
Apparel and leather	-3.3	-0.4	-0.8	-2.9
Paper	-2.3	3.7	3.7	2.6
Chemicals	-5.4	-2.1	-1.6	-6.9
Plastic and rubber	-5.7	-4.4	-4.3	-9.1
Non-metal minerals	-7.1	-2.6	-3.1	-11.9
Metal products	-7.6	-3.1	-2.9	-6.5
MachEq vehicles	-5.9	-2.1	-1.6	-3.1
Whole manufacturing	-4.9	-2.2	-1.9	-4.7
Mean abs error[‡]		4.0	4.1	2.6
Root-mean-square error[§]		4.3	4.4	3.2
Max abs error[¶]		6.9	7.0	5.0

[†] The no leverage column corresponds to the results presented in Table 7 for the stylized investment model.

[‡] The mean absolute error captures a general fit of the model predictions and is computed as $meanAE = (1/\#S)\sum_{s\in S}\left|\Delta^{model}\left(\overline{I/K}_s\right) - \Delta^{data}\left(\overline{I/K}_s\right)\right|$, where S is the set of all sectors in the sample.

[§¶] The max absolute error and the root-mean-square error are computed using the same differences between the model's prediction and the data we use for the mean absolute error.

is even true for those sectors in which profitability conditions improved or fell moderately.

We interpret the results presented in this exercise as informative about the importance of including an analysis of credit conditions during large crises. The example of Greece is particularly notable in the sense that we simultaneously observe a banking crisis and strongly negative investment dynamics. Looking only at productivity and demand conditions faced by firms generates an incomplete description of investment dynamics because of the reinforcing mechanism that a banking crisis generates through an increase in the effective shadow value of capital. In the next section, we will explore this link more in detail.

6.3 The Shadow Value of Capital during a Financial Crisis

To explore how a banking crisis – modeled as a negative shock on ξ – affects investment decisions, we study the marginal benefits and costs of investing implied by our model.

Similar to the model studied in Whited (1992), the value of adjustment summarized in Equation (12) implies two main frictions associated with investment decisions: one related with non-equity funding and the other with borrowing constraints. Allowing λ^B to be the Lagrangian multiplier on the latter constraint and λ^E with the former, the first-order conditions imply

$$
\begin{aligned}
C_{K'}\left(K_{it+1}, K_{it}, \omega_{it}\right)\left(1+\lambda_{it}^{E}\right) =& \beta E_t V_K\left(s_{it+1}\right) \\
-q\left(1+\lambda_{it}^{E}\right)+\lambda_{it}^{B} =& \beta E_t V_B\left(s_{it+1}\right)
\end{aligned}
$$

If we combine these two equations to remove λ_{it}^E, the equilibrium condition can be summarized in the following equation:

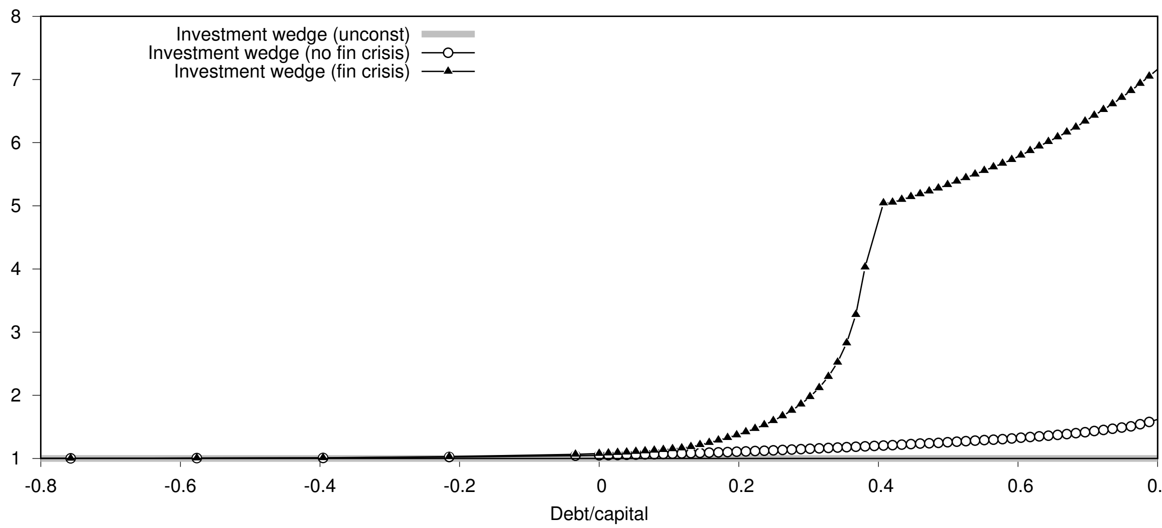
$$
C_{K'}\left(K_{it+1}, K_{it}, \omega_{it}\right) = \beta \frac{E_t V_K\left(s_{it+1}\right)}{\lambda_{it}^{B}\beta^{-1} - E_t V_B\left(s_{it+1}\right)} \tag{13}
$$

where $q=\beta$ and we define the *investment wedge* as

$$
\Upsilon_{it} = \lambda_{it}^{B}\beta^{-1} - E_t V_B\left(s_{it+1}\right) \tag{14}
$$

Note that Equation (13) describes the optimal investment decision associated with constrained firms in our model conditional on investment. This gives us a condition that equates the marginal cost of investment (at the left-hand side) with the marginal benefit (at the right-hand side). Note that the term $\left[\lambda_{it}^{B}\beta^{-1} - E_t V_B\left(s_{it+1}\right)\right]$ generates a wedge in the Euler equation whenever it is larger than 1. But this is, in general, the case if firms are constrained because $\lambda_{it}^E > 0$. That is, firms can only be equity constrained if they are debt constrained, or, otherwise, they would have raised debt. In that case, $\lambda_{it}^B = 0$ and $V_B\left(s_{it+1}\right) = 1$, and this implies that $\lambda_{it}^E = 0$. Being constrained in this environment implies that the effective cost of capital increases, and, therefore, investment becomes smaller. The more severe the credit conditions are, for example, through $\xi = \xi^{low}$, the more important is this wedge. Figure 9 helps us understand the effect of imposing a tight credit environment in our results by extracting the *investment wedge*, $\left[\lambda_{it}^{B}\beta^{-1} - E_t V_B\left(s_{it+1}\right)\right]$, implied in Equation (13) from the model solution. The figure shows the evident impact of adding credit constraints in the model. The gray line in the figure shows the excess of the shadow cost of capital when firms are unconstrained, and, as expected, we observe unresponsiveness with respect the debt level. For constrained firms, however, we observe an increase in this shadow cost for large leverage

Figure 9: *Investment wedge* under different credit condition regimes (no financial crisis ξ^{high} and financial crisis ξ^{low})



Note. The model solved here refers to the *whole manufacturing* sector and uses the same calibration used in Figure 7, with $\omega_{it} = -2.33$ and $K_{it} = 0.23$.

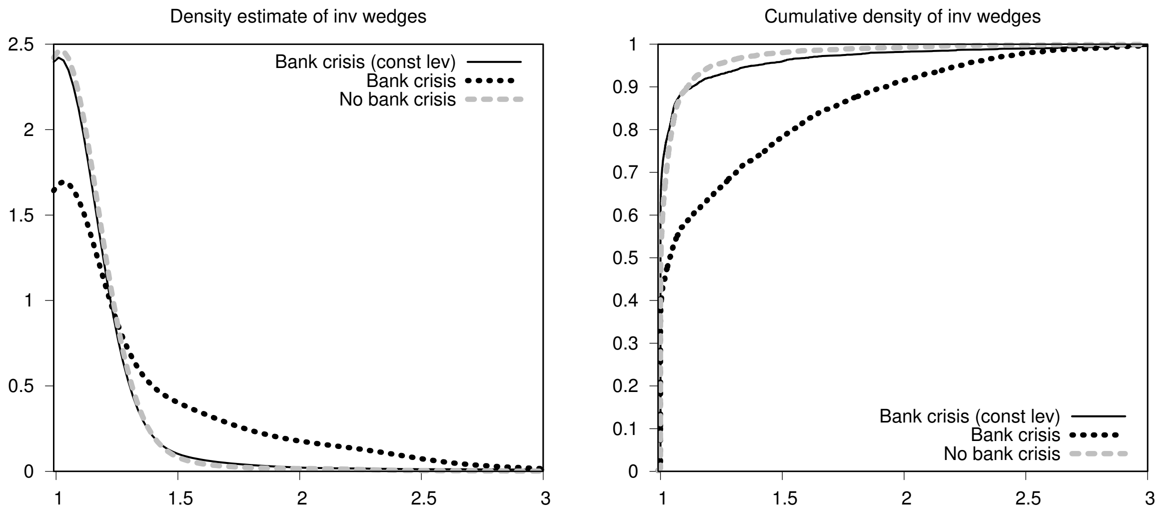
levels, an effect that becomes much more important when credit conditions are tight.[30]

We conclude this section by showing changes in the distribution of these investment wedges for the *post-crisis* period. Figure 10 plots distribution estimates for the investment wedge $\{\Upsilon_{it}\}$ for two alternative regimes: no financial crisis regime, where $\xi = \xi^{high}$, and a financial crisis, where $\xi = \xi^{low}$. It is clear from the figure that the financial crisis affects firms by shifting the distribution of $\{\Upsilon_{it}\}$ to the right, where the average increases from 1.05 to 1.28. This increase in the investment wedges implies a larger collapse of the investment rate given that the effective discount coefficient for the average firm becomes $\tilde{\beta} = \beta/\overline{\Upsilon}_{it} = 0.74$ instead of $\beta = 0.95$. The magnitude in the drop of this effective discount coefficient also explains why firms do not invest as a reaction to other fundamentals like capital or profitability: because "impatience" suddenly increases. The figure also shows a black solid line, where we run a counterfactual experiment for a banking crisis, but where firm leverage is lower and equal to the distribution at the beginning (2003) of the *pre-crisis* period.[31] One can see that

[30]The presence of the kink in the shadow cost depicted in the figure emerges from the fact that the adjustment cost of capital changes when investment shifts from positive to negative as described in Equation (4).

[31]For the whole manufacturing sector we use the 2003 distribution while for each sector we use the 2002-2007 distribution because for some sectors yearly samples are small.

Figure 10: Distribution of investment wedges for the model simulations of the Greek crisis (no financial crisis ξ^{high} and financial crisis ξ^{low})



Note. The simulations shown here refer to the *whole manufacturing* sector and use the same calibration used in Figure 7. Density estimates use the Epanechnikov kernel density estimation. The *bank crisis (const lev)* lines refer to a counterfactual in which there is a banking crisis, but the leverage distribution remains the same as that in the *pre-crisis* period.

the distribution of the investment wedges changes very little relative to the case without a banking crisis (the average becomes 1.07). This essentially shows that, for the model to generate an empirically relevant collapse of the investment rate, we need both a banking crisis and a run-up in leverage during the *pre-crisis* period.

7 Conclusions

Our analysis quantifies the impact of the near-collapse of the Greek banking system and extreme tightening of firm financing constraints in generating the drop in the manufacturing investment rate. Impaired firm balance sheets and the banking crisis account for about half of that drop. The investment slump had a significant short-term impact on the Greek economy. It is also likely to have a long-term impact through its effect on productivity growth. Our results suggest that more effective action to safeguard the banking system during the Greek crisis could have significantly contributed to economic recovery through investment.

Although we focus on a particular dramatic episode, the question we examine is important for all financial crises. And the quantitative answer we give provides an indicative benchmark.

Further work should examine and compare the impact of credit constraints in other episodes of financial crisis.

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Internet Appendix

A Selection Correction: The Sample-Presence Probit

To control for sample selection due to the 10-employee sampling cutoff and also for endogenous firm exit we estimate a discrete choice probit model of firm presence in the sample. Consider our identification assumption which stems from the exogeneity of the profitability process in equation (6)

$$E(\omega_{it}|\omega_{it-1}) = \bar{\omega} + \rho\omega_{it-1} + E(\xi_{it}|\text{Information at } t = K_t, \Pi_{t-1}) = \bar{\omega} + \rho\omega_{it-1} \tag{15}$$

Condition (15) does not necessarily hold in our sample because of endogenous exit, the survey design, and also because our dependent variable is log profits which is not defined for non-positive values of variable profit. Let χ_t denote an indicator function taking the value one if a firm is in our sample. Then the profitability process in our sample is

$$E(\omega_{it}|\omega_{it-1}, \chi_t = 1) = \bar{\omega} + \rho\omega_{it-1} + E(\xi_{it}|K_t, \Pi_{t-1}, \chi_t = 1) \neq \bar{\omega} + \rho\omega_{it-1} \tag{16}$$

This is likely because a small firm, close to the 10-employee threshold, is more likely to exit the sample than a large firm. In addition, a very productive firm is more likely to stay in the sample than a firm that is close to the profitability cutoff for exiting. To correct for sample selection we proceed in a similar manner as Olley and Pakes (1996) and estimate the probability of staying in the sample using a probit model on a set of lagged variables. Our specification takes the following form:

$$\begin{aligned} \text{Prob}(\chi_t = 1) = \Phi(&\alpha_{sector} + \alpha_t + \alpha_l L_{t-1} + \alpha_k \log K_{t-1} + \alpha_s \log \text{sales}_{t-1} + \\ &+\alpha_{lk} L_{t-1} \log K_{t-1} + \alpha_{ks} \log K_{t-1} \log \text{sales}_{t-1} + \alpha_{ls} \log L_{t-1} \log \text{sales}_{t-1} + \\ &+\alpha_{2002} \mathbb{1}\{\text{sample entry year} = 2002\} + \\ &\alpha_{age}(\text{year} - \text{sample entry year}|\text{sample entry year} > 2002) \end{aligned} \tag{17}$$

The last two terms, a 2002 cohort dummy and an age variable, capture the effect of age on survival. Because we measure age as years, since the first appearance of the firm in the sample, we are not able to discern different ages for firms entering the sample the year our sample starts: 2002. Since we expect a nonlinearity in the age variable for the 2002 cohort of firms we use a dummy variable to capture the age effect for the 2002 cohort and use the age variable for firms entering after 2002. Table A1 results from the estimation of the probit model. Note that the 2002 cohort dummy and the age variable have positive coefficients implying that older firms tend to have higher survival probabilities. The sample selection probit is for the sole purpose of controlling for selection in the profit function estimation and has no structural interpretation. The sample presence predicted probabilities $\hat{P}_{it}$ are used in the moment conditions of the profit function estimation either for a single profit function for the whole manufacturing sector or for sector-specific profit functions.

Table A1: Selection correction: a sample presence probit

Lagged independent variables X_{t-1}	Probit model of Prob$(\chi_t = 1 \vert X_{t-1})$
Log number of employees	1.52
	(0.16)
Log sales	-0.91
	(0.10)
Log K	0.12
	(0.056)
Log sales $\times$ Log K	0.18
	(0.015)
Log sales $\times$ Log number of employees	0.58
	(0.037)
Log number of employees $\times$ Log K	-0.096
	(0.018)
(Log sales)^2	-0.34
	(0.017)
(Log number of employees)^2	-0.33
	(0.027)
(Log K)^2	-0.049
	(0.0047)
Years in the sample for firms entering after 2002	0.028
	(0.0074)
2002 cohort dummy	0.050
	(0.030)
N	27187
pseudo R^2	0.12
sector FE	yes
year FE	yes

Heteroskedasticity robust standard errors in parentheses.

B Initial Conditions for the simulation of conditional moments

Since the focus of this paper is to explore what determines observed firm dynamics during a large financial crisis, it seems appropriate to estimate our model conditioning on the distribution of state variables observed in the data. Therefore, the purpose of our modeling is to capture the underlying forces governing firm transitional dynamics during a large shock. The development of a model that also rationalizes the cross-sectional distribution of the state variables such as capital, profitability, and leverage is beyond the scope of this paper.

To simulate conditional investment moments using our model we need to draw from the state variables from the joint distribution implied by our sample. To do so we estimate the joint distribution of our state variables profitability (ω) and capital (K) using a mixture of normal distributions. In particular, we estimate two joint distributions: one from the 2002-07 sample before the crisis $H^{t_0}(\omega, \log K)$ and one using the 2010-14 sample during the crisis $H^{t_1}(\omega, \log K)$. To estimate each distribution we proceed in three steps:

1. Estimate the marginal distribution of $\log K$ by a three-component mixture of normal distributions: $\pi_1 N(\mu_1, \sigma_1) + \pi_2 N(\mu_2, \sigma_2) + (1 - \pi_1 - \pi_2) N(\mu_3, \sigma_3),\ \pi_i \in [0, 1]$.

2. Estimate the conditional mean of ω given $\log K$ by a regression: $\omega = \beta_0 + \beta_1 \log K$.

3. Approximate the residuals of the regression $\varepsilon_{it} = \omega_{it} = \beta_0 + \beta_1 \log K_{it}$ by a two-component mixture of normal distributions: $\pi_1^{\varepsilon} N(\mu_1^{\varepsilon}, \sigma_1^{\varepsilon}) + (1 - \pi_1^{\varepsilon}) N(\mu_2^{\varepsilon}, \sigma_3^{\varepsilon}),\ \pi_i^{\varepsilon} \in [0, 1]$.

To generate model simulated moments for a sample of size N we proceed in five steps:

1. Draw a sample of capital stocks $\{\log K_1, \dots, \log K_N\}$ by drawing from the distribution represented by a mixture of normals $\pi_1 N(\mu_1, \sigma_1) + \pi_2 N(\mu_2, \sigma_2) + (1 - \pi_1 - \pi_2) N(\mu_3, \sigma_3)$.

2. For each capital stock calculate $\bar{\omega}_i = \beta_0 + \beta_1 \log K_i$.

3. Draw a sample of residuals $\{\varepsilon_1, \dots, \varepsilon_N\}$ by drawing from the distribution represented by a mixture of normals $\pi_1^{\varepsilon} N(\mu_1^{\varepsilon}, \sigma_1^{\varepsilon}) + (1 - \pi_1^{\varepsilon}) N(\mu_2^{\varepsilon}, \sigma_3^{\varepsilon}),\ \pi_i^{\varepsilon}$.

4. Create the sample of profitabilities $\{\omega_1, \dots, \omega_N\}$ by adding the residual draws to the mean profitability $\omega_i = \bar{\omega}_i + \varepsilon_i$.

5. For each tuple $(\omega_i, \exp(\log K_i))$ use the dynamic model to generate $\{I_1, \ldots, I_N\}$ and then calculate the moments of interest from the this sample.

Table B1 presents the estimated parameters.

Table B1: The joint distribution of capital $\log K$ and profitability ω in the dataset: estimation by mixtures of normal distributions

Sample	Parameters								
	Marginal distribution of capital $\log K$								
	π_1	μ_1	σ_1	π_2	μ_2	σ_2	π_3^*	μ_3	σ_3
Pre-crisis	0.905	0.110	1.495	0.036	-3.255	1.137	0.059	3.369	1.099
During crisis	0.923	0.448	1.705	0.056	0.100	0.205	0.021	0.942	0.148
	Conditional distribution of profitability ω								
	β_0	β_1	π_1^ϵ	μ_1^ϵ	σ_1^ϵ	$\pi_2^{\epsilon **}$	μ_2^ϵ	σ_2^ϵ	
Pre-crisis	-0.643	0.103	0.492	0.067	0.700	0.508	-0.065	1.244	
During crisis	-0.839	0.220	0.660	0.161	0.887	0.340	-0.312	1.258	

$^*\pi_3 = (1 - \pi_1 - \pi_2)$
$^{**}\pi_2^\epsilon = (1 - \pi_1^\epsilon)$

C Additional stylized facts on the investment collapse

Figure C1: Investment rate distribution before and during the crisis

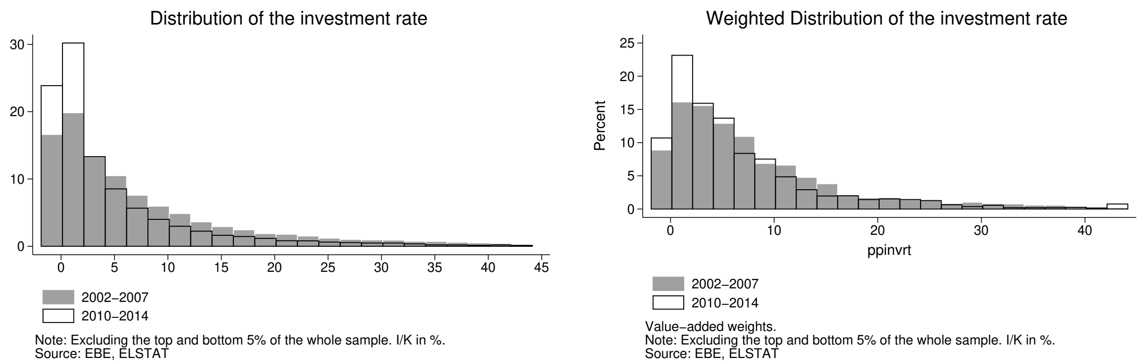


Figure C2: Investment rate distribution before and during the crisis, quartile evolution

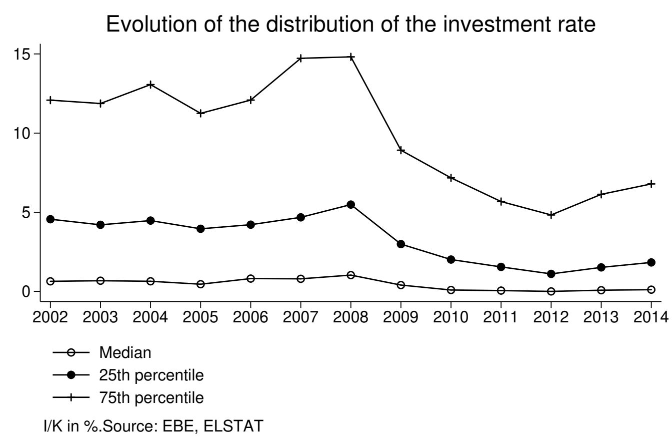


Table C1: Value-added weighted investment models establishing that the investment collapse is important for the aggregate quantities and it is not explained by fundamentals

	Model and Dependent variable		
Model	$LogitProb(y=1\|x)$	$LogitProb(y=1\|x)$	$OrderedLogit(y=j\|x)$
Dependent Var y	$\mathbb{1}\{\|I/K\| \leq .01\}$	$\mathbb{1}\{I/K > .2\}$	Discretized I/K†
2010-2014 Dummy	1.67	0.74	0.69
$\ln K$	0.88	0.82	0.99
$\ln GPM$	0.41	4.39	3.57
$(\ln K)^2$	1.03	0.98	0.99
$(\ln GPM)^2$	1.28	0.23	0.43
$\ln K \times \ln GPM$	0.82	1.16	1.03
sector FE	yes	yes	yes

† The investment rate is discretized according to the following mapping $I/K \mapsto \mathbb{N}$

$$j(I/K) = \begin{cases} 0, & \text{If } I/K \in (-\infty, -.01) \\ 1, & \text{If } |I/K| \in [-.01, .01] \\ 2, & \text{If } I/K \in (.01, .2] \\ 3, & \text{If } I/K \in (.2, \infty) \end{cases}$$

In the output above the results are displayed as proportional odds ratios. For example a dummy coefficient β is transformed to $\exp(\beta)$. From the properties of the logit model the exponentiated coefficient has the interpretation of a relative odds ratio. By odds I refer to the odds for jumping to the immediately higher outcome: $\exp(\beta) = \frac{\text{Prob}(Y=y+1 \mid X=x+1)}{\text{Prob}(Y=y \mid X=x+1)} / \frac{\text{Prob}(Y=y+1 \mid X=x)}{\text{Prob}(Y=y \mid X=x)}$. This also implies that a reported number below 1 reflects a negative coefficient.
Heteroskedasticity robust standard errors in parenthesis.

D Data

D.1 Construction of the capital stock

For the construction of the capital stock series we combine information from ELSTAT's Annual Survey of Manufactures (ASM) on gross investment flows. Investment is broken down to five asset classes: Land, Structures, Machinery, Transportation Equipment, Equipment, and Intangibles. $\tilde{K}_t^r$ represents the value of capital of class r at time t in current prices and $\tilde{I}_t^r$ is the gross investment of class r at time t in current prices. Investment flows are deflated by industry level deflators from the Eurostat to create variables in constant prices I_t^r. The capital stock series of asset class r is created with the perpetual inventory method assuming that investment takes one year to become operational, i.e. $K_t^r = (1-\delta_r)K_{t-1}^r + I_{t-1}^r$. Depreciation rates are industry specific and come from the EU KLEMS database which is based on the BEA depreciation rates.

In order to create the capital stock we need the capital stock for the period a firm appears in the sample which we imputed using the accounting depreciation flow variable and an accounting depreciation rate δ_{acct} calculated from the dataset in Fakos (2015). Suppose the first observation in the data is at time t_0. Last year's capital is $K_{t_0-1} = (\delta_{t_0}^{flow}/\delta_{acct})$. investment at $t_0 - 1$ is unobserved. The capital stock at t_0 is is $K_{t_0} = (\delta_{t_0}^{flow}/\delta_{acct})(1-\bar{\delta})$ where $\bar{\delta}$ is an industry specific weighted average of depreciation rates calculated from the dataset in Fakos (2015).

Let t_0 be the year when the series begins in the ASM database, then

$$K_t^{rI} = (1-\delta_{rI})^{t-t_0} A_{t_0}^{rI}, \ \forall t_0 \leq t, \ \forall rI$$

$$I_t^r = (1-\delta_r)I_{t-1}^r + I_{t-1}^r, \ \forall t \geq t_0 + 1 \ \forall r$$

$$K_t = \sum_r I_t^r + (1-\bar{\delta})^{t-t_0}(\delta_{t_0}^{flow}/\delta_{acct})(1-\bar{\delta}), \ \forall t \geq t_0 + 1$$

D.2 Data Cleaning

We prepare the data for estimation by removing missing or inconsistent observations and then trimming certain distributions that are relevant for our model. In all the analysis the petroleum refining sector and the tobacco manufacturing are excluded from the analysis.

D.2.1 Cleaning

1. We drop firm-year observations that have missing information on: materials expenditure, total labor cost, gross output (manufacturing sales), capital stock, gross investment.

2. We drop firm-year observations that have a non-positive value for: materials expenditure, total labor cost, gross output (manufacturing sales), capital stock, value added (sales - materials expenditure).

D.2.2 Trimming

1. We calculate the 0.5 and 99.5 percentiles of the distribution of the following ratios:

   - capital over labor cost K/wL
   - labor cost over gross output (manufacturing sales) wL/S
   - labor cost over value added (sales - materials expenditure) $wL/(S-M)$
   - materials expenditure over gross output M/S.
   - investment rate I/K
   - profits over capital Π/K.

2. We drop firm-year observations that are below the 0.5 percentile or above the 99.5 percentile of the distribution of ratios.

3. After estimating the profit function and the profitability process, we calculate the profitability innovations $\hat{\nu}_{it} = \hat{\omega}_{it} - \hat{\alpha}_0 - \hat{\rho}\hat{\omega}_{t-1}$.

4. We calculate the 1 and 99 percentiles of the $\hat{\nu}$ distribution.

5. We drop firm-year observations that are bellow the 1 percentile or above the 99 percentile of the innovation ν distribution for the dynamic estimation.

D.3 Summary Statistics

Table D1: Dataset employment coverage of the whole manufacturing

Year	$100 \times \frac{\text{Total Sample Employment}}{\text{Ag. Manuf Empl.}}$ Sample	Weighted Sample*
2002	48.04	48.04
2003	45.66	45.66
2004	46.37	46.37
2005	43.47	43.47
2006	38.46	45.09
2007	41.36	45.68
2008	35.22	44.02
2009	34.95	42.73
2010	42.64	48.49
2011	41.18	47.48
2012	43.59	49.72
2013	45.28	49.98
2014	47.52	50.17
Total	43.47	46.37

Source: EBE ELSTAT and Eurostat for manufacturing aggregate data.
* Until 2005 the survey was a census of firms with at least 10 employees, but, from 2006 onward, it is a census-type survey of plants above the 10-employee threshold accompanied by sampling weights. Sampling weights are the inverse of the probability of being sampled in the data.

Table D2: Summary Statistics of variables related to production

	p5	p10	p25	Med.	Mean	p75	p90	p95	IQR	SD
	2002-2007									
K	0.05	0.10	0.31	1.01	5.52	3.22	10.25	21.50	2.91	20.50
Sales	0.45	0.61	1.12	2.51	11.20	6.51	18.83	39.14	5.39	60.53
L	10.00	11.00	15.67	27.50	70.37	55.67	143.67	254.00	40.00	166.18
Δ log sales	-.39	-.26	-.11	-.0062	-.0034	.11	.24	.36	.21	.26
S/K	0.66	0.91	1.48	2.66	6.10	5.39	11.49	19.33	3.91	15.00
	2007									
K	0.06	0.12	0.38	1.19	5.78	3.41	11.56	22.59	3.04	20.87
Sales	0.49	0.66	1.21	2.74	11.91	7.46	22.12	43.37	6.25	43.44
L	10.00	11.00	15.83	27.00	67.63	55.00	141.67	242.67	39.17	151.52
Δ log sales	-.33	-.22	-.077	.029	.022	.14	.26	.35	.21	.24
S/K	0.69	0.88	1.45	2.56	5.21	5.01	10.32	16.79	3.56	10.27
	2010-2014									
K	0.08	0.16	0.46	1.25	5.06	3.56	10.51	20.08	3.09	15.49
Sales	0.34	0.47	0.87	2.03	9.02	5.76	17.76	34.95	4.89	30.08
L	10.00	10.00	14.00	23.00	54.43	45.00	113.00	203.00	31.00	114.73
Δ log sales	-.59	-.42	-.21	-.052	-.075	.076	.22	.35	.28	.31
S/K	0.39	0.57	0.99	1.87	3.88	3.65	7.23	11.74	2.66	10.70
#Firms	5458									
#Obs.	14656									

Source: EBE, ELSTAT
Variables are in 2010 euros.
K is capital stock, Sales is manufacturing sales, L is number of employees.
IQR is the interquartile range, SD is the sample standard deviation and and pXX is the XXth percentile of the distribution.

Table D3: Summary Statistics of variables related to investment and finance

	p5	p10	p25	Med.	Mean	p75	p90	p95	IQR	SD
	2002-2007									
I/K %	-1.55	0.00	0.64	4.36	11.95	12.47	30.55	52.69	11.83	28.46
log I	-6.46	-5.58	-4.12	-2.61	-2.68	-1.18	0.10	0.84	2.94	2.19
Liab/Assets%	17.33	25.78	42.23	60.56	58.85	76.87	89.11	95.21	34.63	23.39
LT Liab/K%	0.00	0.00	0.00	0.00	57.86	23.43	86.19	161.31	23.43	983.95
	2007									
I/K %	-1.36	0.00	0.79	4.68	13.48	14.72	35.32	57.10	13.93	30.41
log I	-6.41	-5.38	-3.96	-2.35	-2.50	-0.99	0.28	0.90	2.97	2.19
Liab/Assets%	17.84	26.37	42.77	61.90	59.83	77.89	90.31	95.28	35.11	23.63
LT Liab/K%	0.00	0.00	0.00	0.03	55.49	46.69	127.26	212.94	46.69	245.39
	2010-2014									
I/K %	-2.42	0.00	0.06	1.58	6.36	6.13	15.93	27.94	6.07	20.63
log I	-7.11	-6.35	-4.82	-3.17	-3.23	-1.57	-0.32	0.37	3.25	2.30
Liab/Assets%	9.89	17.91	34.75	57.49	55.60	76.49	91.31	98.81	41.74	26.64
LT Liab/K%	0.00	0.00	0.00	5.11	82.22	54.68	144.40	252.97	54.68	765.34

Source: EBE, ELSTAT
Variables are in 2010 euros.
I is gross investment, Liab is total liabilities on the firm's balance sheet, LT Liab is the liabilities on a firm's balance sheet with maturity greater than a year.
IQR is the interquartile range, SD is the sample standard deviation and and pXX is the XXth percentile of the distribution.

Table D4: The deleveraging episode at the sectoral level

	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
	Food and Bev											
MedianLTlev	0.00	0.00	0.00	0.07	0.07	0.16	0.18	0.13	0.09	0.06	0.06	0.05
MeanLTlev	0.18	0.24	0.27	0.31	0.37	0.56	0.49	0.48	0.46	0.45	0.46	0.44
	Textile											
MedianLTlev	0.00	0.00	0.00	0.00	0.00	0.04	0.15	0.06	0.00	0.00	0.00	0.00
MeanLTlev	0.18	0.14	0.14	0.27	0.45	0.21	0.38	0.32	0.23	0.30	0.51	0.39
	Appar. Leather											
MedianLTlev	0.00	0.00	0.00	0.00	0.00	0.02	0.12	0.00	0.00	0.00	0.00	0.00
MeanLTlev	0.19	0.43	0.41	0.58	0.87	0.58	1.08	1.15	1.08	0.87	0.48	0.58
	Wood											
MedianLTlev	0.00	0.00	0.00	0.01	0.09	0.42	0.60	0.54	0.48	0.16	0.16	0.11
MeanLTlev	0.36	0.36	0.60	0.38	0.44	0.87	0.88	0.58	0.68	0.63	0.48	0.76
	Paper											
MedianLTlev	0.01	0.01	0.01	0.17	0.20	0.45	0.27	0.18	0.19	0.17	0.26	0.16
MeanLTlev	0.24	0.28	0.25	0.38	0.42	0.50	0.39	0.39	0.44	0.43	0.45	0.47
	PrintPub											
MedianLTlev	0.00	0.00	0.00	0.13	0.21	0.17	0.14	0.10	0.05	0.05	0.02	0.02
MeanLTlev	0.23	0.25	0.31	0.45	0.43	0.33	0.37	0.37	0.31	0.32	0.44	0.53
	Chemicals											
MedianLTlev	0.00	0.00	0.00	0.00	0.02	0.08	0.08	0.04	0.11	0.04	0.02	0.01
MeanLTlev	0.24	0.17	0.23	0.39	0.48	0.47	0.53	0.56	0.43	0.43	0.37	0.40
	Plastic Rubber											
MedianLTlev	0.01	0.00	0.00	0.17	0.07	0.25	0.31	0.18	0.18	0.14	0.13	0.18
MeanLTlev	0.14	0.20	0.24	0.39	0.40	0.43	0.45	0.45	0.38	0.39	0.41	0.40
	Non-Metalic Minerals											
MedianLTlev	0.00	0.00	0.00	0.00	0.04	0.19	0.14	0.06	0.01	0.06	0.13	0.11
MeanLTlev	0.14	0.18	0.20	0.28	0.35	0.52	0.50	0.48	0.48	0.42	0.44	0.42
	Basic Metals											
MedianLTlev	0.12	0.10	0.09	0.24	0.23	0.44	0.38	0.36	0.24	0.19	0.35	0.37
MeanLTlev	0.21	0.21	0.26	0.39	0.36	0.62	0.46	0.59	0.37	0.54	0.66	0.68
	Metal Products											
MedianLTlev	0.00	0.00	0.00	0.05	0.09	0.23	0.32	0.34	0.16	0.07	0.00	0.00
MeanLTlev	0.16	0.20	0.21	0.22	0.37	0.53	0.56	0.54	0.46	0.33	0.40	0.43
	Machinery, Equipment, Vehicles											
MedianLTlev	0.00	0.00	0.00	0.00	0.00	0.02	0.03	0.00	0.00	0.00	0.00	0.00
MeanLTlev	0.25	0.24	0.31	0.37	0.31	0.39	0.32	0.33	0.40	0.50	0.39	0.59
	Furniture											
MedianLTlev	0.00	0.00	0.00	0.00	0.01	0.04	0.19	0.15	0.16	0.08	0.04	0.00
MeanLTlev	0.38	0.36	0.31	0.37	0.50	0.41	0.66	0.53	0.63	0.62	0.66	0.60

MedianLTlev is the median long-term leverage across firm-year observations. Long-term leverage is the ratio of the liabilities on a firm's balance sheet with maturity greater than a year over the firm's capital stock. MeanLTlev is the mean long-term leverage across firm-year observations.

Table D5: Exporters versus Non-exporters

	Exporters*	Non-Exporters
Median Δ log sales† by period		
2002-2007	-0.008	0.003
2010-2014	-0.067	-0.007
Std. Dev. Δ log sales† by period		
2002-2007	0.255	0.261
2010-2014	0.303	0.311
Statistics for the entire sample 2002-2007, 2010-2014		
Share of obs. %	80.4	19.6
Share of total investment %	62.9	37.1

* Exporters are firms with exports at least 15% of their total revenue.

† Sales is manufacturing sales in 2010 euros.

Source: ELSTAT

E Full tables of specifications appearing in the text

Table E1: The investment collapse during the crisis is not explained by fundamentals

Discrete-outcome models (exponentiated coefficients)¶			
Model	Inaction $LogitProb(y=1\|x)$	Spike$^+$ I/K $LogitProb(y=1\|x)$	Discretized $I/K^\dagger$ $OrderedLogit(y=j\|x)$
Dependent Var y	$\mathbb{1}\{\|I/K\| \leq .01\}$	$\mathbb{1}\{I/K > .2\}$	$j \in \{0,1,2,3\}^\dagger$
2010-14 Dummy	2.10	0.44	0.51
	(0.073)	(0.022)	(0.015)
$\ln K$	0.82	0.81	1.04
	(0.0085)	(0.011)	(0.0098)
$\Delta \ln$ sales	0.45	3.03	2.70
	(0.031)	(0.32)	(0.14)
$(\ln K)^2$	1.01	1.00	1.00
	(0.0037)	(0.0047)	(0.0032)
$(\Delta \ln \text{sales})^2$	1.02	0.80	0.84
	(0.084)	(0.084)	(0.049)
$\ln K \times \Delta \ln \text{sales}$	0.88	1.12	1.06
	(0.033)	(0.058)	(0.036)
N	19748	19748	19748
Pseudo R^2	0.062	0.057	0.034
sector FE	yes	yes	yes

Heteroskedasticity robust standard errors in parentheses.
† The investment rate is discretized according to the following mapping $j\ I/K \mapsto \mathbb{N}$: $j(I/K)$ is equal to 0 if $I/K \in (-\infty, -.01)$; 1 if $I/K \in (-\infty, -.01)$; 2 if $I/K \in (.01, .2]$; and 3 if $I/K \in (.2, \infty)$.
¶¶The results of discrete outcome models are easier to interpret if they are displayed as proportional odds ratios by transforming each estimated coefficient β to $\exp(\beta)$. Thus, a reported number below unity reflects a negative coefficient. From the properties of the logit model, this implies that the exponentiated coefficient has the interpretation of a relative odds ratio. Relative odds refer to the odds for jumping to the immediately higher outcome: $\exp(\beta) = \frac{\text{Prob}(Y=y+1 \mid X=x+1)}{\text{Prob}(Y=y \mid X=x+1)} / \frac{\text{Prob}(Y=y+1 \mid X=x)}{\text{Prob}(Y=y \mid X=x)}$.

Table E2: Investment and the degree of external finance dependence

Continuous-outcome models				
Model	$E(y\|x)$	$Median(y\|x)$	$Quantile_{80}(y\|x)$	$E(y\|x)$
Dependent Var y	I/K	I/K	I/K	$\ln I$
10-14 Dummy × data RZ ‡	-0.010	-0.0054	-0.012	-0.061
	(0.0038)	(0.0011)	(0.0043)	(0.030)
10-14 Dummy	-0.049	-0.024	-0.069	-0.73
	(0.0035)	(0.0011)	(0.0042)	(0.026)
$\ln K$	-0.019	0.0025	-0.016	0.86
	(0.0017)	(0.00031)	(0.0012)	(0.0081)
$\Delta \ln$ sales	0.078	0.029	0.11	0.88
	(0.0071)	(0.0019)	(0.0073)	(0.051)
$(\ln K)^2$	0.0040	-0.00013	0.0030	0.044
	(0.00073)	(0.00011)	(0.00044)	(0.0028)
$(\Delta \ln \text{sales})^2$	0.0038	0.0089	0.042	-0.15
	(0.0077)	(0.0020)	(0.0079)	(0.050)
$\ln K \times \Delta \ln \text{sales}$	-0.012	0.0036	-0.015	0.057
	(0.0060)	(0.0011)	(0.0043)	(0.032)
N	19748	19748	19748	15899
R^2 adjusted	0.044			0.51
Pseudo R^2		0.028	0.045	

Heteroskedasticity robust standard errors in parentheses.
‡RZ is the Rajan and Zingales (1998) external-finance dependence index calculated from the pre-crisis data at the sectoral level. We further transform this index by adding its minimum value plus unity and then taking the log. This variable is then normalized by subtracting the mean and dividing by the SD so that the units of the estimated coefficient are one SD of the RZ index.

Table E3: Investment and the degree of external financial dependence

Discrete-outcome models (exponentiated coefficients)¶			
Model	Inaction $LogitProb(y=1\|x)$	Spike^{+} I/K $LogitProb(y=1\|x)$	Discretized $I/K^{\dagger}$ $OrderedLogit(y=j\|x)$
Dependent Var y	$\mathbb{1}\{\|I/K\| \leq .01\}$	$\mathbb{1}\{I/K > .2\}$	$j \in \{0,1,2,3\}^{\dagger}$
'10-'14 Dummy×RZ ‡	1.07	0.88	0.91
	(0.035)	(0.047)	(0.027)
10-14 Dummy	2.11	0.44	0.51
	(0.073)	(0.022)	(0.015)
$\ln K$	0.82	0.81	1.04
	(0.0085)	(0.011)	(0.0098)
$\Delta \ln$ sales	0.45	3.03	2.70
	(0.031)	(0.32)	(0.14)
$(\ln K)^2$	1.01	1.00	1.00
	(0.0037)	(0.0047)	(0.0032)
$(\Delta \ln \text{sales})^2$	1.02	0.80	0.84
	(0.084)	(0.084)	(0.049)
$\ln K \times \Delta \ln \text{sales}$	0.88	1.12	1.06
	(0.033)	(0.057)	(0.036)
N	19748	19748	19748
Pseudo R^2	0.062	0.058	0.035

Heteroskedasticity robust standard errors in parentheses.

† The investment rate is discretized according to the following mapping j $I/K \mapsto \mathbb{N}$:
$j(I/K)$ is equal to 0 if $I/K \in (-\infty, -.01)$; 1 if $I/K \in (-\infty, -.01)$; 2 if $I/K \in (.01, .2]$; and 3 if $I/K \in (.2, \infty)$.

¶¶The results of discrete outcome models are easier to interpret if they are displayed as proportional odds ratios by transforming each estimated coefficient β to $\exp(\beta)$. Thus, a reported number below unity reflects a negative coefficient. From the properties of the logit model, this implies that the exponentiated coefficient has the interpretation of a relative odds ratio. Relative odds refer to the odds for jumping to the immediately higher outcome: $\exp(\beta) = \frac{\text{Prob}(Y=y+1 \mid X=x+1)}{\text{Prob}(Y=y \mid X=x+1)} / \frac{\text{Prob}(Y=y+1 \mid X=x)}{\text{Prob}(Y=y \mid X=x)}$.

‡RZ is the Rajan and Zingales (1998) external-finance dependence index calculated from the pre-crisis data at the sectoral level. We further transform this index by adding its minimum value plus unity and then taking the log. This variable is then normalized by subtracting the mean and dividing by the SD so that the units of the estimated coefficient are one SD of the RZ index.

Table E4: Firm-level leverage and investment behavior

	Year-specific leverage coefficients	
Model	Inaction $LogitProb(y = 1\|x)$	Loglinear reg. $E(y\|x)$
Dependent Var y	$\mathbb{1}\{\|I/K\| \leq .01\}$	$\log I$
	the High LT Leverage dummy is interacted with yearly dummies[††]	
2010	-0.23 (0.12)	0.24 (0.090)
2011	-0.075 (0.11)	-0.040 (0.094)
2012	0.16 (0.11)	-0.17 (0.10)
2013	0.20 (0.11)	-0.094 (0.10)
2014	0.11 (0.11)	-0.15 (0.098)
$\ln K$	-0.21 (0.018)	0.92 (0.016)
Δ ln sales	-0.81 (0.095)	0.81 (0.080)
$(\ln K)^2$	-0.00080 (0.0067)	0.049 (0.0056)
$(\Delta \ln \text{sales})^2$	-0.021 (0.11)	-0.16 (0.079)
$\ln K \times \Delta \ln \text{sales}$	-0.11 (0.056)	0.093 (0.052)
N	8131	6385
sector FE	yes	yes
year FE	yes	yes

	Restricting the sample to 2012-14 (severe banking crisis years)	
High LT Leverage ($= \beta_c$)	0.15 (0.067)	-0.14 (0.059)
$\ln K$	-0.20 (0.023)	0.92 (0.021)
Δ ln sales	-0.89 (0.12)	0.93 (0.10)
$(\ln K)^2$	-0.0025 (0.0089)	0.049 (0.0078)
$(\Delta \ln \text{sales})^2$	-0.012 (0.14)	-0.21 (0.10)
$\ln K \times \Delta \ln \text{sales}$	-0.20 (0.075)	0.14 (0.071)
$\exp(\beta_c)$[¶]	1.17	
N	4838	3787
sector FE	yes	yes

Heteroskedasticity robust standard errors in parentheses.

[††]This is a dummy variable taking a value one if the ratio of a firm's long-term liabilities over its capital stock is in the top tertile during the years 2007-09 and zero otherwise.

[¶]The results of discrete outcome models are easier to interpret if they are displayed as proportional odds ratios by transforming each estimated coefficient β to $\exp(\beta)$. Thus, a reported number below unity reflects a negative coefficient.

Table E5: Firm-level leverage and investment behavior: debt over assets

	Year-specific leverage coefficients	
Model	Inaction $Logit Prob(y = 1\|x)$	Loglinear reg. $E(y\|x)$
Dependent Var y	$\mathbb{1}\{\|I/K\| \leq .01\}$	$\log I$
	Restricting the sample to 2012-14 (severe banking crisis years)	
High debt over assets†	0.14	-0.099
	(0.072)	(0.066)
$\ln K$	-0.16	0.91
	(0.025)	(0.025)
$\Delta \ln$ sales	-0.88	0.92
	(0.12)	(0.11)
$(\ln K)^2$	-0.012	0.048
	(0.010)	(0.0090)
$(\Delta \ln \text{sales})^2$	0.025	-0.20
	(0.13)	(0.11)
$\ln K \times \Delta \ln \text{sales}$	-0.18	0.13
	(0.078)	(0.077)
N	4570	3633
sector FE	yes	yes

Heteroskedasticity robust standard errors in parentheses.
†This is a dummy variable taking a value one if the ratio of total liabilities in a firm's balance sheet over its total assets is in the top tertile during the years 2007-09 and zero otherwise.

F Robustness

Table F1: The investment collapse during the crisis is not explained by fundamentals, value-added weights

Discrete-outcome models (exponentiated coefficients)¶			
Model	Inaction $LogitProb(y=1\|x)$	Spike^{+} I/K $LogitProb(y=1\|x)$	Discretized $I/K^{\dagger}$ $OrderedLogit(y=j\|x)$
Dependent Var y	$\mathbb{1}\{\|I/K\| \leq .01\}$	$\mathbb{1}\{I/K > .2\}$	$j \in \{0,1,2,3\}^{\dagger}$
2010-14 Dummy	1.56	0.78	0.76
$\ln K$	0.86	0.83	0.96
Δ ln sales	0.37	4.15	4.77
$(\ln K)^2$	1.01	0.99	1.00
$(\Delta \ln \text{sales})^2$	1.60	0.48	0.60
$\ln K \times \Delta \ln \text{sales}$	1.17	1.22	0.78
sector FE	yes	yes	yes

Heteroskedasticity robust standard errors in parentheses.
† The investment rate is discretized according to the following mapping j $I/K \mapsto \mathbb{N}$: $j(I/K)$ is equal to 0 if $I/K \in (-\infty, -.01)$; 1 if $I/K \in (-\infty, -.01)$; 2 if $I/K \in (.01, .2]$; and 3 if $I/K \in (.2, \infty)$.
¶In the output of the discrete outcome models the results are easier to interpret if they are displayed as proportional odds ratios by transforming the estimated coefficient β to $\exp(\beta)$. Thus, a reported number below unity reflects a negative coefficient. From the properties of the logit model, this implies that the exponentiated coefficient has the interpretation of a relative odds ratio. Relative odds refer to the odds for jumping to the immediately higher outcome: $\exp(\beta) = \frac{\text{Prob}(Y=y+1 \mid X=x+1)}{\text{Prob}(Y=y \mid X=x+1)} / \frac{\text{Prob}(Y=y+1 \mid X=x)}{\text{Prob}(Y=y \mid X=x)}$.

Table F2: The investment collapse, continuous outcome models and yearly dummies

Continuous-outcome models				
Model	$E(y\|x)$	$Median(y\|x)$	$Quantile_{80}(y\|x)^\dagger$	$E(y\|x)$
Dependent Var y	I/K	I/K	I/K	$\ln I$
2004 Dummy	0.0061	0.0021	0.0077	-0.0075
	(0.0085)	(0.0021)	(0.0081)	(0.047)
2005 Dummy	-0.0051	-0.00024	-0.0071	-0.063
	(0.0080)	(0.0021)	(0.0081)	(0.047)
2006 Dummy	-0.0049	-0.0032	-0.0085	-0.14
	(0.0085)	(0.0024)	(0.0091)	(0.054)
2007 Dummy	0.013	0.0051	0.031	0.046
	(0.0088)	(0.0024)	(0.0090)	(0.054)
2008 Dummy	0.019	0.0077	0.020	0.052
	(0.0096)	(0.0028)	(0.011)	(0.060)
2009 Dummy	-0.014	-0.0066	-0.028	-0.21
	(0.0093)	(0.0026)	(0.0099)	(0.057)
2010 Dummy	-0.030	-0.016	-0.048	-0.46
	(0.0080)	(0.0024)	(0.0091)	(0.055)
2011 Dummy	-0.044	-0.021	-0.063	-0.75
	(0.0075)	(0.0023)	(0.0085)	(0.054)
2012 Dummy	-0.056	-0.024	-0.068	-0.94
	(0.0073)	(0.0023)	(0.0087)	(0.055)
2013 Dummy	-0.055	-0.026	-0.071	-0.87
	(0.0074)	(0.0023)	(0.0086)	(0.054)
2014 Dummy	-0.050	-0.023	-0.066	-0.78
	(0.0075)	(0.0023)	(0.0085)	(0.054)
$\ln K$	-0.020	0.0026	-0.017	0.86
	(0.0016)	(0.00031)	(0.0012)	(0.0077)
$\Delta \ln$ sales	0.079	0.029	0.10	0.89
	(0.0065)	(0.0018)	(0.0068)	(0.048)
$(\ln K)^2$	0.0037	-0.00017	0.0029	0.043
	(0.00067)	(0.00011)	(0.00040)	(0.0026)
$(\Delta \ln \text{sales})^2$	-0.0061	0.0064	0.034	-0.15
	(0.0064)	(0.0016)	(0.0061)	(0.042)
$\ln K \times \Delta \ln \text{sales}$	-0.0095	0.0041	-0.011	0.059
	(0.0053)	(0.0010)	(0.0039)	(0.028)
N	21983	21983	21983	17809
sector FEs	Yes	Yes	Yes	Yes

Heteroskedasticity robust standard errors in parentheses.
†This is the top quintile of the investment rate distribution i.e. the 80th percentile.

Table F3: The investment collapse, discrete outcome models and yearly dummies

Discrete-outcome models (exponentiated coefficients)¶			
Model	Inaction $LogitProb(y = 1\|x)$	Spike^{+} I/K $LogitProb(y = 1\|x)$	Discretized $I/K^{\dagger}$ $OrderedLogit(y = j\|x)$
Dependent Var y	$\mathbb{1}\{\|I/K\| \leq .01\}$	$\mathbb{1}\{I/K > .2\}$	$j \in \{0, 1, 2, 3\}^{\dagger}$
2004 Dummy	1.02	1.17	1.02
	(0.072)	(0.094)	(0.060)
2005 Dummy	1.07	1.06	0.93
	(0.075)	(0.087)	(0.054)
2006 Dummy	1.11	1.12	0.95
	(0.089)	(0.10)	(0.062)
2007 Dummy	1.02	1.42	1.07
	(0.083)	(0.13)	(0.073)
2008 Dummy	1.03	1.41	1.12
	(0.099)	(0.15)	(0.083)
2009 Dummy	1.21	0.79	0.85
	(0.10)	(0.091)	(0.056)
2010 Dummy	1.71	0.65	0.66
	(0.13)	(0.070)	(0.041)
2011 Dummy	2.09	0.50	0.52
	(0.15)	(0.053)	(0.030)
2012 Dummy	2.50	0.42	0.45
	(0.18)	(0.048)	(0.026)
2013 Dummy	2.44	0.45	0.43
	(0.17)	(0.048)	(0.026)
2014 Dummy	2.21	0.49	0.49
	(0.16)	(0.050)	(0.029)
$\ln K$	0.82	0.81	1.03
	(0.0082)	(0.010)	(0.0095)
$\Delta \ln$ sales	0.46	3.19	2.77
	(0.032)	(0.31)	(0.14)
$(\ln K)^2$	1.01	1.00	1.00
	(0.0036)	(0.0044)	(0.0030)
$(\Delta \ln \text{sales})^2$	1.07	0.77	0.82
	(0.10)	(0.060)	(0.038)
$\ln K \times \Delta \ln \text{sales}$	0.89	1.13	1.07
	(0.031)	(0.053)	(0.033)
N	21983	21983	21983
sector FE	yes	yes	yes

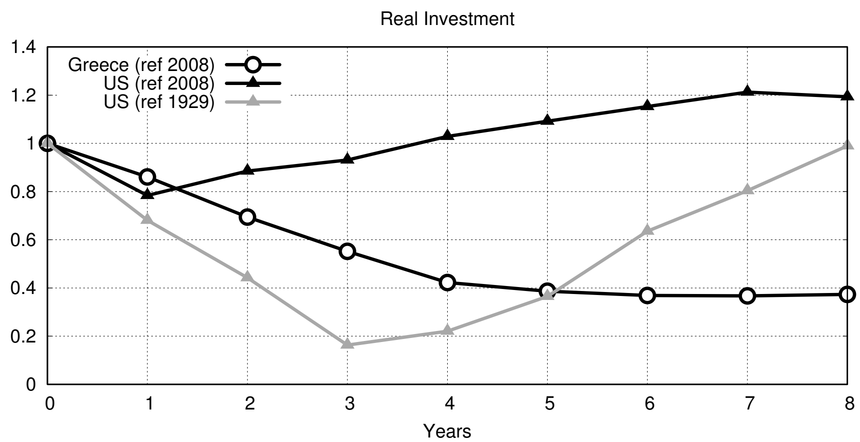
Heteroskedasticity robust standard errors in parentheses.

† The investment rate is discretized according to the following mapping $j\ I/K \mapsto \mathbb{N}$: $j(I/K)$ is equal to 0 if $I/K \in (-\infty, -.01)$; 1 if $I/K \in (-\infty, -.01)$; 2 if $I/K \in (.01, .2]$; and 3 if $I/K \in (.2, \infty)$.

¶In the output of the discrete outcome models the results are easier to interpret if they are displayed as proportional odds ratios by transforming the estimated coefficient β to $\exp(\beta)$. Thus, a reported number below unity reflects a negative coefficient. From the properties of the logit model, this implies that the exponentiated coefficient has the interpretation of a relative odds ratio. Relative odds refer to the odds for jumping to the immediately higher outcome: $\exp(\beta) = \frac{\text{Prob}(Y=y+1 \mid X=x+1)}{\text{Prob}(Y=y \mid X=x+1)} / \frac{\text{Prob}(Y=y+1 \mid X=x)}{\text{Prob}(Y=y \mid X=x)}$.

G Figures

Figure G1: The Greek crisis



Source: FRED and Eurostat.

Figure G2: The deleveraging episode: three leverage measures

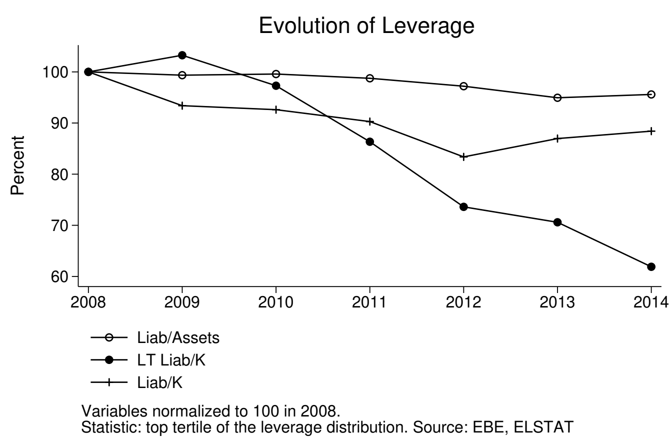


Figure G3: The leverage distribution across time

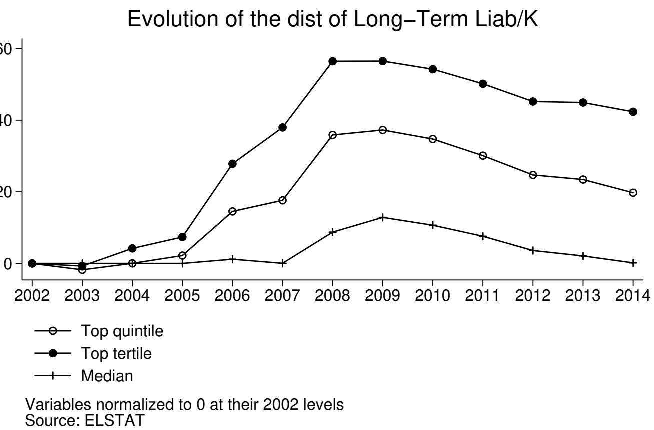
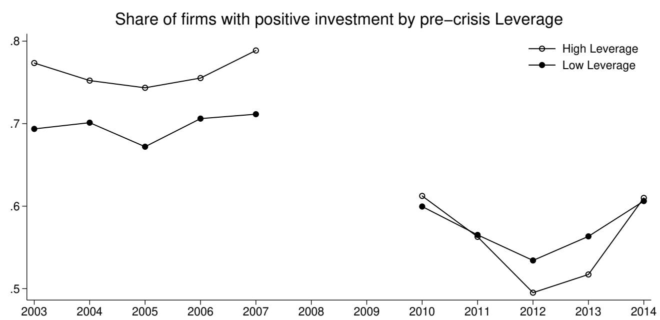


Figure G4: Probability of positive investment rate by pre-crisis leverage



Note: High Leverage is LT Liabilities/K in the top tertile of the leverage distribution over the years 2002–2007. Investment is considered positive if investment rate >=.01. Source: EBE, ELSTAT

H Technical

H.1 Firm optimal profit function

In this section, we show how an optimal profit function can be derived from standard assumptions about production technology and output demand. We first describe the production function of a particular firm i and the demand for its respective output which, jointly, determine the variable profit. In what follows t is an indicator of time. The firm production function takes a Cobb-Douglas form, specified as:

$$Q_{it} = A_{it} K_{it}^{a_K} L_{it}^{a_L} M_{it}^{a_M} \tag{18}$$

We may want to assume that the above function displays constant returns to scale by letting $a_K + a_L + a_M = 1$, although this is not fundamental to generate our results. In the above equation, A_{it} is physical total factor productivity, K_{it} is the physical capital stock, L_{it} is the amount of effective labor employed, and M_{it} is materials input. Capital is quasi-fixed in the sense that a firm arrives at period t with capital stock K_{it} which is used to produce period's t output Q_{it}. This assumption is referred to as time-to-build in the sense that any investment in physical capital at period t becomes only productive at period $t+1$. The firm buys labor and materials in competitive markets at prices w_{Lt} and w_{Mt}, respectively, and its total variable cost is $TVC_{it} = w_{Mt}M_{it} + w_{Lt}L_{it}$.

Demand for firm i's output Q_{it} takes an iso-elastic form, given by:

$$Q_{it} = B_{it} P_{it}^{-\eta}, \quad \eta > 1 \tag{19}$$

where B_{it} depends on consumer income and the prices of other firms in the industry, P_{it} is the firm's price of output, and η is the elasticity of demand. Combining equations (18) and (19), we obtain the sales-generating production function:

$$S_{it} = \Omega_{it}^{sales} K_{it}^{\beta_K} L_{it}^{\beta_L} M_{it}^{\beta_K}$$

where the above coefficients correspond to:

$$\begin{aligned}
\beta_K &= a_K(1 - 1/\eta) \\
\beta_L &= a_L(1 - 1/\eta) \\
\beta_M &= a_M(1 - 1/\eta) \\
\Omega_{it}^{sales} &= A_{it}^{1-1/\eta} B_{it}^{1/\eta}
\end{aligned}$$

and Ω_{jt}^{sales} is the revenue total factor productivity or $TFPR$. At the beginning of each period t, firms observe their physical productivity A_{it} and idiosyncratic demand B_{it}, their predetermined capital stock K_{it}, variable-input prices w_{Lt}, w_{Mt} and choose the level of their variables inputs L_{it}, M_{it} in order to maximize variable profits $P_{it}Q_{it} - w_{Lt}L_{it} + w_{Mt}M_{it}$. Profit maximization implies that the revenue production function coefficient is equal to the input expenditure share in sales:

$$\beta_L = \frac{w_{Lt}L_{it}}{S_{it}}$$
$$\beta_M = \frac{w_{Mt}M_{it}}{S_{it}}$$

Substituting for the optimal variable input levels we get the maximum-variable-profit function conditional on capital K_{it} and Ω_{it}^{sales} (which corresponds to TFPR):

$$\Pi(K_{it}, \Omega_{it}^{sales}) = \lambda_t \left(\Omega_{it}^{sales}\right)^{\frac{1}{\beta_k + \eta^{-1}}} K_{it}^{\frac{\beta_K}{\beta_K + \eta^{-1}}} \equiv \Omega_{it} K_{it}^{\beta}$$

where

$$\lambda_t = \left(\beta_K + \epsilon^{-1}\right) \left(\frac{\beta_L}{w_{Lt}}\right)^{\frac{\beta_L}{\beta_K + \epsilon^{-1}}} \left(\frac{\beta_M}{w_{Mt}}\right)^{\frac{\beta_M}{\beta_K + \epsilon^{-1}}}$$

Allowing for $\omega_{it} = \log(\Omega_{it})$, we then get the optimal profit function form used throughout this paper:

$$\Pi(K_{it}, \omega_{it}) = \exp(\omega_{it}) K_{it}^{\beta}$$

One should finally note that the profitability shock potentially confounds variations in idiosyncratic physical productivity (A_{it}), product level demand (B_{it}), and input prices (w_{Lt}, w_{Mt}).

H.2 Analysis of the collateral constraints investment model

Khan and Thomas (2013) show that the model specified in section 6 can be decomposed into constrained and unconstrained firms. Following their analysis we define constrained firms as those that have a positive probability of entering a state where the collateral constraint binds in any future state of the world; and otherwise firms are defined as unconstrained.

Unconstrained firms. Unconstrained firms are indifferent between financial savings and dividends as they already accumulated enough capital or financial wealth to ensure that collateral constraints will never affect their financial decisions. This understanding of unconstrained firms can only be achieved if the support for the profitability shock realization is finite $\omega_{it} \in [\omega_{low}, \omega_{high}]$. This is immediately guaranteed by the standard discretization of an $AR(1)$ process (as in equation [6]) proposed by Tauchen (1986). Let us represent unconstrained firms value by W, defined by:

$$W(s_{it}) = \max\left\{W^a(s_{it}), W^i(s_{it})\right\} \tag{20}$$

where the value of capital adjustment W^a is given by:

$$\begin{aligned}
W^a(s_{it}) &= \max_{I_{it}\neq 0}\left\{\Pi(K_{it},\omega_{it}) - C((1-\delta)K_{it} + I_{it}, K_{it}, \omega_{it}) - B_{it} + \beta E_{\omega_{it},\xi_{it}}[W(s_{t+1})]\right\} \\
s_{t+1} &= \{(1-\delta)K_{it} + I_{it}, 0, \omega_{it+1}, \xi_{t+1}\}
\end{aligned}$$

Note that we are imposing that the choice of future debt is zero, $B_{t+1} = 0$. This follows from the fact that, by definition, unconstrained firms are indifferent about B_{it+1} and the current level of debt doesn't affect investment decisions. That implies that the current value moves one-to-one with debt: $W(K_{it}, B_{it}, \omega_{it}, \xi_t) = W(K_{it}, 0, \omega_{it}, \xi_t) - B_{it}$. But then the entire problem can be reformulated with $W(K_{it}, 0, \omega_{it}, \xi_t)$ and the value of an unconstrained firm with any amount of debt just taken by subtracting that value with the current amount of debt. Similarly, the value of inaction is given by:

$$\begin{aligned}
W^i(s_{it}) &= \Pi(K_{it},\omega_{it}) - B_{it} + \beta E_{\omega_{it},\xi_t}[W_0(s_{it+1})] \\
s_{it+1} &= \{(1-\delta)K_{it}, 0, \omega_{it+1}, \xi_{t+1}\}
\end{aligned}$$

Given the above structure, it is easy to show that the solution of an unconstrained firm's problem implies a (s, S) type of capital policy captured with $K^w(K_{it}, \omega_{it})$. Note that we drop the collateral constraint shock ξ_t from the capital policy functions as unconstrained firms are indifferent about any particular choice of debt, therefore implying that they are indifferent as well to any particular realization of ξ. One should also note that the problem defined in (20) is equivalent to the standard model of firm investment represented in equation (1). That is, unconstrained firms in a model with collateral constraints just behave as firms from standard investment models without these source of constraints.

Since unconstrained firms are indifferent on choices of future debt B_{it+1}, any saving rule that implies a zero probability that the firm becomes constrained in any future date and state of the world is consistent with the equilibrium. We derive such a rule by solving for the firms maximum debt policy $B^w(K_{it}, \omega_{it}, \xi_t)$ characterized by the following recursive problem:

$$B^w(K_{it}, \omega_{it}, \xi_t) = min_{\omega', \xi'} \left\{ \tilde{B}(K^w(K_{it}, \omega_{it}), \omega', \xi') \right\}$$

st

$$\tilde{B}(K_{it}, \omega_{it}, \xi_t) = \Pi(K_{it}, \omega_{it}) - C(K^w(K_{it}, \omega_{it}), K_{it}, \omega_{it}) + q \min\{B^w(K_{it}, \omega_{it}, \xi_t), \xi_t K_{it}\}$$

Given the above maximum debt policy, a dividend policy consistent with an unconstrained firm optimal decision is derived from

$$D^w(s_{it}) = \Pi(K_{it}, \omega_{it}) - C(K^w(K_{it}, \omega_{it}), K_{it}, \omega_{it}) + q \min\{B^w(K_{it}, \omega_{it}, \xi_t), \xi_t K_{it}\} - B_{it}$$

Constrained firms. Note that if a constrained firm accumulates enough capital or financial savings that allows it to adopt the optimal dividend policy of an unconstrained firm, then the firm becomes effectively unconstrained. Since the value of being unconstrained is at least as large as the value of being constrained, we represent the value of a potentially constrained firm as

$$V(s_{it}) = \begin{cases} W(s_{it}) & if \quad D^w(s_{it}) > 0 \\ V^{liq}(s_{it}) & if \quad D^w(s_{it}) \leq 0 \end{cases}$$

where V^{liq} is the value when a firm is effectively constrained and is given by

$$V^{liq}(s_{it}) = \begin{cases} \tilde{V}^0(s_{it}) & if \quad \Psi(s_{it}) = 1 \\ V^x(s_{it}) & if \quad \Psi(s_{it}) = 0 \end{cases}$$

where $\Psi(s_{it})$, defined in 10, is the indicator that forces non-viable firms to exit. Firms that can sustain a dividend policy given by $D^w(s_{it}) > 0$ are unconstrained ones. If, however, a firm is constrained, the choice of dividend payout is effectively zero $D = 0$ since that allows it to get closer to an unconstrained policy (see Caggese, 2007 for a formal argument). It follows that the value of a constrained viable firm can be characterized with

$$\tilde{V}^0 (s_{it}) = \max \left\{ \tilde{V}^a (s_{it}), \tilde{V}^i (s_{it}) \right\}$$

with the value associated with adjusting capital given by

$$\tilde{V}^a (s_{it}) = \max_{I_{it} \in \Omega(s_{it})} \{ \beta E_{\omega_{it}, \xi_t} [V (s_{it+1})] \} \tag{21}$$

$$\begin{aligned} s.t. & \\ B_{t+1} &= \frac{1}{q} \{ -\Pi (K_{it}, \omega_{it}) + C ((1-\delta) K_{it} + I_{it}, K_{it}, \omega_{it}) + B_{it} \} \\ D_{it} &= 0 \end{aligned}$$

and the value associated with inaction as

$$\begin{aligned} \tilde{V}^i (s_{it}) &= \beta E_{\omega, \xi} [V (s_{it+1})] \\ s.t. & \\ B_{it+1} &= \frac{1}{q} \{ -\Pi (K_{it}, \omega_{it}) + B_{it} \} \\ D_{it} &= 0 \\ K_{it+1} &= (1-\delta) K_{it} \end{aligned}$$

The set of maximum affordable investment, $\Omega (s_{it})$, is defined as:

$$\begin{aligned} \Omega (s_{it}) &\equiv \left[\max \left\{ I^{low} (s_{it}), -(1-\delta) K_{it} \right\}, I^{upp} (s_{it}) \right] \\ I^{upp} (s_{it}) &= \arg\max_I \{ \Pi (K_{it}, \omega_{it}) - C ((1-\delta) K_{it} + I, K_{it}, \omega_{it}) - B_{it} + q \xi_t K_{it} \} \\ I^{low} (s_{it}) &= \arg\min_I \{ \Pi (K_{it}, \omega_{it}) - C ((1-\delta) K_{it} + I, K_{it}, \omega_{it}) - B_{it} + q \xi_t K_{it} \} \end{aligned}$$