Bank and Firm Behavior in Times of Crisis

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das größte Geschenk, das Eltern ihren Kindern machen können, weit über das Materielle hinausgeht; es ist die Aufmerksamkeit und Zuwendung, die Eltern ihren Kindern schenken, denn diese sind später einmal der Schlüssel zu persönlicher Selbstentfaltung und individueller Freiheit. Diese Dissertation widme ich daher meinen Eltern, Inge und Georg.

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Preface

Now that the Global Financial Crisis of 2008 (GFC) has ceded its status of being the most recent major global crisis event to the Covid-19 Global Pandemic, memories of this bygone era should not fade away as side notes in our history books or decay as dusty relics in the museums of modern history. They should rather be kept in mind as expressions of an epochal event that fundamentally affected the lives of millions of individuals and entire societies around the globe. I am one of these individuals. Back in fall 2008, I was working as student assistant at the local library, and as I was sorting the latest newspapers and magazines on Saturday, September 20, 2008, my eyes could not escape the major headlines on the front pages: "Banks in Crisis" (Financial Times), "Market crash shakes world" (FT Weekend), "AIG, Lehman Shock Hits World Markets" (Wall Street Journal), "What Next?" (The Economist). Looking back, I can unequivocally say that it was this moment that sparked my interest for macroeconomic and financial market-related topics. This interest has stayed with me ever since, so that after graduating from high school in 2011, I decided to study economics. Today, after participating in countless lectures and seminars involving controversial debates around the discipline of economics, it is time for me to take stock: What were the driving forces of the GFC, to what extent do these factors represent actual economic problems, what is their impact on the real economy and welfare, and what has been done in the aftermath of the crisis to ensure that history does not recur? This dissertation attempts to shed light on these questions.

When analysing economic crisis events in general, the concept of endogenous risk is particularly useful. According to Danielsson & Shin (2002), crises can result from the following two circumstances.[1] On the one hand, there are crises that arise due to purely exogenous factors stemming from outside the system. Here, the most prominent example is the Covid-19 Global Pandemic, which hit the world economy at the beginning of 2020 like an asteroid crashing into earth: it came as a surprise, it could not have been prevented and it has caused tremendous economic (and health) harm (Danielsson *et al.* 2020). On the other hand, there

[1] While Danielsson & Shin (2002) relate their concept of endogenous risk to financial crises, they also stress the possibility of transferring that concept to other contexts, e.g., economic crises.

are crises whose origin is endogenous, implying that they are generated within the system. From the perspective of the financial sector, the GFC was clearly caused by endogenous factors. As stated by Danielsson *et al.* (2020), "2008 was a global systemic financial crisis fuelled by the endogenous interactions of market participants. The forces of the crisis fed on deep weaknesses in the financial system that had built up out of sight." What were these weaknesses and why did they arise?

The central answer to these questions lies in the concept of externalities. Externalities – whether positive or negative – occur whenever the decisions of economic agents affect parties that are not directly involved in the transactions.[2] If those indirect effects are not reflected in market prices, differences between the private and the social returns (or costs) of actions lead to potentially inefficient market outcomes.[3] In the context of financial markets, a range of externalities led to the buildup of systemic risks and thus contributed significantly to the outbreak of the GFC in 2008. These were externalities related to interconnectedness, externalities related to strategic complementarities and externalities related to fire sales (Nicolo *et al.* 2012).

While all of these factors individually pose a major threat to financial stability, there is one group of financial intermediaries that were particularly affected by two of these externalities: systemically important financial institutions (SIFIs). For these institutions, the social (system-wide) costs of their collapse are huge ('too-big-to-fail') and by far exceed the costs incurred by the institutions' stake- and shareholders. This is because SIFIs are highly interconnected with the financial system, which gives rise to harmful spillover and contagion effects (externalities related to interconnectedness). The bankruptcy of Lehman Brothers is the most prominent and illustrative example for this. Moreover, individual financial entities have an incentive to either become systemically relevant or at least to correlate their exposures and risks with those of SIFIs in order to benefit from government interventions in the case of default (externalities related to strategic complementarities). At this point, endogenous risk emerges. Since government bailouts are often cheaper for the public than letting SIFIs go bankrupt, severe moral hazard issues arise within the affected institutions: while SIFIs do fully benefit from the upside risks of their actions, extreme downside risks are expected to be covered by the public. In expectation of being bailed out in a crisis event, SIFIs might now be incentivized to shift their business operations towards riskier activities. This in turn makes the financial system as a whole more vulnerable and hence the probability of an actual crisis event increases (endogenously).

[2]The notion of this concept goes back to two British economists, Henry Sidgwick (1838-1900) and Arthur C. Pigou (1877-1959).

[3]See Helbling (2010) for a brief summary on externalities.

In the aftermath of 2008, regulators and policy-makers repeatedly drew attention to the problem of externalities related to SIFIs. In a speech in 2009, then Federal Reserve Chairman Ben Bernanke called 'too-big-to-fail' considerations a severe problem that undermines market discipline and distorts incentives (Bernanke 2009). In 2012, the Basel Committee on Banking Supervision finally set up an international regulatory framework aimed at making failures of SIFIs less likely and potential failures less costly for society (Basel Committee on Banking Supervision 2011). Thereby, a special focus was placed on Global Systemically Important Banks (G-SIBs). In its core, the international G-SIB framework was designed to make these banks more liable for their actions and to reduce the aforementioned market externalities by imposing higher capital requirements and (more) credible resolution schemes. Chapter 1 of this doctoral thesis studies the effects of the introduction of that regulatory framework on the lending behavior of G-SIBs. It finds evidence that the international G-SIB framework has been effective in mitigating moral hazard behavior and hence reducing market externalities associated with systemically important institutions.

In his 2009 speech, Ben Bernanke stressed the role of one particular factor that led to the distortion of incentives at SIFIs and therefore contributed significantly to the outbreak of the GFC: executive compensation. According to the Federal Reserve Chairman, "poorly designed compensation policies can create perverse incentives that can ultimately jeopardize the health of the banking organization" (Bernanke 2009). This view is supported by the US Treasury Secretary Timothy Geithner, who also identified executive compensation practices as a major contributing factor to the GFC. As stated by Geithner, managerial incentives should be aligned with long-term value creation and should accordingly match the time structure of the institution's risk profile (Geithner 2009). The problem of misaligned managerial incentive schemes, however, is not one that is specific to the financial sector nor is it historical in its occurrence during the GFC. It is rather a quite general phenomenon that affects entire economies, independently of timing and location. Policy-makers, executives and investors have frequently warned about the dangers of increasing short-term profits at the cost of long-term value (e.g., Dimon & Buffet 2018 or Barton 2011). Such short-term oriented compensation practices could be particularly detrimental to economic growth and welfare. Chapter 2 of this dissertation studies this issue in the context of the private industrial sector more formally and analyzes the macroeconomic implications of distorted managerial incentive schemes. It finds evidence that relatively small deviations in incentives away from long-term compensation schemes can cause substantial declines in economic growth and welfare.

Beyond its disruptive effects on the financial sector, the GFC plunged the world economy into a severe recession. The global production of goods and services dropped dramatically, millions of people lost their jobs and suffered massive financial losses from falling asset prices and crashing stock markets, which wiped out retirement savings and placed them on the brink of poverty. While the GFC was clearly an endogenous crisis from the perspective of the financial sector, it hit the private industrial sector like an asteroid crashing into earth: firms suddenly faced tightened credit lines, were confronted with sharp increases in risk premiums and saw their cash resources shrinking. This in turn left them struggling to pay down wage bills and to undertake real investment opportunities. Moreover, due to impending income losses, households cut back consumption spending, which put further downward pressure on corporate sales and production – the Keynesian multiplier kicked in. Stock & Watson (2012) disentangle the channels leading to the Great Recession of 2008 and identify two predominant factors. First, and not surprisingly, there was a large financial shock in 2008. Second, and this is somewhat more surprising, the recession was caused by a large increase in uncertainty: "the main contributions to the decline in output and employment [...] are estimated to come from financial and uncertainty shocks" (Stock & Watson 2012, p. 119). Although the concept of uncertainty relates to changes in the second moment of a distribution while leaving the respective mean unchanged, it can lead to substantial demand shortages: firms scale back investment decisions because they are uncertain over future business conditions (e.g., Leahy & Whited 1996). Households postpone consumption spending on durables since they face high uncertainty over future income (e.g., Romer 1990). Hence, uncertainty can clearly suppress aggregate demand.

In general, heightened uncertainty is a typical phenomenon accompanying economic crises and is not specific to the GFC. Trends in common uncertainty indicators over the past decades show that uncertainty has increased steadily, especially in recent years. This trend peaked in spring 2020, during the first wave of the Covid-19 Global Pandemic, when indicators measuring economic policy uncertainty reached scores that were twice as high as the September 2008 levels.[4] The real effects of uncertainty on output and employment can be vast. Baker *et al.* (2020) use model-based GDP forecasts to illustrate that about half of the projected output contraction is caused by Covid-19-induced uncertainty. Therefore, their results underline the devastating effects of uncertainty on economic activity, similar to the analysis by Stock & Watson (2012). In Chapter 3 of this dissertation, I contribute to this literature by studying the effects of uncertainty on corporate investment decisions. I provide evidence that long-term investments, such as buildings and machinery investments, decline more strongly in response to increases in uncertainty than short-term investments, such as advertising and IT investments. Therefore, the durability of capital is an important

[4]See Baker *et al.* (2016) for the construction of economic policy uncertainty indicators. Data on the evolution of these indicators can be found at `http://www.policyuncertainty.com`. Moreover, Altig *et al.* (2020a) give a comprehensive summary on economic uncertainty before and during the Covid-19 Global Pandemic.

determinant for corporate investment decisions under uncertainty.

In the following, I describe the three chapters of my dissertation in more detail. In Chapter 1, I use granular data on syndicated loans to analyze the impact of international reforms for G-SIBs on bank lending behavior. Using a difference-in-differences estimation strategy, I find no effect of the reforms on overall credit supply while at the same time documenting a substantial decline in borrower- and loan-specific risk factors for the affected banks. Relative to the control group, G-SIBs shifted lending towards less riskier companies in the period following the reforms and also increased the share of collateralized lending. My estimates further show that other banks decreased their interest rates on loans more than G-SIBs after 2012, which suggests more conservative loan pricing by G-SIBs relative to the banks in the control group. Overall, my results provide suggestive evidence that the post-crisis reforms have effectively limited excessive risk taking and reduced funding cost subsidies for G-SIBs, while potential side effects for the real economy that could be associated with a potential reduction in credit supply have been contained. The documented decline in borrower- and loan-specific risk factors for G-SIBs indicates a more liable risk management, in line with the intention of stricter loss absorbance requirements and resolution reforms. Moreover, the decline in competitive pricing advantages is consistent with a reduction in implicit funding cost subsidies for G-SIBs, which may be seen as indirect evidence that the reforms credibly reduced bailout expectations associated with 'too-big-to-fail' considerations. At the same time, I do not find a reduction in the overall credit supply provided by G-SIBs, indicating that the delayed and gradual implementation of the framework gave G-SIBs sufficient time to adapt without excessively restricting the provision of key services to the economy. This suggests that negative effects for the real sector are likely to be contained.

In Chapter 2 and 3, I focus on firm behavior and analyze how executive compensation and uncertainty affect corporate investment decisions. More precisely, Chapter 2 studies the impact of managerial incentives on the allocation of capital inside firms. I first provide empirical evidence that short-termist distortions of managerial incentives affect within-firm capital (mis)allocation. Since compensation practices and investment policies are endogenous firm choices, I use the reform of the FAS 123 accounting statement in the US as an exogenous shock to short-termist incentives. This reform, effective for US public companies after 2005, abolished an accounting advantage of option-based employee compensation and thereby raised the relative costs of equity-linked compensation to the benefit of monetary bonuses. I find that the reform-induced increase in short-term managerial incentives caused a wedge in investment expenditures. Firms that were subject to more short-term managerial incentives shifted investment expenditures towards assets with a shorter life span. This alteration of the firm-specific capital mix effectively shortened the durability of firms' capital stock. I then build a dynamic model of firm investments in which managers determine investment policies that I calibrate to the US economy to quantify the economic impact of such incentive distortions on output, investment and capital (mis)allocation. In my model, bonus-equity incentive contracts induce managers to make quasi-hyperbolic investment decisions and raise differences in the marginal products of capital goods. I show that even moderate increases in short-termist incentives, such as those around the accounting reform, may cause substantial inefficiencies. These inefficiencies lead to large within-firm spreads in the marginal products of capital goods, causing long-run declines in output and real wages.

In Chapter 3, I study the role of capital durability for the investment response under uncertainty. Exploiting within-firm variation in the holdings of capital goods with different durabilities, I show empirically that firms reduce durable investments more strongly than short-term investments when they face an increase in firm-specific uncertainty. Besides this shift in the investment composition, I also document implications for total corporate investments: firms with more durable capital cut total investments more strongly in response to an uncertainty shock. Hence, capital durability matters for the investment response under uncertainty, both at the asset- and at the firm-level. I rationalize my empirical findings by embedding them in the existing theory on real options. When investments are costly to revert, uncertainty generates option values of waiting that induce firms to scale back investment expenditures. It turns out that long-term investments have particularly high option values of waiting since these investments are tied to the firm's capital stock for a long period of time. In contrast to that, short-term investments can be adjusted more frequently, which is due to the higher depreciation rate, and give therefore the firm more flexibility in tracking the optimal capital stock when future business conditions are uncertain. Simulating uncertainty shocks in the framework of the neoclassical dynamic investment model yields investment responses that are qualitatively consistent with the investment dynamics found in the empirical part of this chapter.

I hope this thesis will provide a better understanding of bank and firm behavior in the macroeconomy. Although the research questions addressed are of particular relevance in times of crisis, parts of the insights gained can hopefully be applied to normal times as well. It should motivate researchers to further seek truth and should help policy-makers to take wiser decisions.

Chapter 1

The Impact of G-SIB Identification on Bank Lending: Evidence from Syndicated Loans*†

*This chapter is based on joint work with Markus Behn (European Central Bank). An earlier version is available as ECB Working Paper Series No. 2479.

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1.1 Introduction

The collapse of Lehman Brothers in September 2008 vividly demonstrated that the failure of an individual large institution can create significant stress in the financial system as a whole, with severe implications for economic growth and welfare. The failure was an exemplification of the so called 'too-big-to-fail' problem, whereby the system-wide costs of the failure of a systemically important bank oftentimes outweigh the social costs related to a bailout. 'Too-big-to-fail' considerations in turn create severe moral hazard problems within the affected banks, which take on more risk than socially optimal in the expectation of being bailed out in a stress event. In the aftermath of the financial crisis, policy-makers around the world adopted a series of reforms that were meant to address such problems by inducing banks to better internalize the negative externalities associated with their business activities. Key elements of the framework comprised additional loss absorbency and resolution requirements for Global Systemically Important Banks (G-SIBs), aimed at making these institutions less likely to fail and at making potential failures less costly for society.

In this study, we examine how the G-SIB reforms after 2012 affected the lending behavior of the designated institutions. The reforms are expected to have a positive impact on financial intermediation in the long-run since better capitalized and more resilient institutions should be better able to absorb shocks while sustaining the provision of key services to the real economy (e.g., Gambacorta & Shin 2018, Begenau 2020 or Bahaj & Malherbe 2020). In the short-term, however, banks could constrain credit supply as they adapt to the higher regulatory requirements associated with the new framework (e.g., Behn *et al.* 2016, Fraisse *et al.* 2019, Gropp *et al.* 2019). Moreover, if the reforms credibly mitigate the 'too-big-to-fail' problem, G-SIBs may experience a reduction in implicit funding cost subsidies that reflect bailout probabilities (e.g., Berndt *et al.* 2019), and they could partially pass on the resulting increase in funding costs to their borrowers. Finally, the reforms may have an effect on G-SIBs' risk taking, in line with the framework's intention to reduce moral hazard and make banks internalize both up- and downside risks of their investments.

While we cannot analyze the long-run effects of the reforms, our study examines potential short-term adjustments for the affected banks, using a difference-in-differences estimation methodology that distinguishes between G-SIBs and other banks. We rely on granular data on the global market for syndicated loans to the non-financial private sector, obtained from Dealogic Loanware. For the companies that are active in this market, syndicated loans represent a major source of funding and are therefore of high importance for the smooth functioning of their business operations (Sufi 2007). The high granularity of the loan-level data enables us to study potential effects along the various dimensions spelled out above, including effects of the reforms on loan volumes, portfolio composition, loan pricing, pricing sensitivity to borrower risk and loan maturity. Moreover, the inclusion of multi-dimensional fixed effects allows us to systematically control for a large variety of factors that could also exert an influence on the variables of interest.

Our findings illustrate that G-SIB designation did not exert a significant impact on overall credit supply of the affected banks. This holds true in a variety of specifications that control for both observed and unobserved factors affecting bank lending, including factors relating to credit demand. At the same time, G-SIB designation significantly affected the banks' risk appetite, leading to changes in portfolio composition. Relative to the control group, G-SIBs shifted lending towards better rated companies in the period following the reforms and also increased the share of collateralized lending – even within the same risk class of borrowers. Our estimates further show that other banks decreased their interest rates on loans by 7.3 percent more than G-SIBs after 2012, which suggests more conservative loan pricing by G-SIBs and may be interpreted as indirect evidence for a reduced implicit funding cost subsidy. This effect is most pronounced in the segment of less risky borrowers, whereas we do not see significant differences in the pricing of loans to riskier borrowers. Finally, we do not find any impact of G-SIB designation on the geographical composition of loans or on loan maturities.

Overall, our results provide suggestive evidence that the post-crisis reforms have effectively limited excessive risk taking and reduced funding cost subsidies for G-SIBs, while potential side effects for the real economy that could be associated with a potential reduction in credit supply have been contained. The documented decline in borrower- and loan-specific risk factors for G-SIBs indicates a more liable risk management, in line with the intention of stricter loss absorbance requirements and resolution reforms. Moreover, the decline in competitive pricing advantages is consistent with a reduction in implicit funding cost subsidies for G-SIBs, which may be seen as indirect evidence that the reforms credibly reduced bailout expectations associated with 'too-big-to-fail' considerations. At the same time, we do not see a reduction in the overall credit supply provided by G-SIBs, indicating that the delayed and gradual implementation of the framework gave G-SIBs sufficient time to adapt without excessively restricting the provision of key services to the economy. This suggests that negative effects for the real sector are likely to be contained, even before considering possible substitution effects that may arise if other banks take up the slack in cases where G-SIBs reduce certain business activities.

Our study adds to the literature on the role of 'too-big-to-fail' considerations and government guarantees in the banking sector, with particular focus on the lending process. Most closely related is the paper by Degryse *et al.* (2020), which was developed in parallel to our own and also studies the effect of G-SIB designation on corporate lending. The two papers complement each other as they are relying on different data sets and study different borrower characteristics, and also differ in the way in which credit risk is measured. Further, we add to their analysis by considering additional dimensions, such as pricing sensitivity to risk and geographical composition of the loan portfolio. While the findings of the two papers are broadly consistent with each other, Degryse *et al.* (2020) tend to find a slightly more pronounced effect of G-SIB designation on overall credit supply. Two other closely related papers are those by Gropp *et al.* (2014) and Beck *et al.* (2020). The former shows that the removal of *explicit* government guarantees in the German banking sector in the early 2000s induced banks to reduce credit risk by cutting off the riskiest borrowers from credit. Our findings suggest that the post-crisis G-SIB reforms credibly reduced *implicit* government guarantees relating to 'too-big-to-fail' considerations, with similar effects on credit risk taking of the affected banks. The latter paper examines the real effects of the bail-in of a major Portuguese institution in 2014. While that paper examines credit supply effects relating to an *application* of the post-crisis 'too-big-to-fail' framework (i.e., the resolution of a significant institution), our analysis focuses on potential effects relating to the *implementation* of the new framework. Besides these papers focusing on credit supply, there are a number of studies examining the evolution of implicit funding cost subsidies for G-SIBs in the post-reform period (e.g., Ueda & Weder di Mauro 2013, Gudmundsson 2016, Schich & Toader 2017, Cetorelli & Traina 2018, Berndt *et al.* 2019). Generally, these papers tend to find evidence for a reduction in funding cost subsidies – consistent with the relative increase in loan interest rates which we document – while the subsidies remain positive also after the implementation of the G-SIB reforms.[1]

In addition, our study also relates to the literature examining the relation between bank regulation and lending, which often focuses on capital regulation. As mentioned above, there is an emerging consensus in the literature that better capitalized institutions are better able to lend in the long-term, while the transition to higher capital requirements may induce short-term costs as banks constrain lending while adapting their balance sheets to the new rules (see also Van den Heuvel 2008, Admati & Hellwig 2013, Mendicino *et al.* 2019, in addition to the papers cited above). Recently, a number of papers examine the effects of higher macroprudential capital requirements on bank lending, mostly focusing on the Basel III Countercyclical Capital Buffer that is meant to be varied over time (e.g., Aiyar *et al.* 2014, Jimenez *et al.* 2017, Basten 2020). Cappelletti *et al.* (2019) study the impact of higher capital

[1]In addition, some papers examine the effects of the reforms on bank behavior more broadly, for example analyzing the evolution of G-SIB balance sheets or window dressing behavior (e.g., Violon *et al.* 2017, Behn *et al.* 2019).

buffers for systemic banks in a European context, finding limited effects on overall credit supply and a shift towards less risky borrowers, which is consistent with our own findings. Compared with their paper, we use much more granular data – thus improving identification – while focusing on the G-SIB framework and a much more international sample. Moreover, we examine not only the effects on aggregate loan volumes and risk weights, but also study the effects of reforms on loan pricing and portfolio composition more broadly, as well as loan maturity and pricing sensitivity to risk.

The remainder of this study is structured as follows. In the following Section 1.2, we present details on the regulatory framework that comes along with G-SIB designation. Section 1.3 gives an overview of the dataset we use in our empirical analysis. In Section 1.4, we outline our empirical strategy that we use to analyze the effect of the regulatory changes on lending behavior. Section 1.5 presents the main findings. After presenting additional robustness tests in Section 1.6, we conclude in Section 1.7.

1.2 The International G-SIB Framework

The Global Financial Crisis of 2008 (GFC) had illustrated that problems in individual large institutions can impose substantial stress on the financial system as a whole. Many banks were considered as 'too-big-to-fail', which generated severe moral hazard problems and eventually imposed significant costs on taxpayers, as massive public sector interventions were necessary in order to reinstate confidence in the banking sector. A clear lesson from the crisis was that measures needed to be taken in order to address the systemic and moral hazard risks associated with the existence of systemically important financial institutions.

A key element of the post-crisis regulatory framework that was designed in order to tackle these issues is the international framework for Global Systemically Important Banks (G-SIBs). The framework imposes additional capital requirements on G-SIBs and thereby increases their resilience against shocks (Basel Committee on Banking Supervision 2011). The identification of G-SIBs rests on an indicator-based approach that aggregates information from five individual risk categories, capturing banks' systemic importance through their size, interconnectedness, cross-jurisdictional activity, complexity and the substitutability of financial infrastructure or services they provide. Each of the five risk categories is broken down further into two or three risk indicators that are then aggregated into the G-SIB score. Banks for which the score exceeds a specific threshold are designated as G-SIBs and sorted into five different buckets associated with different additional capital requirements (ranging from 1 to 3.5 percent of risk-weighted assets). Moreover, G-SIBs need to fulfill minimum Total Loss Absorbing Capacity (TLAC) requirements and are subjected to more intense supervisory oversight as well as specific resolution planning requirements (see, e.g., Financial Stability Board 2011a,b, 2015 for the key elements of the framework).

The post-crisis framework for G-SIBs aims to reduce both the probability of a G-SIB failure (by imposing additional capital requirements) and the cost resulting from such a failure (by ensuring that G-SIBs can be resolved without severe systemic disruptions or exposing taxpayers to losses). Thus, in the long-run the reforms should make G-SIBs and the banking sector as a whole more resilient and better able to absorb shocks while keeping up lending to the real economy. In the short-run, however, G-SIBs may feel pressure to adjust their balance sheets in response to the new framework, and such adjustments could involve reductions in loan supply or substitution of riskier loans with safer ones. For example, a credible resolution framework could reduce implicit funding cost subsidies for G-SIBs, which could in turn translate into lower lending if G-SIBs pass on (part of) this increase in funding costs to their borrowers by increasing the interest rates on loans. Moreover, G-SIBs could adjust their risk taking behavior as the new framework is intended to reduce excessive risk taking by making it more likely that losses are imposed on G-SIB shareholders and creditors in case of a failure. Our study aims to examine these potential short-term adjustments in response to the new framework, while an analysis of the long-run effects mentioned above is out of scope.

The post-crisis reforms for G-SIBs have been implemented in a gradual manner, so that splitting the sample into pre- and post-reform periods is challenging. In particular, different reform elements followed different implementation timelines, were first announced globally and then implemented at national level, and usually included phase-in arrangements that further delayed the application of the final standard. Given these challenges, we follow a simple approach and split the sample into pre- and post-reform periods by using the Financial Stability Board's first publication of the G-SIB list in November 2011 as an event date (Financial Stability Board 2011b). Although the post-crisis framework was not yet fully implemented from 2012 onward, key elements of the future framework were published in parallel and gave banks an idea of how the new requirements would look like. Moreover, following the publication of the list banks knew for the first time whether or not they would be subjected to the new requirements for G-SIBs. For both reasons, banks may have started to adapt their lending behavior from 2012 onward in response to the reforms.

1.3 Data

This study combines two different types of data. We merge granular loan-level data on syndicated loans with bank balance sheet and income statement information. This section describes the data sources used and provides summary statistics on the relevant sample.

1.3.1 Loan-Level Data on Syndicated Loans

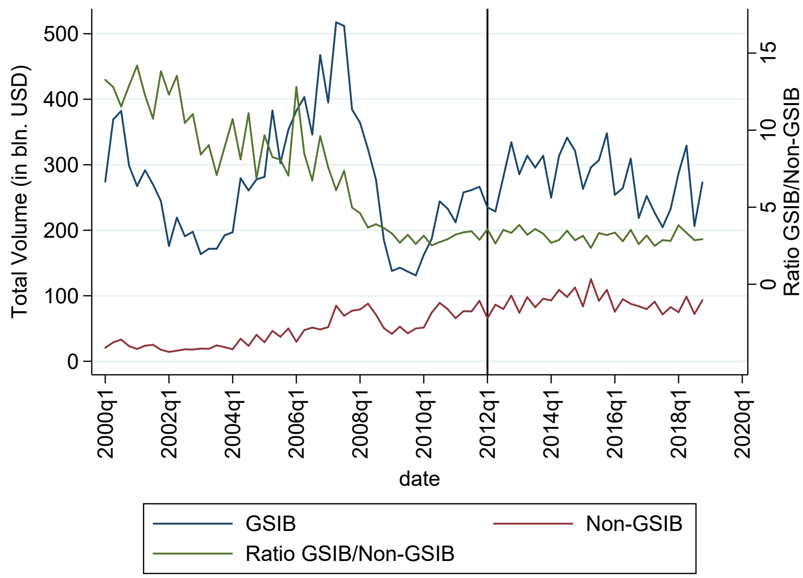
Our empirical analysis relies on data from the international syndicated loan market. A syndicated loan is granted jointly by a group of banks, including one or more lead banks and several participating banks. Before the loan agreement is signed, the lead banks have to assess the quality of the borrower and negotiate the conditions. Once the main conditions are set, lead banks offer parts of the loan to participating banks while remaining responsible for monitoring the borrower. Typically, a deal over a loan syndication is issued in several tranches, which can be seen as separate lines of credit that vary by volume, terms and conditions. Since the composition of the syndicate may also change across tranches within a given deal, we choose the tranche as the main unit of observation in our analysis.

Our primary source of data is Dealogic Loanware, which has been widely used for studying the evolution of the global syndicated loan market (e.g., Esty & Megginson 2003, Carey & Nini 2007, Popov & Van Horen 2015). The data contains tranche-level information on loan-specific characteristics such as volume, margin and maturity. Since it does not contain information on the amount lent by each participant in a tranche, we follow previous literature and allocate the entire tranche volume to the lead banks (e.g., Ivashina & Scharfstein 2010, Giannetti & Laeven 2012), where the allocation takes place based on an equal weight whenever a given loan is extended by more than one lead bank.[2] To focus on the real economy, we restrict the estimation sample to include only loans to the non-financial private sector. That is, we exclude interbank loans and loans granted to the public sector since the latter might be reflecting subsidized credit, special agreements or hidden guarantees. Moreover, Figure 1.1 illustrates how aggregate syndicated loan volumes for G-SIBs and other banks have evolved over time. Over the last 20 years, G-SIBs have issued substantially higher volumes than the group of all other banks. The ratio between volumes issued by both groups indicates strongly diverging trends in the run-up to and during the GFC, where G-SIBs reduced loan volumes both in absolute and in relative terms. To avoid issues with the parallel trends assumption in a difference-in-differences setup, we focus on the period between 2010 and 2018 in the empirical analysis.[3]

[2]Dealogic Loanware does not provide sufficient information on how the tranche volume is distributed among the lead banks, nor on what proportion of the tranche is allocated to the participating banks. However, according to Simons (1993) lead banks keep a substantial stake of the loan in their own portfolio. Our estimates could be biased if either G-SIBs or other banks systematically changed their roles after the reforms, e.g., increasingly acting as lead banks rather than participating banks or vice versa (since we consider only the former in our analysis). However, as shown in Figure A.2, the share of G-SIBs in total lead banks and participating banks is relatively stable over time and did not change after 2012, which mitigates this concern.

[3]In robustness checks, we have also estimated all specifications on the full sample ranging from 2000 to

Figure 1.1: Aggregate Lending Volumes over Time



Notes: We aggregate lending volumes by quarter and group of G-SIBs/Non-G-SIBs. For the ratio (right y-axis), we divide both volumes in a given quarter.

Table 1.1 shows descriptive statistics for the 160,000 tranche-level observations that are included in our sample, covering a total of 20,232 distinct borrowing firms from 149 countries.[4] The average tranche size for G-SIBs is USD 88 million, which compares with an average tranche size of USD 60 million for other banks, while both groups of banks charge similar interest rates on the loans.[5] G-SIBs tend to lend with a shorter average maturity and with a lower share of collateralized loans. Furthermore, we have information on the credit ratings of 1,476 firms at the time of the signing of the deal, representing around 25 percent of the observations in our overall sample.[6] G-SIBs lend to slightly better-rated borrowers on average. Moreover, G-SIBs are more involved in foreign lending, with almost 53 percent of tranches being granted to borrowers abroad, compared with 40 percent for other banks. The last row indicates that the average tranche structure does not substantially differ across both groups of banks. On average, a tranche is originated by 4.7-4.8 lead banks.

2018 (see Section 1.6 for further discussion on this).

[4] An overview of the major borrowing countries and industries in the sample is provided in Figure A.3.

[5] The information on interest rates is available for slightly less than half of the sample. For the baseline setting, we use the overall margin, which includes all incurred costs. Later on, we also distinguish between the fee and the pure interest rate margin component. Moreover, in the context of syndicated loans, it is common practice for interest rates to be expressed as premiums on base rates (e.g., LIBOR, EURIBOR, HKIBOR). We also run robustness checks where we include these base rates.

[6] We take a simple average of the credit rating from Moody's and Standard & Poor's. When one of them is missing, we rely solely on the other (non-missing) rating. Firms for which we are unable to obtain any information on the rating are excluded from the corresponding regressions on borrower risk.

Table 1.1: Syndicated Loan Market – Tranche-Level Information

	G-SIBs			Non-G-SIBs		
	N	Mean	Std. Dev.	*N*	Mean	Std. Dev.
Tranche Size (in USD k)	108,929	88230.1	142901.7	52,354	59527.5	104141.6
Margin (in bp)	51,251	270.01	154.52	20,646	264.13	163.61
Maturity (in yrs)	106,051	5.0036	3.3155	49,941	5.6395	4.1000
Rating	33,223	10.5550	3.3146	7,838	10.0995	3.0446
Secured Y/N	108,818	0.3240	0.4680	52,331	0.4481	0.4973
Domestic Y/N	108,929	0.4792	0.4996	52,354	0.6071	0.4884
Number of Lead Banks	108,929	4.8064	4.6359	52,354	4.6796	4.3375

Notes: This table summarizes our tranche level data for the period 2010-2018. We calculate summary statistics for the rating variable by transforming the S&P rating scale to a numerical scale starting with '0' representing 'D' up to '21' representing 'AAA'. A rating of '10' corresponds to 'BB'.

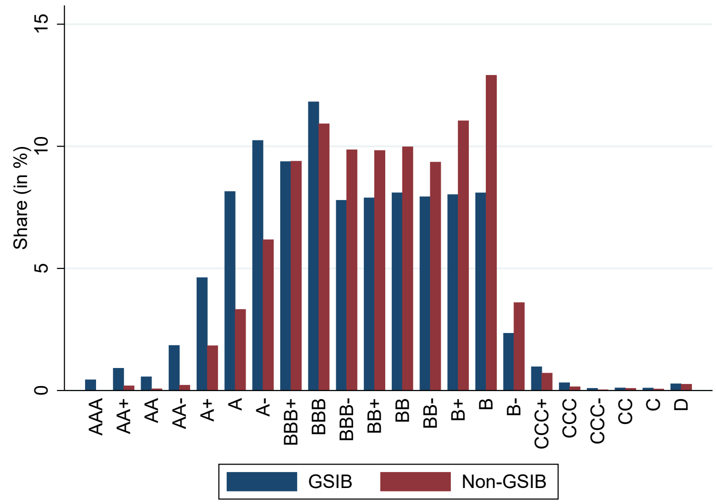
Further information on the type of loans included in the sample is shown in Figure A.3, which provides an overview of the predominant borrowing countries and industries. In addition, Figure 1.2 illustrates the lending allocation with respect to the borrower's credit rating for the subsample of observations for which this information is available. Generally, most of the loans are granted to medium-graded as well as non-investment speculative and highly speculative graded companies. Reflecting the better average rating, the distribution for G-SIBs is somewhat shifted to the left relative to the distribution for other banks. Nevertheless, there is significant overlap between the two distributions, which is important for identification purposes in the empirical analysis. Descriptive information on the pricing of loans is shown in Figure 1.3, which illustrates that interest rates vary substantially across risk classes. Both groups of banks demand higher interest rates from poorly-rated borrowers.[7] Thus, banks are clearly demanding compensation for taking on more risk.

1.3.2 Bank-Level Data on Balance Sheets and Income Statements

We match the syndicated loan data with bank balance sheet and income statement information from SNL Financial (provided by S&P Global Market Intelligence). Unfortunately, Dealogic Loanware and SNL Financial do not share a common identifier, which makes the matching process quite challenging as the only commonality lies in the name of the bank. To improve the matching, we make use of a web search-based matching method in the spirit of

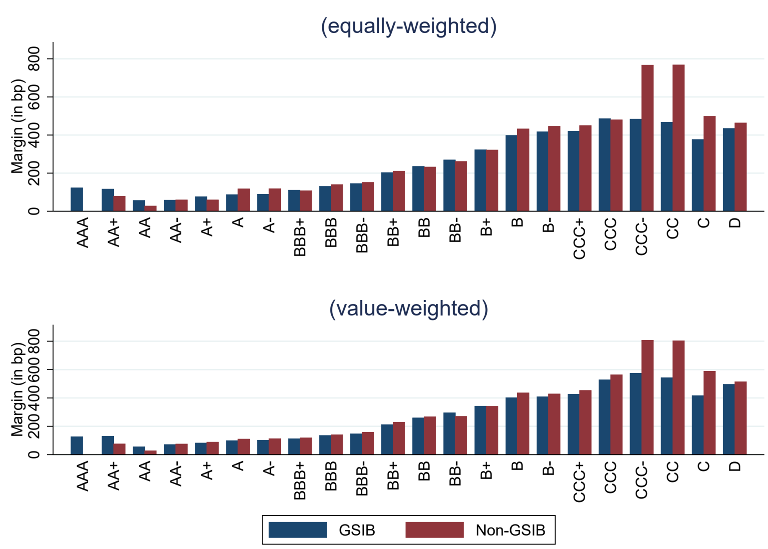
[7]Interestingly, the interest rates for extremely poorly rated borrowers seem to be stagnating or, in some cases, even slightly declining. Possible explanations for this, inter alia, include cross-subsidization of other products sold to the same borrower or evergreening of exposures to the respective borrower. Given the extremely low credit volumes for these risk classes (recall Figure 1.2), we do not think that this pattern constitutes a severe challenge for our empirical analysis.

Figure 1.2: Lending Volume by Risk Class



Notes: We aggregate lending volumes by credit rating of the borrowing party and group of G-SIBs/Non-G-SIBs. If the ratings from Moody's Corporation and S&P Financial Services LLC differ by an odd number of notches, we round the average to the next lower rating notch. Then, we calculate the respective portfolio share for each group of banks.

Figure 1.3: Margins by Risk Class



Notes: For each group of banks, we calculate the margin per credit rating by applying an unweighted mean in the top panel and a value-weighted average in the bottom panel. If the ratings from Moody's Corporation and S&P Financial Services LLC differ by an odd number of notches, we round the average to the next lower rating notch.

Autor *et al.* (2016) (see Annex A1 for further details). Our final sample comprises 683 banks (34 G-SIBs and 649 Non-G-SIBs) from 80 different countries, which account for 86 percent of total lending in the Dealogic Database. As quarterly bank characteristics are often missing, we use bank controls at the annual frequency to account for time-varying differences across banks in the empirical analysis.

In Table 1.2, we provide summary statistics for the banks in our matched sample. Not surprisingly, G-SIBs are much larger: total assets of the median G-SIB exceed the median counterpart of the control group by a factor of 29. Moreover, G-SIBs are relatively less involved in providing loans, which is evident by the consistently lower Loan-to-Deposit (or Loan-to-Asset) ratio and the lower Net Interest Income relative to Total Assets. The problem of non-performing loans is also less severe. Finally, syndicated loans account for approximately 6.5 percent of the total loan portfolio of the median G-SIB, while this share is at about one percent for the median Non-G-SIB.

Table 1.2: Summary Statistics on Balance Sheet Items and P&L Metrics

(a) G-SIBs

G-SIBs	*N*	Mean	P10	P50	P90	Std. Dev.
Total Assets (in USD bn)	289	1598.6	663.50	1578.5	2589.8	756.93
Total Net Loans (in USD bn)	286	673.39	125.72	700.63	1040.3	380.52
Total Deposits (in USD bn)	286	819.53	187.82	721.94	1668.0	552.39
Net Interest Income (in USD bn)	266	24.634	6.3566	18.534	49.483	16.903
Loan-to-Deposit Ratio	286	0.9099	0.5670	0.7681	1.2551	0.4909
Tier 1 Capital Ratio	248	0.1369	0.1088	0.1319	0.1722	0.02503
NPL Ratio	198	0.01377	0.001728	0.008733	0.02831	0.01570
Return on Average Assets (in %)	287	0.4978	-0.02963	0.4433	1.1692	0.4926
Synd Loan Volume to Total Net Loans (in %)	286	12.868	1.0359	6.5342	23.462	20.201

(b) Non-G-SIBs

Non-G-SIBs	*N*	Mean	P10	P50	P90	Std. Dev.
Total Assets (in USD bn)	2,805	135.14	8.2008	53.814	379.85	218.44
Total Net Loans (in USD bn)	2,709	77.103	4.0488	32.262	208.64	126.85
Total Deposits (in USD bn)	2,557	78.459	5.8299	37.117	212.24	124.54
Net Interest Income (in USD bn)	2,651	2.5750	0.1677	0.9744	6.0348	4.3862
Loan-to-Deposit Ratio	2,557	1.0701	0.6237	0.8994	1.6136	0.6461
Tier 1 Capital Ratio	2,406	0.1283	0.08667	0.1232	0.1764	0.03406
NPL Ratio	1,999	0.02042	0.002344	0.01291	0.05191	0.02149
Return on Average Assets (in %)	2,713	0.8745	0.09135	0.8140	1.9729	0.7408
Synd Loan Volume to Total Net Loans (in %)	2,709	5.9465	0.2964	1.0227	7.8790	18.504

Notes: Both panels show summary statistics for annual bank-specific financial indicators obtained from SNL Financial for the period 2010-2018. For the last row in each panel, we sum up tranche volumes of syndicated loans (provided by Dealogic Loanware) by bank-year and divide them by Total Net Loans (provided by SNL Financial).

1.4 Empirical Strategy

This section describes the difference-in-differences methodology that we use to assess whether banks that were designated as G-SIBs have adjusted their lending behavior relative to other banks after the reforms. The focus in this respect is on loan volumes, portfolio composition, loan pricing and maturity, and the sensitivity of loan pricing to loan risk.

1.4.1 Effect on Lending Volumes

The way in which our data set is constructed requires aggregation of data at various levels in order to draw conclusions about lending behavior. Specifically, the data set records each loan tranche only once – at the time of issuance – so that it is not possible to track the evolution of a specific firm-bank relationship over time (as it is often done in the credit supply literature relying on credit register data). While running regressions at tranche level would allow to assess how average tranche size has evolved, it would ignore the fact that banks can also change the number of loans granted. The latter, however, is particularly important for the evolution of total bank lending in the syndicated loan market, as stressed by Giannetti & Laeven (2012). For this reason, we start the empirical analysis by aggregating lending volumes at the bank × quarter level and then estimate the following equation:

$$\mathit{Log(Lending}_{i,t}\mathit{)} = \beta_1 \times GSIB_i \times Post2012_t + \beta_2 \times \mathit{Bank\text{-}Controls}_{i,t} + \lambda_i + \lambda_t + u_{i,t} \quad (1.1)$$

The dependent variable $\mathit{Log(Lending}_{i,t}\mathit{)}$ is the logarithm of the total loan volume that was originated by bank i in quarter t. $GSIB_i$ is a dummy variable taking the value of 1 if the bank was designated as G-SIB at least once between 2012 and 2016, and zero otherwise.[8] $Post2012_t$ is another binary variable, which is equal to 1 for all observations occurring after $2011Q4$, and otherwise equal to zero. The coefficient of interest is β_1, which indicates how G-SIBs have adjusted their average loan volumes after 2012 relative to banks in the control group. To account for time-varying heterogeneity between banks, the specification includes measures of bank size, profitability and capital adequacy as control variables. Moreover, bank fixed effects λ_i control for both observed and unobserved structural differences between different banks, including differences in size, complexity and systemic importance that relate to G-SIB designation itself. In the same manner, the quarterly dummies λ_t control for

[8] To address systematic differences between treatment and control group in terms of bank size, we also conduct robustness checks where we restrict the control group to include only larger banks (i.e., banks with total assets larger than USD 100 bn or banks included in the G-SIB assessment sample; see Section 1.6). In additional robustness checks, we include only the banks designated in November 2011 as G-SIBs while excluding the five banks that were first designated at a later point from the analysis. All our results are robust to this change.

heterogeneity over time. Finally, the stochastic error terms $u_{i,t}$ are clustered at the bank-level.

While results for Equation 1.1 can provide insights on the evolution of aggregate loan volumes for G-SIBs and other banks, the specification cannot control for possible differences in credit demand that could also affect the results. For example, G-SIBs could be lending to firms in different countries or industries with different economic conditions, and such differences would complicate the identification of supply side effects in Equation 1.1. To address this issue, we estimate a modified version of the Khwaja & Mian (2008) estimator, that is widely used in the credit supply literature (e.g., Behn *et al.* 2016, Jimenez *et al.* 2017, Fraisse *et al.* 2019). Specifically, we aggregate lending volumes by bank, quarter and country-industry ('*natind*') of the borrowing firm and include country-industry × quarter fixed effects $\lambda_{t,natind}$ to account for time-varying credit demand shocks and other types of heterogeneity that are specific to a given country-industry. In principle, the disaggregated structure of our data would have allowed us to go even more granular and conduct analysis at the level of the individual borrower while including firm fixed effects. However, we choose the country-industry level instead since the average number of syndicated loans granted to a specific firm is relatively small, particularly when looking at the same time period (see, e.g., Berg *et al.* 2016a, Acharya *et al.* 2017 or Gropp *et al.* (2019) for similar approaches).[9] Taking all this into account, our second specification is the following:

$$\begin{aligned} \mathit{Log(Lending}_{i,t,natind}) = &\beta_1 \times GSIB_i \times Post2012_t + \beta_2 \times \mathit{Bank\text{-}Controls}_{i,t} \\ &+ \lambda_i + \lambda_{t,natind} + u_{i,t,natind} \end{aligned} \tag{1.2}$$

The dependent variable $\mathit{Log(Lending}_{i,t,natind})$ is the logarithm of the total loan volume which a specific bank i grants over quarter t to a specific country-industry *natind*. Besides the different level of aggregation and the inclusion of more granular fixed effects, all other variables in the regressions are defined as above. Moreover, standard errors in these and the subsequent regressions are double-clustered at the bank and country-quarter level.

1.4.2 Effect on Portfolio Composition

The high granularity of our data also allows analyzing whether the reforms had any differential effects on portfolio composition for G-SIBs relative to other banks. Specifically, we can test whether there are any differential effects with respect to borrower risk, the amount of secured lending and the amount of domestic versus foreign lending.

[9] Reassuringly, Degryse *et al.* (2019) show that borrower fixed effects based on firm clusters yield bank credit supply shocks that are comparable to those obtained using firm fixed effects.

Borrower Risk

To analyze potential effects of the reforms on borrower risk, we aggregate tranche volumes by bank i, quarter t, company rating rat and borrower country c, and then estimate the following regression equation:[10]

$$\begin{aligned} \mathit{Log(Lending}_{i,t,rat,c}) = &\beta_1 \times GSIB_i \times Post2012_t \times Rating_{rat} \\ &+ \lambda_{i,t} + \lambda_{t,rat,c} + \lambda_{i,rat,c} + u_{i,t,rat,c} \end{aligned} \tag{1.3}$$

The dependent variable $\mathit{Log(Lending}_{i,t,rat,c})$ is the amount of all loans which a given bank i grants to companies with rating rat in country c at time t. The *Rating* variable is a categorial variable that separates the observations in our sample into five risk classes based on the borrowers' credit rating, where a lower value of this variable corresponds to a riskier rating (see Annex A2 for further information). All other variables are defined as above. The coefficient β_1 for the triple interaction term indicates whether G-SIBs differentially adjusted their lending relative to the control group after 2012, depending on the riskiness of the borrower. A positive coefficient would indicate that the reform has encouraged G-SIBs, relative to other banks, to shift more lending from riskier towards safer borrowers (or to shift less lending from safer towards riskier borrowers). The use of multi-dimensional fixed effects allows us to shut down a multitude of possible channels which could have had an effect on the risk-taking behavior of banks. Bank $\times$ quarter fixed effects $\lambda_{i,t}$ absorb all time-varying bank-specific factors that affect loans in different risk classes to the same extent.[11] Quarter $\times$ rating $\times$ country fixed effects $\lambda_{t,rat,c}$ control for time-varying demand shocks on the country-rating level. These are particularly relevant if there were changes in the demand for credit that are specific to firms in a given rating class within a given country. Finally, bank $\times$ rating $\times$ country fixed effects $\lambda_{i,rat,c}$ absorb all structural differences in the banks' preferences for specific risk-profiles within a geographical destination.

[10] As explained in Section 1.3, the information on the borrower's credit ratings is missing for about 75 percent of the tranche level observations in our sample, so that this aggregation is based on a reduced sample. Since the introduction of the rating dimension adds an additional level of aggregation, which further thins out the number of identifying observations within a fixed effect cluster, we additionally aggregate at the country rather than the country-industry level in these tests, to not lose too much explanatory power.

[11] As some banks extend loans only to a single rating class within a given quarter (so that these observations are absorbed by the bank $\times$ quarter FEs and do not help to identify β_1), we also estimate an alternative specification that includes bank control variables instead of bank $\times$ quarter fixed effects and thus increases the number of identifying observations. Alternatively, we also aggregate our data at annual rather than quarterly level to obtain more variation within a given bank-time period.

Secured vs Unsecured Lending

While the company rating is a firm-specific risk indicator, the riskiness of an individual loan is also affected by the loan-specific terms and conditions, e.g., the amount of collateralization. To test whether G-SIBs have adjusted the share of collateralized lending after 2012, we make use of loan tranche-specific information that indicates whether the respective loan tranche is secured with collateral or not.[12] We aggregate lending volumes by bank i, quarter t, status of collateralization *sec* and borrowing country c, and then estimate a modified version of Equation 1.3, where we replace the rating classification with the binary variable that indicates the status of collateralization. Furthermore, to account for the possibility that the status of collateralization depends on the riskiness of the respective borrower, we also aggregate lending volumes by bank, quarter, status of collateralization and credit rating, and estimate the effect on secured lending within a particular risk class:[13]

$$\begin{aligned} \mathit{Log(Lending}_{i,t,sec,rat}) = &\beta_1 \times GSIB_i \times Post2012_t \times \mathit{Secured}_{sec} \\ &+ \lambda_{i,t} + \lambda_{t,sec,rat} + \lambda_{i,sec,rat} + u_{i,t,sec,rat} \end{aligned} \tag{1.4}$$

The dependent variable $\mathit{Log(Lending}_{i,t,sec,rat})$ is the amount of all loans which a given bank i grants to companies with collateralization status *sec* and rating *rat* at time t. The *Secured* variable indicates collateralization status and all other variables are defined as above. A positive coefficient for β_1 would indicate that the reform has encouraged G-SIBs, relative to other banks, to require a higher share of collateralization for loans to firms in a given rating class. Multi-dimensional fixed effects account for time-varying heterogeneity across banks, time-varying heterogeneity between the amount of secured lending that is obtained by firms in a specific rating class and bank-specific heterogeneity with respect to the amount of secured lending for loans to firms in a specific risk class.

Domestic vs Foreign Lending

To test whether G-SIBs have altered the geographical composition of their lending activities relative to other banks in the post reform era, we aggregate lending volumes at the bank $\times$

[12] The data set does not include information on the value of the respective collateral or on the fraction of the loan tranche that is secured. It only indicates whether the loan tranche is secured or not.

[13] Ignoring borrower risk could lead to an omitted variable problem, for example if banks generally require more collateral for riskier borrowers. We omit the country dimension in this regression since otherwise the number of identifying observations within a given fixed effect cluster becomes too small.

quarter × borrower country level and estimate the following equation:

$$\begin{aligned} \mathit{Log(Lending}_{i,t,c}) = &\beta_1 \times GSIB_i \times Post2012_t \times \mathit{Domestic} \\ &+ \lambda_{i,t} + \lambda_{t,c} + \lambda_{i,c} + u_{i,t,c} \end{aligned} \tag{1.5}$$

$\mathit{Log(Lending}_{i,t,c})$ specifies the amount of all loans which a given bank i granted to companies in a given country c at time t. *Domestic* is a binary variable, which is equal to 1 if the home country of the bank coincides with the home country of the borrower, and otherwise equal to zero. The regression includes bank × quarter, quarter × country and bank × country fixed effects to improve identification. In this equation, the coefficient β_1 captures whether G-SIBs differentially adjusted their shares of domestic and foreign lending activities relative to banks in the control group. A positive coefficient for β_1 would imply that G-SIBs have increased the share of domestic lending since 2012.

1.4.3 Effect on Interest Rate and Maturity

We also analyze whether and how G-SIBs have adjusted their pricing behavior and the maturity of their loans in the post-reform period. This issue can be examined directly at tranche level, i.e., the most granular level of observation in our data set.[14] This is because in these tests we are interested in how average margins and maturities for the originated loans have evolved, in contrast to the loan volume regressions where we were interested in the evolution of total bank lending and not in average loan volumes. Our most saturated regression equation in this section takes the following form:

$$\begin{aligned} X_{i,tranche} = &\beta_1 \times GSIB_i \times Post2012_t + \beta_2 \times \mathit{Controls}_{tranche} \\ &+ \beta_3 \times \mathit{Bank\text{-}Controls}_{i,t} + \lambda_i + \lambda_{t,natind} + u_{i,tranche} \end{aligned} \tag{1.6}$$

with $X \in$ (*Log(Margin), Maturity*).[15] The coefficient β_1 measures how G-SIBs have changed their pricing behavior and the average maturity of originated tranches after the reforms when compared with other banks. Bank control variables are the same as above, and the specification further includes bank and country-industry × quarter fixed effects. Moreover, we control for a number of tranche and firm characteristics, which might have an effect on

[14] As one tranche could be originated by more than one lead bank, our precise unit of observation is the tranche-bank level, where the allocation among lead banks takes place based on an equal weight (see Section 1.3).

[15] To better capture the right-skewed distribution of interest rate margins, we take logarithm for this dependent variable. Results are very similar when we use the margin in absolute terms instead. We cannot include bank × quarter fixed effects in these regressions, since they would absorb the coefficient of interest, β_1.

the contractual interest payment and the maturity. These are the tranche amount, the status of collateralization, the credit rating of the borrowing firm and the tranche maturity (in the case where we use the margin as dependent variable; when the maturity is the dependent variable, we include the interest rate margin as a control). To account for possible correlation across tranches within a particular deal, we also double-cluster standard errors at bank and deal level in alternative specifications for the tranche level regressions (in addition to the usual clustering at bank and country-quarter level).[16]

1.4.4 Effect on the Pricing Sensitivity to Risk

Finally, we investigate whether G-SIBs have changed their behavior when pricing borrower risk. Specifically, we estimate the following regression equation:

$$\begin{aligned} \mathit{Log(Margin}_{i,tranche}) = {} & \beta_1 \times GSIB_i \times Post2012_t \times Rating_{rat} + \beta_2 \times Controls_{tranche} \\ & + \lambda_{i,t} + \lambda_{t,rat,c} + \lambda_{i,rat,c} + u_{i,tranche} \end{aligned} \tag{1.7}$$

All variables are defined as above. A positive coefficient for β_1 would imply that G-SIBs have more strongly increased (or less strongly decreased) the margins for better rated companies than for lower rated companies when compared with banks in the control group (i.e., they have reduced the pricing differential for risk in relative terms). The regression includes tranche-level control variables and multiple high-dimensional fixed effects to control for other factors, in the same way as specified above.[17]

1.5 Results

This section presents our main findings on the effects of reforms on G-SIBs' lending behavior, including loan volumes, portfolio composition, loan pricing, pricing sensitivity to borrower risk and loan maturity.

1.5.1 Effect on Lending Volumes

Table 1.3 shows the results for a variety of specifications analyzing the impact of the reforms on loan volumes. We do not identify a significant differential effect for G-SIBs relative to the control group in any of these specifications.

[16] As the borrowing company does not change within a given deal, credit conditions of tranches within a deal could possibly depend on each other.

[17] To increase the number of identifying observations, we also replace bank × quarter fixed effects with bank controls and re-estimate Equation 1.7.

Table 1.3: Effects of the G-SIB Reforms on Lending Volumes

VARIABLES	(1) Log(Lending)	(2) Log(Lending)	(3) Log(Lending)	(4) Log(# of Deals)	(5) 1(Lending > 0)
Post2012 × GSIB	0.0595	-0.0229	0.0246	0.00761	0.000875
	(0.0972)	(0.0513)	(0.123)	(0.00542)	(0.00651)
Observations	6,145	52,820	693,996	693,996	693,996
R-squared	0.801	0.656	0.215	0.138	0.215
Bank Controls	×	×	×	×	×
Bank FE	×	×	×	×	×
Quarter FE	×				
Qtr x Ctr x Ind FE		×	×	×	×
Firms	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind
Time	2010 - 2018	2010 - 2018	2010 - 2018	2010 - 2018	2010 - 2018
Clustering	Bank	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Ctr x Ind x Qtr
Margin	Int	Int	Ext & Int	Ext & Int	Ext
Model	Log w/o zeros	Log w/o zeros	Log w/ zeros	Log w/ zeros	LPM
Frequency	Quarterly	Quarterly	Quarterly	Quarterly	Quarterly
Unit of Obs	Bank x Qtr	Bank x Qtr x Ctr x Ind	Bank x Qtr x Ctr x Ind	Bank x Qtr x Ctr x Ind	Bank x Qtr x Ctr x Ind
Nr. of Banks	377	375	541	541	541

Notes: Table 1.3 estimates the effect on lending volumes. Column 1 includes quarter FE, columns 2-5 make use of quarter, borrower-country, industry FE. While column 1 and 2 capture the intensive margin only, column 3 and 4 focus on both intensive and extensive margin. Column 4 uses number of deals as dependent variable, and column 5 estimates a Linear Probability Model. ***, **, and * indicate statistical significance at the 1%-, 5%- and 10%-level.

Column 1 shows the results for Equation 1.1, where we aggregate lending volumes at the bank × quarter level. The remaining columns include the results for the Khwaja & Mian (2008)-type estimator outlined in Equation 1.2, where loan volumes are aggregated at the bank × quarter × country-industry level in order to control for time-varying credit demand shocks at the country-industry level. Column 2 focuses on the intensive lending margin and includes only non-zero observations, while column 3 includes also quarters in which the respective bank did not extend any loans to firms in the respective country-industry and thus captures both the intensive and the extensive lending margin.[18] Results continue to be insignificant when we use the number of deals instead of the lending volume as a dependent variable (column 4). In the last column, we test for possible effects at the extensive margin only by estimating a Linear Probability Model that uses as dependent variable a binary variable, which is equal to one if the respective bank extended a loan to the respective

[18]That is, the sample in column 3 is a balanced panel in which we assign the value of zero to bank × quarter × country-industry observations that did not record positive lending volumes. We omit bank × country-industry clusters that never record any positive lending volumes throughout the sample period.

country-industry in the relevant quarter, and zero otherwise. The coefficient of interest remains insignificant.

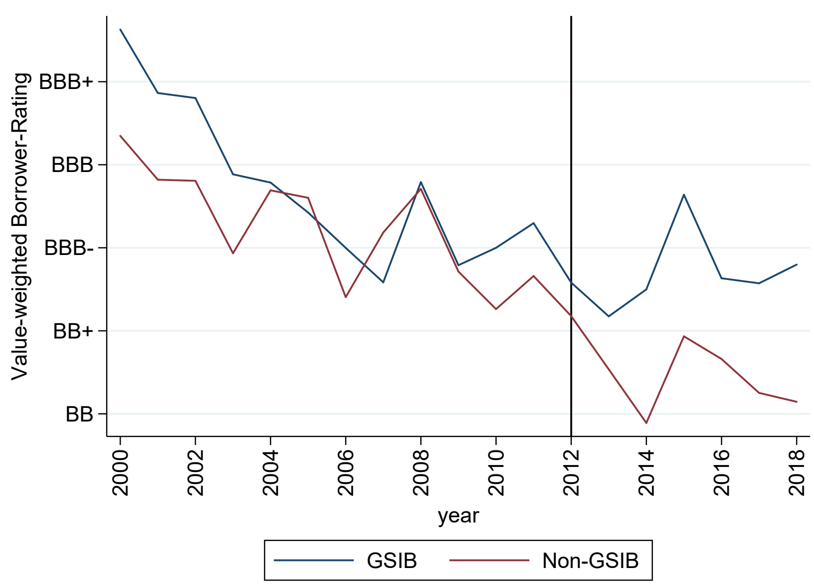
1.5.2 Effect on Portfolio Composition

This subsection examines whether the reforms had any effects on the banks' portfolio composition, including differentiation by borrower risk, status of collateralization and borrower location (domestic vs. foreign).

Borrower Risk

Figure 1.4 illustrates that the (weighted) average borrower credit rating (at origination) continuously declined for both G-SIBs and other banks in the period until 2012. Thereafter, the average rating stabilized for G-SIBs, while the declining trend continued for other banks.

Figure 1.4: Value-Weighted Borrower Rating over Time



Notes: For both G-SIBs and Non-G-SIBs, we calculate the share of funds which is attributed to a specific rating class in a given year. We transform the credit ratings to a numerical Standard & Poor's scale with '0' representing 'D' up to '21' representing 'AAA' and compute a weighted average. For illustration purpose, we leave the labels of the y-axis with the original rating classification.

Table 1.4 complements the descriptive evidence in Figure 1.4 with a formal regression analysis. In Panel (a), columns 1-3, we aggregate lending volumes by bank, quarter, credit rating and borrower country. Column 1 includes the full set of multidimensional fixed effects (Equation 1.3) and is therefore our most stringent specification. The significant coefficient for the triple interaction term indicates that G-SIBs shifted less lending to borrowers with worse credit ratings in the post-reform period when compared with other banks, consistent with the patterns documented in Figure 1.4. Column 2 estimates a less stringent specification by replacing bank × quarter fixed effects with bank control variables, using the same sample as in column 1. The coefficient of interest remains significantly positive. For this less stringent specification, we can increase the number of identifying observations by including also loans from banks that only lend to firms in a single rating class within a given quarter.[19] The triple interaction term on this expanded sample is still positive but loses statistical significance (column 3). As an alternative way to obtain more rating variation within a given bank-time, we also aggregate lending volumes by bank, year (instead of quarter), credit rating and borrower country, and apply exactly the same estimation procedure as before. Results are presented in columns 4-6 of Panel (a) and show a positive and significant coefficient for the triple interaction term in all three specifications. Overall, although not significant in all specifications, the results in this panel suggest that G-SIBs shifted lending towards less risky companies when compared with the control group in the post-reform period.

To test whether differential adjustments between G-SIBs and other banks are stronger in any specific segment of loans, Panel (b) of Table 1.4 splits the sample into more and less risky borrowers, where we consider borrowers with an investment grade credit rating as less risky (these are all firms with ratings of *BBB-* or better). Results reveal that the relative adjustment mainly took place in the segment of less risky (investment grade) borrowers, i.e., for loans to companies in the top two of our five risk classes. The coefficient in column 1 indicates that after the reforms G-SIBs have granted 27.5 percent more loans to investment grade firms in a given country, relative to banks in the control group. We do not detect any significant differences in the more risky segment (column 2), and the same pattern emerges when using yearly instead of quarterly data in columns 3 and 4.

Secured vs Unsecured Lending

Next, we analyze the role of collateralized lending. In general, requiring collateral helps to address frictions arising from asymmetric information and mitigates the impact of possible borrower defaults, thus reducing the risk of the loan portfolio. Figure 1.5 shows that for most of the sample period G-SIBs collateralize around 20-25 percent of their loans by volume. From 2015, however, there is a sharp increase in the collateralization ratio to about 40 percent. This increase also occurred for banks in the control group, but earlier and to even

[19]The number of banks in this specification more than doubles, while the number of observations increases only by about eight percent. For the specification in column 1, the additional observations are absorbed by the bank × quarter fixed effect.

Table 1.4: Effects of the G-SIB Reforms on Portfolio Riskiness

(a) Lending Sensitivity to Risk

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Log(Lending)	Log(Lending)	Log(Lending)	Log(Lending)	Log(Lending)	Log(Lending)
Post2012 × GSIB × Rat	0.219**	0.160*	0.124	0.203*	0.227**	0.203**
	(0.0976)	(0.0933)	(0.0835)	(0.106)	(0.0928)	(0.0882)
Post2012 × GSIB		-0.594	-0.425		-0.806***	-0.625**
		(0.365)	(0.328)		(0.300)	(0.300)
Observations	9,525	9,525	10,297	6,284	6,284	6,542
R-squared	0.850	0.814	0.815	0.826	0.802	0.803
Bank Controls		×	×		×	×
Bank x Time FE	×			×		
Rat x Ctr x Time FE	×	×	×	×	×	×
Bank x Rat x Ctr FE	×	×	×	×	×	×
Firms	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind
Time	2010 - 2018	2010 - 2018	2010 - 2018	2010 - 2018	2010 - 2018	2010 - 2018
Clustering	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Ctr x Yr	Bank & Ctr x Yr	Bank & Ctr x Yr
Frequency	Quarterly	Quarterly	Quarterly	Yearly	Yearly	Yearly
Sample	Full	Condensed	Full	Full	Condensed	Full
Unit of Obs	Bank x Qtr x Rat x Ctr	Bank x Qtr x Rat x Ctr	Bank x Qtr x Rat x Ctr	Bank x Yr x Rat x Ctr	Bank x Yr x Rat x Ctr	Bank x Yr x Rat x Ctr
Nr. of Banks	58	58	119	68	68	119

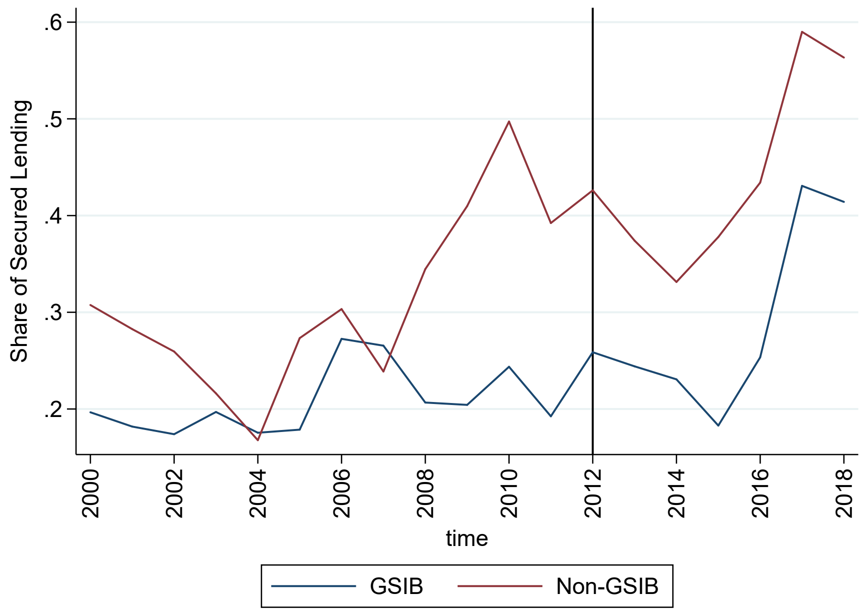
(b) Breakdown by Risk Segment

	(1)	(2)	(3)	(4)
VARIABLES	Log(Lending)	Log(Lending)	Log(Lending)	Log(Lending)
Post2012 × GSIB	0.275**	-0.118	0.405**	0.0952
	(0.127)	(0.158)	(0.159)	(0.170)
Observations	5,186	4,459	3,320	2,892
R-squared	0.697	0.683	0.558	0.595
Bank Controls	×	×	×	×
Bank FE	×	×	×	×
Country x Time FE	×	×	×	×
Firms	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind
Time	2010 - 2018	2010 - 2018	2010 - 2018	2010 - 2018
Clustering	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Ctr x Yr	Bank & Ctr x Yr
Frequency	Quarterly	Quarterly	Yearly	Yearly
Risk Segment	Safe	Risky	Safe	Risky
Unit of Obs	Bank x Qtr x Ctr	Bank x Qtr x Ctr	Bank x Yr x Ctr	Bank x Yr x Ctr
Nr. of Banks	102	114	102	113

Notes: Panel (a) estimates the effect on the lending sensitivity to risk. In columns 1-3, we aggregate lending volumes by bank, risk class, borrowing country and quarter, in columns 4-6 we aggregate by bank, risk class, borrowing country and year. *Rat* is our own-created, five-bin rating variable. In Panel (b), we estimate the effect for a particular risk segment, where the safe segment includes all investment grade credit ratings, i.e., ratings equal to or greater than *BBB-*. The risky segment contains all the remaining credit ratings (i.e., less than *BBB-*). ***, **, and * indicate statistical significance at the 1%-, 5%- and 10%-level.

higher levels than for G-SIBs. Specifically, other banks started to request more collateral already during the GFC, while G-SIBs did not adjust at that time. Thus, G-SIBs have been catching up with other banks in the post-reform period.

Figure 1.5: Share of Secured Lending over Time



Notes: For both G-SIBs and Non-G-SIBs, we calculate the share of funds which is secured by collateral in a given year.

Table 1.5 analyzes this issue in more detail by presenting results for the regression analysis. In columns 1-3, we aggregate lending volumes by bank, quarter, borrower country and status of collateralization (i.e., secured vs unsecured lending), and otherwise follow an estimation procedure that is similar to the one for Table 1.4. Column 1 makes use of the full set of multidimensional fixed effects and is therefore our preferred specification. According to the coefficient for the triple interaction term, G-SIBs have increased the proportion of new loans that are secured by roughly 21 percent after 2012 when compared with the control group. The effect weakens and becomes insignificant when we replace bank $\times$ quarter fixed effects with bank control variables (with column 2 using the same sample as in column 1, and column 3 expanding the sample in a similar manner as explained in the previous section).

Albeit illustrative, the results in columns 1-3 of Table 1.5 might suffer from an omitted variable problem. Specifically, the majority of secured tranches are issued to borrowers with low credit ratings, so that a borrower's credit rating may simultaneously determine the amount of lending and the requirement for collateral. In the previous section, we have shown that in relative terms G-SIBs have increased their lending to better-rated companies after the reforms, which should bias against finding a positive effect for the triple interaction term in Table 1.5. Nevertheless, to systematically address this issue and fully isolate the effect of reforms on collateralized lending, we additionally condition on the borrower's credit rating. That is, we aggregate loan volumes by bank, quarter, status of collateralization and credit rating, and then estimate the effect on collateralized lending within a given risk class (Equation 1.4).

Table 1.5: Effects of the G-SIB Reforms on Secured Lending

VARIABLES	(1) Log(Lending)	(2) Log(Lending)	(3) Log(Lending)	(4) Log(Lending)	(5) Log(Lending)	(6) Log(Lending)
Post2012 × GSIB × Sec	0.207**	0.144	0.107	0.436**	0.477*	0.532**
	(0.0956)	(0.0949)	(0.0906)	(0.213)	(0.243)	(0.236)
Post2012 × GSIB		-0.0588	0.0172		-0.141	-0.126
		(0.0775)	(0.0721)		(0.139)	(0.141)
Observations	27,409	27,409	30,075	6,447	6,447	7,186
R-squared	0.725	0.671	0.668	0.696	0.580	0.593
Bank Controls		×	×		×	×
Bank x Quarter FE	×			×		
Sec x Ctr x Qtr FE	×	×	×			
Bank x Sec x Ctr FE	×	×	×			
Sec x Rat x Qtr FE				×	×	×
Bank x Sec x Rat FE				×	×	×
Firms	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind
Clustering	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Rat x Qtr	Bank & Rat x Qtr	Bank & Rat x Qtr
Frequency	Quarterly	Quarterly	Quarterly	Quarterly	Quarterly	Quarterly
Sample	Full	Condensed	Full	Full	Condensed	Full
Time	2010 - 2018	2010 - 2018	2010 - 2018	2010 - 2018	2010 - 2018	2010 - 2018
Unit of Obs	Bank x Qtr x Sec x Ctr	Bank x Qtr x Sec x Ctr	Bank x Qtr x Sec x Ctr	Bank x Qtr x Sec x Rat	Bank x Qtr x Sec x Rat	Bank x Qtr x Sec x Rat
Nr. of Banks	173	173	344	65	65	125

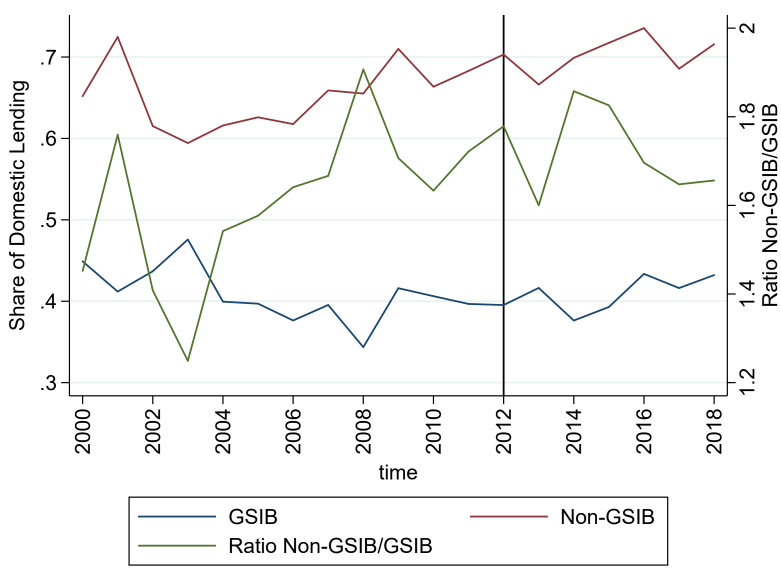
Notes: Table 1.5 estimates the effect on secured lending. In columns 1-3, we aggregate lending volumes by bank, quarter, status of collateralization and borrower country, and estimate the effect within a given borrower country. In columns 4-6, we aggregate by bank, quarter, status of collateralization and rating class, and estimate the effect within rating class. *Sec* is a binary variable, which is one if lending volumes are secured, and zero otherwise. ***, **, and * indicate statistical significance at the 1%-, 5%- and 10%-level.

Results are shown in columns 4-6 and illustrate that after the reforms G-SIBs have increased the proportion of collateralized lending within a given risk class when compared with banks in the control group. Coefficients are significant in all three columns and have more than doubled in magnitude relative to the ones in columns 1-3, in line with the intuition for the direction of the potential bias in these columns that we provided above.[20]

Domestic Lending vs Foreign Lending

We also examine whether G-SIBs have adjusted cross-border lending in response to the regulatory changes. Cross-jurisdictional activity is one of the categories determining systemic importance in the G-SIB framework, and it could be that G-SIBs have tried to reduce their global footprint in the aftermath of the reforms. To analyze this graphically, Figure 1.6 plots the evolution of the share of domestic loans in total loans for G-SIBs and other banks over the sample horizon. In line with intuition, the figure shows that G-SIBs are generally much more involved in foreign activities, with the share of domestic loans being consistently lower than the one for other banks (between 35 and 45 percent for G-SIBs and between 60 and 70 percent for other banks). The most striking development can be observed in the run-up to the GFC, where G-SIBs considerably decreased the proportion of domestic lending, while other banks displayed the opposite trend. Since then, however, the share of domestic lending has been relatively stable for both groups of banks.

Figure 1.6: Share of Domestic Lending over Time



Notes: For each bank, we compute the domestic loan share by dividing the amount of domestic loans issued by the total loan volume. We then calculate an average across the individual banks.

[20]Columns 4-6 include only loans to rated companies, so that the sample in these specifications is reduced relative to columns 1-3. To make sure that the more pronounced effect in columns 4-6 is not driven by differences in sample composition, we also estimate column 1 while including only loans to rated companies in the estimation. We obtain a point estimate for the triple interaction term of 0.27, which is somewhat higher than in column 1 but considerably lower than in column 4.

Our regression analysis in Table 1.6 confirms this pattern, as we do not obtain a clear direction for the triple interaction term in Equation 1.5 (which is in any case always insignificant). In columns 1-3, we aggregate lending volumes by bank, quarter and borrower country. The order of specifications shown in the table is the same as in previous sections. Column 1 is our most conservative specification and includes the entire set of two-dimensional fixed effects. In column 2, we use the sample from column 1 and replace bank × quarter fixed effects with bank control variables, while column 3 additionally includes loans from banks that lend to only foreign or only domestic firms within a given quarter (which cannot contribute to identification of coefficients in Equation 1.5). For robustness, we also use a broader aggregation of lending volumes by bank, quarter and domestic-or-foreign exposures. Coefficients for the triple interaction term in this alternative specification remain insignificant (columns 4-6).

Table 1.6: Effects of the G-SIB Reforms on Foreign Lending

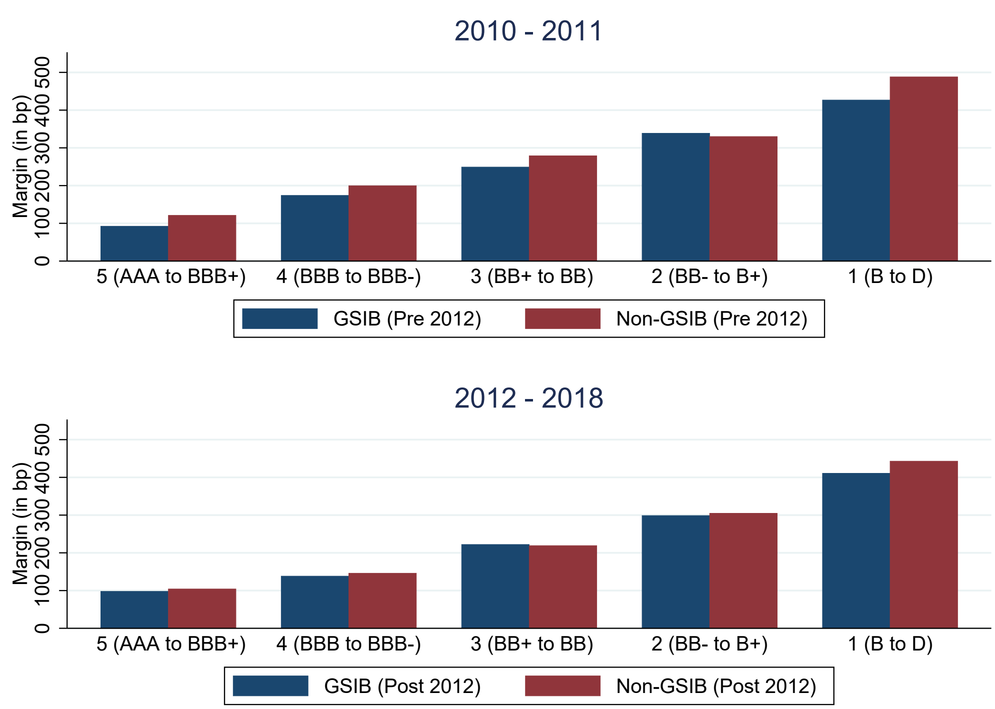
VARIABLES	(1) Log(Lending)	(2) Log(Lending)	(3) Log(Lending)	(4) Log(Lending)	(5) Log(Lending)	(6) Log(Lending)
Post2012 × GSIB × Dom	-0.0517	-0.0700	-0.0542	0.0670	0.0670	0.101
	(0.0776)	(0.0833)	(0.0814)	(0.128)	(0.128)	(0.131)
Post2012 × GSIB		0.00787	0.0459		0.0204	-0.0117
		(0.0663)	(0.0642)		(0.118)	(0.117)
Observations	21,963	21,963	25,199	5,452	5,452	8,852
R-squared	0.707	0.653	0.645	0.898	0.783	0.766
Bank Controls		×	×		×	×
Bank x Qtr FE	×			×		
Dom x Qtr FE				×	×	×
Bank x Dom FE				×	×	×
Ctr x Qtr FE	×	×	×			
Bank x Ctr FE	×	×	×			
Firms	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind
Clustering	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank	Bank	Bank
Frequency	Quarterly	Quarterly	Quarterly	Quarterly	Quarterly	Quarterly
Time	2010 - 2018	2010 - 2018	2010 - 2018	2010 - 2018	2010 - 2018	2010 - 2018
Sample	Full	Condensed	Full	Full	Condensed	Full
Unit of Obs	Bank x Qtr x Ctr	Bank x Qtr x Ctr	Bank x Qtr x Ctr	Bank x Qtr x Dom	Bank x Qtr x Dom	Bank x Qtr x Dom
Nr. of Banks	141	141	361	162	162	368

Notes: Table 1.6 estimates the effect on foreign lending. In columns 1-3, we aggregate lending volumes by bank, quarter and borrower country. In columns 4-6, we aggregate by bank, quarter and domestic/foreign lending. *Dom* is a binary variable, which is one if the nationality of the parent bank is the same as the country of credit exposure, and zero otherwise. ***, **, and * indicate statistical significance at the 1%-, 5%- and 10%-level.

1.5.3 Effect on Pricing Behavior

Besides loan volumes and composition, it is also possible that G-SIBs have adjusted their loan pricing after the reforms. For example, to the extent that the reforms helped to mitigate 'too-big-to-fail' considerations, they may have reduced (implicit) funding cost subsidies for G-SIBs (e.g., Cetorelli & Traina 2018, Berndt *et al.* 2019). If G-SIBs (partially) passed on the resulting increase in funding costs to their borrowers, this could have an effect on loan pricing. Figure 1.7 gives descriptive evidence on average interest rate margins before and after the reforms, broken down by risk class of the borrower. Overall, interest rate margins have declined universally after 2012, reflecting the low interest rate environment in the recent period, which also had an impact on the pricing of corporate loans. Furthermore, G-SIBs charged on average lower margins than other banks, both before and after 2012. However, as shown in the lower panel this pricing gap has narrowed after 2012, in particular for the best-rated borrowers.

Figure 1.7: Margin by Risk Class over Time



Notes: Each bar represents the average margin for a given risk segment. We aggregate tranche margins by calculating an equal (unweighted) average for each group of banks.

To further examine this pattern, we use the panel dimension in our data and run various versions of the regression model specified in Equation 1.6. Since our observational unit is the tranche-level now, we include tranche characteristics as additional control variables (comprising the loan amount, maturity, borrower rating and status of collateralization). Including these control variables is important for attributing observed changes to a potential reduction in funding cost subsidies since unconditional adjustments in loan pricing could also be due to relative changes in borrower composition, status of collateralization or other loan characteristics.

Table 1.7: Effects of the G-SIB Reforms on the Pricing of Tranches

VARIABLES	(1) Log(Margin)	(2) Log(Margin)	(3) Log(Margin)	(4) Log(Margin)	(5) Log(Margin)	(6) Log(Margin)
Post2012 × GSIB	0.0874**	0.0727**	0.0359	0.0874***	0.0727***	0.0359*
	(0.0387)	(0.0351)	(0.0321)	(0.0326)	(0.0264)	(0.0213)
Amount	0.0218***	0.0208***	0.0135***	0.0218***	0.0208***	0.0135***
	(0.00582)	(0.00552)	(0.00488)	(0.00534)	(0.00467)	(0.00430)
Maturity	0.0460***	0.0502***	0.0519***	0.0460***	0.0502***	0.0519***
	(0.00699)	(0.00601)	(0.00642)	(0.00629)	(0.00513)	(0.00514)
Rating	-0.149***	-0.141***	-0.137***	-0.149***	-0.141***	-0.137***
	(0.00619)	(0.00506)	(0.00512)	(0.00546)	(0.00374)	(0.00344)
Secured	0.0270	0.00732	-0.00516	0.0270	0.00732	-0.00516
	(0.0219)	(0.0226)	(0.0227)	(0.0215)	(0.0219)	(0.0224)
Observations	25,177	25,118	24,978	25,177	25,118	24,978
R-squared	0.656	0.748	0.827	0.656	0.748	0.827
Bank Controls	×	×	×	×	×	×
Bank FE	×	×	×	×	×	×
Quarter FE	×			×		
Qtr x Ctr FE		×			×	
Qtr x Ctr x Ind FE			×			×
Firms	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind
Time	2010 - 2018	2010 - 2018	2010 - 2018	2010 - 2018	2010 - 2018	2010 - 2018
Clustering	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Deal	Bank & Deal	Bank & Deal
Unit of Obs	Tranche x Bank	Tranche x Bank	Tranche x Bank	Tranche x Bank	Tranche x Bank	Tranche x Bank
Nr. of Banks	119	119	118	119	119	118

Notes: Table 1.7 estimates the effect on charged interest rates. In column 1, we include quarter FE, in column 2 quarter, borrower-country FE and in column 3 quarter, borrower-country, industry FE. In column 4-6, we double-cluster standard errors at bank and deal level, and follow, apart from that, the same estimation procedure as in column 1-3. ***, **, and * indicate statistical significance at the 1%-, 5%- and 10%-level.

Regression results are presented in Table 1.7. In columns 1-3, we successively decrease the coarseness of the fixed effect clusters, using quarter fixed effects in column 1, quarter-country fixed effects in column 2 and quarter-country-industry fixed effects in column 3. The coefficient for the interaction term between the G-SIB and the reform dummies is positive in all specifications (though statistically insignificant in the most stringent specification in column 3). The coefficient in column 2 indicates that G-SIBs decreased the average interest rate margin by 7.3 percent less than other banks after the reforms, after controlling for possible differences in loan terms and borrower risk. Columns 4-6 repeat the estimations in columns 1-3 while using a different level of clustering that accounts for possible correlation in error terms for observations within the same deal (see Section 1.4.3 for further details). Results are statistically significant in all three columns with this alternative level of clustering. Overall, the results in Table 1.7 suggest that G-SIBs have become more conservative in pricing their loans in the period after 2012, which is consistent with a potential reduction in funding cost subsidies.[21]

Next, we examine the sensitivity of pricing to risk. As shown in Figure 1.7, after 2012 other banks had decreased their interest rates margins in particular for the safest borrowers, i.e., in a risk sensitive manner. To analyze this more formally, we estimate Equation 1.7 and show the results in Table 1.8. The first column of Panel (a) is the most saturated specification as it contains the full set of multidimensional fixed effects. The positive coefficient for the triple interaction suggests that other banks have increased differentiation between safe and risky borrowers when pricing their loans in the post-reform period, relative to G-SIBs. Column 2 and 3 replace bank-quarter fixed effects with bank control variables, where column 2 uses the same sample as in column 1, and column 3 includes additional observations that were previously absorbed by the bank-quarter fixed effects. Results remain very stable. Finally, columns 4-6 repeat the estimations in columns 1-3 while using the alternative level of clustering. While the coefficient in the most stringent specification remains statistically significant (column 4), it becomes insignificant in columns 5 and 6.

In a final step, we want to ascertain where in the risk scale an adjustment of interest rate margins has been made. In order to examine this issue, we perform a sample split (investment vs. non-investment grade) and estimate the effect on the interest rate margin for each risk segment separately. Panel (b) of Table 1.8 shows that the relative adjustment mainly took place in the segment of investment grade borrowers (in line with Figure 1.7), while we do not detect any differential effects for the borrowers with worse credit ratings. The coefficient in column 1 indicates that other banks decreased the margins on investment grade loans by 12.6 percent when compared with G-SIBs.

[21] As shown by Berg *et al.* (2016b), an important part of syndicated loan pricing comes in the form of fees. The granularity of our data allows us to further decompose the interest rate charged by the banks into a fee component and a pure interest rate component. We find suggestive evidence that the less pronounced decrease in interest rate margins relative to other banks was mainly due to the pure interest rate component, whereas fee structures were adjusted in a similar manner. Specifically, coefficients for the interaction term remain relatively stable when using the pure interest rate component as a dependent variable in Equation 1.6, while they become insignificant when using the fee component. Detailed regression results are available upon request.

Table 1.8: Effects of the G-SIB Reforms on the Pricing Sensitivity to Risk

(a) Pricing Sensitivity to Risk

VARIABLES	(1) Log(Margin)	(2) Log(Margin)	(3) Log(Margin)	(4) Log(Margin)	(5) Log(Margin)	(6) Log(Margin)
Post2012 × GSIB × Rat	0.0734***	0.0530*	0.0503*	0.0734**	0.0530	0.0503
	(0.0241)	(0.0312)	(0.0291)	(0.0344)	(0.0400)	(0.0368)
Post2012 × GSIB		-0.0766	-0.0751		-0.0766	-0.0751
		(0.0578)	(0.0547)		(0.0892)	(0.0826)
Observations	24,240	24,240	24,461	24,240	24,240	24,461
R-squared	0.795	0.783	0.786	0.795	0.783	0.786
Bank Controls		×	×		×	×
Tranche Controls	×	×	×	×	×	×
Bank x Quarter FE	×			×		
Rat x Ctr x Qtr FE	×	×	×	×	×	×
Bank x Rat x Ctr FE	×	×	×	×	×	×
Firms	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind
Time	2010 - 2018	2010 - 2018	2010 - 2018	2010 - 2018	2010 - 2018	2010 - 2018
Clustering	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Deal	Bank & Deal	Bank & Deal
Sample	Full	Condensed	Full	Full	Condensed	Full
Unit of Obs	Tranche x Bank	Tranche x Bank	Tranche x Bank	Tranche x Bank	Tranche x Bank	Tranche x Bank
Nr. of Banks	102	102	111	102	102	111

(b) Breakdown by Risk Segment

VARIABLES	(1) Log(Margin)	(2) Log(Margin)	(3) Log(Margin)	(4) Log(Margin)
Post2012 × GSIB	0.126*	0.0405	0.0927	0.0300
	(0.0679)	(0.0314)	(0.0608)	(0.0306)
Observations	7,131	18,031	7,098	17,970
R-squared	0.449	0.374	0.789	0.455
Bank Controls	×	×	×	×
Tranche Controls	×	×	×	×
Bank FE	×	×	×	×
Quarter FE	×	×		
Quarter x Country FE			×	×
Clustering	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Ctr x Qtr
Unit of Obs	Tranche x Bank	Tranche x Bank	Tranche x Bank	Tranche x Bank
Risk Segment	Safe	Risky	Safe	Risky
Nr. of Banks	86	97	86	97

Notes: Panel (a) estimates the effect on the pricing sensitivity to risk. *Rat* is our own-created, five-bin rating variable. Tranche controls include tranche amount, maturity, borrower rating and status of collateralization. In columns 1-3, we double-cluster standard errors at bank and quarter-country level, in columns 4-6 at bank and deal level. In Panel (b), we estimate the effect for a particular risk segment, where the safe segment includes all ratings equal to or greater than *BBB-*. The risky segment contains all the remaining credit ratings (i.e., less than *BBB-*). In column 1 and 2, we include quarter fixed effects, column 3 and 4 uses quarter, borrower-country FE. ***, **, and * indicate statistical significance at the 1%-, 5%- and 10%-level.

While it is difficult to take definite conclusions, one possible explanation for these differential effects on pricing could be that prime borrowers are more eager to do business with G-SIBs, so that G-SIBs have more pricing power with them and therefore do not have to reduce interest rates on their loans so much for firms in this category. Such demand-side effects would make it difficult for other banks to gain market share in the safe borrower segment and could hence also explain the volume effects discussed in Section 1.5.2 (which illustrated that other banks gained market share on the risky segments, in relative terms). Of course, this is just one potential explanation and others are possible as well. Pinning down the exact mechanism behind our findings would require further information and is beyond the scope of this study.

1.5.4 Effect on Maturity

Figure 1.8 illustrates the evolution of the weighted average loan maturity for both groups of banks over the sample horizon. In general, G-SIBs grant loans with shorter maturities, with an apparent structural break at the time of the GFC, where G-SIBs considerably shortened average loan maturities. Since then, however, there have not been any differential patterns for the two groups of banks, at least not at this aggregate level.

Figure 1.8: Value-Weighted Maturity over Time

Notes: For both G-SIBs and Non-G-SIBs, we calculate the share of funds which is attributed to a specific maturity in a given year. We then use these weights to compute a value-weighted maturity for each group of banks.

Using the tranche-level data, we formally investigate this issue by estimating Equation 1.6. Indeed, the results in Table 1.9 do not reveal any significant differences between G-SIBs and other banks for the period after 2012. As before, columns 1-3 successively decrease the coarseness of the fixed effect clusters while columns 4 and 5 include additional robustness tests. Specifically, column 4 uses a logarithmic version of the dependent variable, and column 5 omits the credit rating as control variable, which allows us to more than double our sample size (the inclusion of the interest rate margin as a control variable in this specification allows to still (at least partially) control for counterparty credit risk). All estimates are insignificant and the coefficient of interest varies in sign, which leads us to conclude that there has been no differential adjustment in tranche maturities in the post-reform era.

Table 1.9: Effects of the G-SIB Reforms on the Tranche Maturity

VARIABLES	(1) Maturity	(2) Maturity	(3) Maturity	(4) Log(Maturity)	(5) Maturity
Post2012 × GSIB	0.0280	-0.00238	-0.0634	-0.0194	0.00952
	(0.125)	(0.0705)	(0.0515)	(0.0173)	(0.0691)
Amount	0.0169	0.0134	0.0573**	-0.00990	0.121***
	(0.0245)	(0.0241)	(0.0222)	(0.00610)	(0.0269)
Margin	0.00205***	0.00222***	0.00231***	0.000252**	0.00214***
	(0.000308)	(0.000305)	(0.000335)	(0.000101)	(0.000251)
Rating	-0.0583***	-0.0533***	-0.0685***	-0.0307***	
	(0.0172)	(0.0151)	(0.0153)	(0.00492)	
Secured	0.582***	0.481***	0.435***	0.110***	0.553***
	(0.0921)	(0.0909)	(0.0984)	(0.0311)	(0.0956)
Observations	25,177	25,118	24,978	24,978	63,935
R-squared	0.193	0.352	0.513	0.480	0.589
Bank Controls	×	×	×	×	×
Bank FE	×	×	×	×	×
Quarter FE	×				
Qtr x Ctr FE		×			
Qtr x Ctr x Ind FE			×	×	×
Firms	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind
Time	2010 - 2018	2010 - 2018	2010 - 2018	2010 - 2018	2010 - 2018
Clustering	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Ctr x Qtr
Unit of Obs	Tranche x Bank	Tranche x Bank	Tranche x Bank	Tranche x Bank	Tranche x Bank
Nr. of Banks	119	119	118	118	271

Notes: Table 1.9 estimates the effect on tranche maturities. In column 1, we include quarter FE, in column 2 quarter, borrower-country FE and in column 3 quarter, borrower-country, industry FE. In column 4, we use the logarithmized maturity (in yrs) as dependent variable. In column 5, we omit the credit rating as control variable. ***, **, and * indicate statistical significance at the 1%-, 5%- and 10%-level.

1.6 Robustness

This section provides a number of robustness tests and alternative specifications. The first set of robustness tests concerns the effects on credit supply. Columns 1-4 of Table A.2 re-estimate Equation 1.2 while using different estimation samples. First, to further enhance comparability between treatment and control group, we restrict the sample to include only the largest banks. Specifically, column 1 includes only banks with total assets larger than USD 100 bn, while column 2 considers only banks that are included in the Basel Committee on Banking Supervision's G-SIB assessment sample. In both cases, the coefficient of interest is insignificant and close to 0, similar to the main regression in column 3 of Table 1.3. Second, we include loans to public entities and loans to the financial sector in addition to loans to the non-financial private sector, and continue to find an insignificant coefficient for the interaction term (column 3). Third, we extend the pre-treatment period up to the year 2000 (column 4). The coefficient of interest is now negative and weakly significant, reflecting differential developments for G-SIBs and other banks in the run-up to and during the GFC (recall Figure 1.1). As noted in Section 1.3, we think that these differential developments may create issues with the parallel trends assumption in a difference-in-differences setting, which is why our preferred specification is the one where the sample is restricted to the years from 2010 to 2018.[22] In column 5, we include interaction terms between the reform dummy and our bank-level control variables to allow them to have a time-varying effect on the outcome variable. The coefficient of interest remains insignificant. Finally, in column 6 we use a Poisson Pseudo-Maximum Likelihood (PPML) Estimator to estimate the effect on loan volumes and continue to find insignificant results.[23]

Table A.3 presents results for several robustness tests for the regressions on portfolio allocation. Columns 1-4 refer to borrower risk. In order to show that our results do not depend on a specific classification of the rating variable, columns 1 and 2 show the results for alternative classifications: column 1 is based on a binary rating variable that distinguishes between firms with investment grade ratings and firms with non-investment grade ratings, whereas column 2 groups credit ratings into deciles. In both cases, the coefficient for the interaction term remains significantly positive. In columns 3 and 4, we include only larger banks in the control group in order to ensure a more homogeneous sample. Results are again

[22] Our remaining results tend to be robust when using the extended sample ranging from 2000 to 2018.

[23] As stressed by Silva & Tenreyro (2006, 2011), the PPML Estimator yields unbiased and robust results for log-linearized models in the presence of many zero observations and of heteroscedastic error terms. When applied to credit exposure data, this estimator has already been used in the literature (e.g., Popov & Van Horen 2015). To include multiple levels of fixed effects, we rely on Correia *et al.* (2020). The reduced number of identifying observations in these regressions (in comparison to column 3 in Table 1.3) is due to separation in the context of Poisson models (Correia *et al.* 2019).

consistent with the main table, only in column 4 the coefficient is marginally insignificant. In columns 5-8 of Table A.3, we present a number of robustness tests relating to the impact of the reforms on secured lending. In columns 5 and 6, we conduct tranche-level regressions, using as dependent variable a dummy variable, that is equal to one when the respective tranche is secured, and zero otherwise. Consistent with the main findings, the estimates show that tranches issued by G-SIBs are relatively more likely to be secured after the reforms, both in a linear probability (column 5) and in a logit model (column 6). The coefficient in column 5 indicates that since 2012 the probability that G-SIBs require collateral increased by 13.4 percent relative to the control group. Finally, we apply the familiar restriction to larger banks in columns 7 and 8, and continue to find a significantly positive triple interaction term. Overall, the results support the empirical findings in the main text. G-SIBs shifted more lending to less risky borrowers and also increased the demand for collateral relative to the control group.

The last set of robustness checks in Table A.4 concerns the effects of the reforms on the pricing behavior of G-SIBs. Columns 1-3 are about the average effect on interest rate margins. In line with the main results in Table 1.7, the coefficient for the interaction term remains significantly positive when we include the base rate on which the margin is added in column 1, suggesting more conservative pricing of loans by G-SIBs in the post-reform period.[24] Results are also robust when we restrict the control group to include only larger banks, similar to the previous tables (columns 2-3). Columns 4-7 analyze the pricing sensitivity to risk. In column 4, we add up margins and base rates, and use the logarithm of the sum as dependent variable (similar to column 1), column 5 replaces the rating variable with a binary rating classification in the same way as column 1 in Table A.3 and columns 6 and 7 apply the familiar sample restrictions to larger banks. All the results support the findings in Table 1.8, Panel (a), indicating a less risk sensitive pricing for G-SIBs since 2012 in relative terms.

1.7 Conclusion

In this study, we use granular data on syndicated loans to analyze the impact of the post-crisis reforms for G-SIBs on bank lending behavior. We find that – compared with other banks – G-SIBs have reduced credit risk taking after the reforms, with respect to both borrower- and loan-specific risk factors. Specifically, G-SIBs shifted lending towards better-rated companies and also increased the amount of secured lending in the post-reform period. The latter is

[24]We consider the following four base rates: LIBOR, EURIBOR, HKIBOR and US Prime. These four base rates cover 90 percent of the observations in our sample.

a catch-up effect relative to other banks, which already increased the amount of secured lending during and immediately after the GFC. When analyzing interest rate margins, we find evidence for more conservative pricing behavior by G-SIBs in the post-reform period. While the interest rates charged by G-SIBs were considerably lower than those charged by other banks before the reforms, this pricing gap has narrowed after 2012. The narrowing is consistent with a relative increase in funding costs for G-SIBs – potentially due to a reduction in implicit funding cost subsidies – which was then at least partially passed on to the banks' borrowers.

Overall, our findings suggest that the post-crisis reforms at least partially mitigated moral hazard problems associated with systemically important banks. They effectively limited excessive risk taking and reduced funding cost subsidies for G-SIBs. The latter may be seen as indirect evidence for a credible reduction in bailout expectations associated with 'too-big-to-fail' considerations. At the same time, potential side effects that could be associated with tighter regulation appear to be limited since we do not detect significant effects on overall credit supply or cross-border lending of G-SIBs. While the findings in our analysis suggest that the reforms were going into the right direction, the extent to which they have solved the 'too-big-to fail' problem remains an interesting topic for further research.

Chapter 2

Capital (Mis)allocation and Incentive Misalignment*†

*This chapter is based on joint work with Alexander Schwemmer (University of Munich) and Jan Schymik (University of Mannheim). An earlier version is available as CRC TR 224 discussion paper.

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2.1 Introduction

Economists have long proposed that the role of management is key in explaining the large and persistent differences in productivity levels across businesses (Syverson 2011, Bloom & Van Reenen 2007). In this study, we analyze a specific channel how firm performance is shaped by managers – the within-firm (mis)allocation of capital caused by distorted managerial incentives. While many durable investment goods have a life span that lasts several years, typical CEO compensation schemes in public US firms feature much shorter vesting periods of the different CEO pay components.[1] When the private marginal products of capital goods that decision-makers in firms face do not match the social marginal products of capital, this can cause capital misallocation within firms. The mismatch between the horizon of managers' incentives and the durability of firms' assets hence suggests that there is a risk that managers opt for investment policies that are substantially biased towards more short-term investment goods as these have a lower time to pay off. Economic output would be larger if capital expenditures were reallocated away from the capital goods with a shorter life span towards more durable capital goods. Furthermore, when managers in the economy systematically face short-term incentives and do not invest sufficiently into long-term assets, this can be impedimental for aggregate growth.

We approach this topic in two ways. First, we provide empirical evidence on the existence of such a within-firm misallocation channel caused by short-termist incentives. Second, we develop a dynamic model of firm investments with incentive frictions that rationalizes our empirical results and that we calibrate to the US economy to quantify the economic impact of this misallocation channel.

In the first part of this study, we provide reduced-form empirical evidence by exploiting the introduction of the FAS 123 accounting reform in the US as a quasi-natural experiment. This change in accounting rules effectively raised the opportunity costs of more durable executive compensation causing a shorter horizon of managerial incentives in treated firms. Combined with a within-firm estimator that exploits variation across investment goods that differ in their life span, we show that short-term incentives cause capital misallocation inside businesses as incentive distortions asymmetrically affect investments across capital goods. To empirically study the changing investment composition inside firms, we use data on the population of stock listed firms in the US. Listed firms disclose investment expenditures

[1] Gopalan *et al.* (2014) find an average duration of CEO pay of about 1.5 years, computed as the weighted average of the vesting periods of the different components of executive pay including salary, bonus, stocks and options. Following on that, a duration of 1.5 years would correspond to a depreciation rate of 66.7%, which by far exceeds the estimates of capital depreciation rates from the literature (e.g., Nadiri & Prucha 1996).

across different asset categories such that we can exploit variation in durability across asset groups to distinguish between short- and long-term investments, similar to Garicano & Steinwender (2016) or Fromenteau *et al.* (2019). Combining these data on firm investments in land, buildings, machinery, transport equipment, R&D, computer equipment and advertising with information on compensation practices allows us to measure how incentives affect the capital allocation within firms.

The main identification challenge in this empirical exercise is that both, compensation practices and investment policies are endogenous firm choices. We address this endogeneity of compensation packages by studying firms around the revision of accounting rule FAS 123 in the year 2005. This revision, effective for US public companies after 2005, abolished an accounting advantage of option-based employee compensation and thereby raised the relative costs of equity-linked compensation to the benefit of monetary bonuses (Hayes *et al.* 2012). The accounting reform prohibited companies to expense option compensation to employees at its intrinsic value such that firms were obliged to expense option compensation at fair value after the revision took effect. Additionally, the Financial Accounting Standards Board (FASB) allowed firms to accelerate unvested options to fully vest prior to the compliance date, further increasing short-term incentives. We document that firms which offered option-based compensation to their management prior to the reform, and thus were subject to treatment, shifted compensation towards less durable compensation parts such as higher salaries or bonuses after the accounting reform.[2] This shift in the compensation structure of CEOs induced by the reform also lowered the durability of CEO compensation as measured by Gopalan *et al.* (2014).

We find that the reform-induced increase in short-term managerial incentives caused a wedge in investment expenditures. Firms that were subject to more short-term managerial incentives shifted investment expenditures towards assets with a shorter life span. Our within-firm estimator – comparing investment expenditures across categories for treated and untreated firms around the introduction of the accounting reform – allows us to estimate a statistically and economically significant effect of incentives on investment policies. Furthermore, we document that the observed changes in investment policies tilt capital stocks towards more short-term capital and increase firm-specific depreciation rates. Compared to untreated firms, treated firms invest 6% more into capital goods with a 10 percentage points higher depreciation rate. This shift towards more short-term assets is reflected in a 1.58 percentage-point increase in firm-specific depreciation rates causing substantial refinancing

[2] This is consistent with Hayes *et al.* (2012), who document such a shift of compensation around the introduction of FAS 123R in a setting that is not based on difference-in-differences variation but on overall pay variation over time.

costs related to this decrease in the durability of capital stocks. We calculate additional financing costs of USD 15.29 per each USD 1,000 invested, which materialize in the form of interest payments.

We then quantify the impact of such short-termist incentive distortions on within-firm misallocation and economic outcomes in the second part of this study. We develop a model that builds on a neoclassical model of dynamic firm investments, similar to the models in Bond & Van Reenen (2007), Cooper & Haltiwanger (2006), Hsieh & Klenow (2009) or Bloom (2009), and extend it in two dimensions. First, we introduce a decision-maker that faces monetary incentives from a compensation package that is composed of a fixed salary, a bonus component based on current profits and a share of total equity, similar to Nikolov & Whited (2014). The larger is the equity share of firm value that accrues to the decision-maker, the closer her incentives are aligned with value maximization.[3] Second, in the spirit of Aghion *et al.* (2010) or Rampini (2019), we introduce two types of capital that differ in their durability, measured by different depreciation rates. Both types of capital are subject to convex capital adjustment costs and firms combine capital and labor to produce output. We show analytically that such a compensation package based on bonuses and equity induces investment short-termism as the decision-makers' optimization problem mirrors quasi-hyperbolic preferences (i.e., quasi-geometric discounting), which implies time inconsistency. These time inconsistencies in our model are driven by a too strong focus on current profits induced by the combination of bonus payments and equity ownership.[4]

We use our model to quantify the economic effects of managerial incentives on capital misallocation within firms and carry out an evaluation of FAS 123R in this regard. We calibrate the model to match specific firm- and sector-level moments for the US economy in a simulated sample of firms prior to the reform and then simulate the effects of an unexpected, persistent shock to decision-makers' incentive structure that resembles the empirical variation around the accounting reform. From a computational point of view, our model shares many similarities with models of quasi-hyperbolic discounting, including the numerical challenges in solving them with Euler-equation-based methods (Krusell & Smith 2003 and Maliar & Maliar 2005, 2016). Hence, as suggested by Maliar & Maliar (2016), we adapt the method of endogenous gridpoints (Carroll 2006) to solve for dynamic firm behavior. Using this method, we are able to compute the implied effects of the reform on various firm-level variables and

[3]We do not derive the form of optimal contracts but instead approximate contracts that we observe in the data and that may or may not be optimal. This approach allows us to identify the effects of changing contract features on firms' investment policies.

[4]Time inconsistencies from hyperbolic discounting have been studied in the context of consumption-saving problems (e.g., Laibson 1997). Furthermore, the corporate finance literature has also suggested that myopic decision-making can lead to suboptimal equilibria (e.g., Stein 2003).

compare them to a counterfactual scenario without a change in managerial incentives. Our quantification shows that firms respond to the reform with a short-run cut in investments consistent with the empirical findings by Ladika & Sautner (2019), who report a reform-induced investment cut in the years after the implementation of FAS 123R. Importantly, this investment cut is asymmetric across capital goods and the drop in long-term investments is substantially larger, which tilts the within-firm allocation of capital toward short-term capital goods. These model-implied investment responses are quantitatively similar to their empirical counterparts. While the shift in firms' investment behavior is relatively mild, it causes a substantial rise in within-firm capital misallocation – the average difference in the rates of return across capital goods increases by 3.7 basis points, which corresponds to an average increase in the marginal product gap by 50.4%. This within-firm shift in the capital mix away from the social optimum lowers long-run profits by 0.2% on average. In a general-equilibrium extension, we find that the reform lowered real wages by 0.2%, even though the reform-induced changes in incentives were rather small.

Policy-makers, executives and investors have often warned about the dangers of boosting short-term profits at the cost of long-term value (e.g., Dimon & Buffet 2018 or Barton 2011). Our analysis relates to the literature studying the origins of short-term behavior and its consequences for corporate decisions. On the theoretical side, models by Bénabou & Tirole (2016) and Garicano & Rayo (2016) formulate managerial short-termism as an intertemporal version of a multitasking model in which agents must choose between projects that maximize short-term objectives versus projects that maximize long-run objectives. Similar to our model, Aghion *et al.* (2010) study an investment model with two types of capital to analyze the role of credit constraints on the composition of investment. We rely on these ideas in our investment model by letting decision-makers solve an intertemporal optimization problem with the choice between two types of capital with different durabilities.

Empirically, Edmans *et al.* (2017a,b) and Ladika & Sautner (2019) find that short-term incentives proxied by vesting equity are associated with a decline in total capital expenditures. Our estimated effects of incentive distortions relate to Ladika & Sautner (2019) or Glover & Levine (2015), who also study short-termism in the context of the FAS 123 accounting reform. While both studies consider aggregate capital expenditures, our focus is on capital (mis)allocation caused by incentive distortions. Since our estimates are based on within-firm variation across investment categories, we are also able to effectively account for idiosyncratic demand or technology shocks, which are absorbed by firm-year fixed effects. Asker *et al.* (2014) provide evidence that private firms, whose management is presumably less prone to short-termism, have substantially higher capital expenditures and are more responsive to investment opportunities. Terry (2015) shows that short-termist pressures from investors can lower investment and aggregate growth. We contribute to that literature by identifying a specific microeconomic channel – incentive distortions – causing misallocation of capital inside firms leading to aggregate output losses. These adjustments via within-firm capital (mis)allocation across capital goods also add to the literature that discusses and quantifies causes of factor misallocation (e.g., Hsieh & Klenow 2009, Alder 2016, Midrigan & Xu 2014, David & Venkateswaran 2019 or Peters 2018).

The remainder of this study is structured as follows. In the following section, we present empirical evidence on the effect of incentive distortions on capital (mis)allocation. Section 2.3 quantifies these effects based on our model of firm investments. Finally, Section 2.4 concludes.

2.2 Empirical Evidence on Incentives and Capital Allocation

This section provides empirical evidence how changes in managers' financial incentives distort investment decisions and affect the allocation of capital within firms. Since financial incentives are chosen endogenously, our identification strategy exploits the revision of the FAS 123 accounting standard in the US, and we study how reform-induced changes in incentives distorted the investment behavior of publicly traded firms.

2.2.1 Data

Our sample combines annual data on firm investments with executive remuneration data. We focus on the sample of publicly traded US firms from 2002 to 2007 and consider seven broad investment categories which differ along their durability. Following the approach suggested by Garicano & Steinwender (2016) and Fromenteau *et al.* (2019), we consider investments in the following seven categories: land, buildings, machinery, transport equipment, R&D, computer equipment and advertising, and assign category-specific depreciation rates listed in Table 2.1.

Table 2.1: Assigned Depreciation Rates

Category	*Land*	*Buildings*	*Machines*	*Transport*	*R&D*	*Computer*	*Advertising*
Depreciation	0%	3%	12%	16%	20%	30%	60%

Notes: Assigned category-specific depreciation rates following Garicano & Steinwender (2016) and Fromenteau *et al.* (2019).

We directly obtain annual expenses on R&D and advertising from Compustat North

America. Data on the remaining categories of Property, Plant & Equipment are provided by Factset. We use a perpetual inventory method to transform stock variables into annual gross investment. Negative investments and missing values are excluded from the analysis.[5] We further keep only active firms in the sample and exclude utilities, financial and public sector firms in our baseline estimations as it is standard in the literature (e.g., Clementi & Palazzo 2019, Ottonello & Winberry 2018).

ExecuComp serves as our primary data source for executive compensation. Since CEOs arguably have the largest impact on the investment decisions of firms, we concentrate on the remuneration of the current CEO in the year before the reform (2004) and construct the following three proxies for treatment eligibility: a dummy indicating if the executive was awarded any stock option (*option dummy*), the share of an executive's stock option awards in his total current compensation (*option per TDC*) and his position in the respective distribution (measured in quintiles). We then merge the CEO data with the investments panel. To motivate our empirical strategy, we additionally make use of another data source of executive compensation, which is BoardEx. BoardEx offers a more detailed listing on the individual components and time-structure of manager remuneration than ExecuComp, which comes at the cost of having less matches with our investment sample.[6]

Table 2.2 lists selected summary statistics. Our comprised sample entails about 700 firms. Most of firms' resources are on average spent on machinery, R&D and advertising, whereas a smaller proportion goes into land and IT investment. The relatively high standard deviation and the large heterogeneity in expenditures per category do not only reflect differences in the investment pattern across firms but also imply lumpiness on the firm level as it is well documented in the literature (e.g., Doms & Dunne 1998). Overall, each investment category seems to play a substantial non-negligible role for the investment policy of a firm. The last two rows of Table 2.2 summarize the firms' compensation policies in 2004. On average, 74% of CEOs were awarded stock options and about a third of total CEO compensation falls to option grants. Thus, awarding stock options is a widely and strongly used method in CEO compensation.

2.2.2 Empirical Strategy

This section outlines our empirical strategy. In a first step, we consider how the revision of FAS 123 changed managerial incentives. In our main analysis, we then examine how this

[5] We show that our results are also valid if we treat negative investment as true negatives or if we set them to zero.

[6] See Appendix B1.1 for a comprehensive and detailed description of the variables used in the empirical analysis.

Table 2.2: Selected Summary Statistics

Variable	Mean	Std. Dev.	Min	p25	p50	p75	Max	Obs	Sample
Firm-Investment Data									
Land	33.45	192.64	0.00	0.10	1.95	9.99	3,929.20	2,126	2002 - 2007
Buildings	118.60	526.41	0.00	3.77	15.46	59.81	10,978.46	3,027	2002 - 2007
Machines	461.21	2,264.74	0.03	20.09	78.71	291.36	78,706.20	2,997	2002 - 2007
Transport	143.19	622.46	0.00	0.50	2.16	19.60	7,587.88	409	2002 - 2007
Research	282.71	956.11	0.00	2.74	28.33	128.15	12,183.00	2,765	2002 - 2007
Computer	101.20	386.99	0.19	9.86	21.49	77.30	7,800.70	602	2002 - 2007
Advertising	261.27	663.45	0.00	7.95	40.95	169.00	7,937.00	1,884	2002 - 2007
Compensation Data									
Option per TDC	0.33	0.27	0.00	0.00	0.32	0.53	0.99	700	2004
Option Dummy	0.74	0.44	0	0	1	1	1	700	2004

Notes: Investment expenditures are denoted in millions USD. Option per TDC is calculated as the value of all granted options divided by total current compensation. Option Dummy takes 1 if any options are awarded, zero otherwise.

reform-induced increase in short-term incentives affected the investment behavior around the reform.

Reform of FAS 123: Changes in Accounting Rules for Equity Payments

To study the causal effect of short-term incentives on the allocation of capital, we exploit an unexpected and unprecedented change in accounting practices for US firms caused by the revision of FASB Statement No. 123 (FAS 123R). In December 2004, the Financial Accounting Standard Board (FASB) revised this practice that establishes standards to account for transactions in which an entity exchanges its equity instruments for goods or services. The revision then became effective for companies with their first full reporting period beginning after June 15, 2005.

The principal reason for revising this accounting rule was to remove an accounting advantage that affected the issuance of equity-based employee compensation leading to potential misrepresentation of economic transactions. Before the reform, companies were allowed to expense equity compensation to employees at its intrinsic value, i.e., the difference between the stock price on the granting date and the strike price. This had the consequence that equity-linked compensation could often be granted without causing according accounting expenses. For example, options with a strike price equal to current stock prices had no intrinsic value and therefore did not show up as an expense. After introduction of the reform, firms were obliged to expense option compensation at fair value, which effectively abolished this accounting advantage of equity compensation. Other stated reasons for this revision were to simplify US Generally Accepted Accounting Principles (GAAP) and to make them more comparable with international accounting rules by moving towards fair-value accounting.

There are two channels how FAS 123R has shortened the horizon of incentives for option-paying firms. First, as the costs of equity compensation increased, firms might want to substitute towards other forms of incentive compensation such as paying bonuses on profits. As profits are inherently more short-term than equity value, this distorts incentives towards the presence. Second, as part of the reform, the FASB also allowed firms to accelerate unvested options to fully vest prior to the compliance date to swiftly move towards a fair-value accounting for equity compensation. Accelerating options that were out-of-money was free of charge, while accelerating in-the-money options implied expense claims equal to the difference between the acceleration date stock price and the strike price. Whenever options were not very deep in the money, this expense was below the options' fair value such that firms had an incentive to accelerate the vesting of slightly in- as well as out-of-money options, which gave rise to an additional source of short-term managerial incentives caused by the reform (Ladika & Sautner 2019).

The Effects of the FAS 123 Reform on Incentives

We begin our empirical analysis by illustrating that the reform indeed induced a shift of the compensation structure towards more short-term compensation for treated firms based on a difference-in-differences estimation. As documented by Hayes *et al.* (2012), the structure of CEO compensation changed substantially around the adoption of FAS 123R. For example, firms reduced the value of equity-linked compensation after the revision and increased bonus compensation at the same time. We exploit the fact that firms that granted stock options to their CEOs prior to the reform were most affected by the reform. If these firms were to keep compensating managers with equity in the future, they would have to incur additional accounting expenses. Additionally, these firms had the option to accelerate unvested options. We split our sample into a treatment and a control group, where the former includes all firms that have granted stock options in the pre-reform year and the latter comprises all the remaining firms, respectively.[7] After having merged remuneration data provided by BoardEx with our firm-investment panel, we calculate for each firm a manager-specific measure of bonus payments by scaling the amount of bonus paid with total compensation. For the equity share, we divide all equity linked compensation by total compensation. In addition, to better capture the term structure of compensation schemes and therefore to give a more

[7] This difference-in-differences approach is where we deviate from Hayes *et al.* (2012), who study the average effect of FAS 123R on compensation components using panel regressions. Given that our identification strategy outlined in Section 2.2.2 is based on differences in investment practices across firms which differ by their exposure to the reform, we are interested in the differential adjustment in the firms' compensation structure in response to the reform.

nuanced view of how FAS 123R created short-term incentives for option-paying firms, we also construct a measure of manager compensation duration in the spirit of Gopalan *et al.* (2014), which explicitly accounts for the payout horizon of each compensation component separately.[8]

Table 2.3: The FAS 123R Accounting Reform and the Structure of Compensation

	Bonus Share			Equity Share		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Interaction with Pre-FAS123 Option Dummy						
FAS123 × Option-Dummy	0.0620***	0.0500***	0.0449***	-0.134***	-0.114***	-0.111***
	(0.0171)	(0.0150)	(0.0142)	(0.0224)	(0.0201)	(0.0190)
Panel B: Interaction with Pre-FAS123 Option Share						
FAS123 × Option-Share	0.155***	0.139***	0.131***	-0.267***	-0.239***	-0.237***
	(0.0237)	(0.0199)	(0.0204)	(0.0334)	(0.0290)	(0.0293)
Year FE	×	×	×	×	×	×
Firm FE	×	×	×	×	×	×
Observations	3,392	6,638	4,435	3,392	6,638	4,435
No. Firms	578	578	757	578	578	757
Sample Period	2002 - 2007	2000 - 2014	2002 - 2007	2002 - 2007	2000 - 2014	2002 - 2007
Sample			incl. fin. & util.			incl. fin. & util.

Notes: The Table reports the results on the relationship between the FAS 123R reform and the structure of managerial compensation. *Option-Dummy* in Panel A is a dummy that indicates if any options are awarded in 2004. *Option-Share* in Panel B is given by the option share in total compensation in 2004. *FAS123* takes value 0 for each year until 2005 and value 1 afterwards. *Bonus Share* is the fraction of bonus payments in total compensation and *Equity Share* is the fraction of equity payments in total compensation (both obtained from BoardEx). Standard errors (reported in parentheses) are clustered at the firm-level. ***, **, and * indicate statistical significance at the 1%-, 5%- and 10%-level.

Our empirical results in Table 2.3 reveal that the reform led to a shift in the CEO compensation structure for our treated sample firms. Compared to non-option-paying firms, we find that treated firms reduced equity-based compensation by about 13 percentage points after the reform was introduced. Furthermore, these firms raised bonus compensation by

[8] Duration d of firm i at time t is calculated as $d_{i,t} = \frac{(bonus_{i,t}+salary_{i,t})\cdot 0+\sum_{j=1}^{N}(Restr.stock_{i,j,t}+options_{i,j,t})\cdot \tau_j}{(salary_{i,t}+bonus_{i,t})+\sum_{j=1}^{N}(Restr.stock_{i,j,t}+options_{i,j,t})}$, where τ_j is the vesting period of equity-based component j.

about 6 percentage points.[9] We argue that this shift of compensation away from equity-linked compensation towards other parts of incentive compensation has contributed to a rise in short-term managerial incentives as bonuses are not necessarily tied to underlying long-term equity prices but current profits. This view is further supported when we focus directly on the duration of compensation packages in Table 2.4. The estimates suggest that the CEOs of treated firms experienced an average reduction in their compensation duration due to the FAS 123 reform by almost 2 months compared to CEOs of untreated firms. Furthermore, CEOs with more durable compensation structures prior to the reform experienced larger cuts in compensation duration post reform.

Identification of Within-Firm Distortions in Capital Allocation

To identify the effects of managerial incentives on investment decisions, we compare the investment behavior of firms that were affected by the reform to the investment behavior of unaffected firms during the time span around the revision of FAS 123 in 2005. We consider all firms that compensated their CEOs with options in the pre-reform year 2004 as the set of treated firms. Relating to the arguments made in the previous subsection on the short-termist effects of the reform, we consider these firms as affected for two reasons. First, the costs of equity-linked compensation effectively increased for firms that compensated managers with options before FAS 123R, while firms that did not choose to offer options before 2005 did not necessarily face any additional costs. Second, firms that compensated managers with options before FAS 123R were allowed to let these options vest earlier, effectively reducing the duration of executive compensation, while non-option paying firms remained unaffected.

We estimate the following within-firm triple-differences specification, where $invest_{i,c,t}$ denotes a measure of investments by firm i in investment category c at time t:

$$invest_{i,c,t} = \beta_1 \times \mathit{FAS123R}_t \times X_{i,2004} \times \delta_c + \beta_2 \times X_{i,2004} \times \delta_c + \lambda_{i,t} + \lambda_{c/t} + \varepsilon_{i,c,t}. \qquad (2.1)$$

Our sample includes firms' expenditures on seven investment categories c: advertising, computer equipment, R&D, transportation equipment, machinery equipment, buildings and land. The parameter of interest is β_1, which identifies a distortion in the relative composition of firm investments created by a shift in incentives due to the accounting reform. This parameter is the coefficient of the triple interaction $\mathit{FAS123R}_t \times X_{i,2004} \times \delta_c$, where $\mathit{FAS123R}_t$ is a time-specific dummy variable that equals one for years succeeding the reform (i.e., for $t > 2005$) and zero otherwise. Furthermore, $X_{i,2004}$ is our firm-specific treatment indicator, which – depending on the specification – measures whether firms granted options

[9] Hayes *et al.* (2012) find an average increase in the bonus share of around 3% around the reform.

Table 2.4: The FAS 123R Accounting Reform and the Duration of Incentives

	Duration		
	(1)	(2)	(3)
Panel A: Interaction with Pre-FAS123 Option Dummy			
FAS123 × Option-Dummy	-0.156**	-0.174**	-0.104
	(0.0715)	(0.0768)	(0.0701)
Observations	3,392	6,638	4,435
No. Firms	578	578	757
Panel B: Interaction with Pre-FAS123 Duration			
FAS123 × Pre-FAS123-Duration	-0.396***	-0.341***	-0.403***
	(0.0323)	(0.0344)	(0.0378)
Observations	3,373	6,601	4,411
No. Firms	573	573	751
Panel C: Interaction with Pre-FAS123 Duration Quintile			
FAS123 × Pre-FAS123-Duration Quint.	-0.224***	-0.201***	-0.235***
	(0.0203)	(0.0204)	(0.0193)
Observations	3,373	6,601	4,411
No. Firms	573	573	751
Year FE	×	×	×
Firm FE	×	×	×
Sample Period	2002 - 2007	2000 - 2014	2002 - 2007
Sample			incl. fin. & util.

Notes: The Table reports the results on the relationship between the FAS 123R reform and the duration of managerial incentives. *Duration* is measured as in Gopalan *et al.* (2014). *Option-Dummy* in Panel A is a dummy that indicates if any options are awarded in 2004. *Pre-FAS123 Duration* in Panel B is given by the duration of total compensation in 2004. *Pre-FAS123 Duration Quintiles* in Panel C are given by the quintile categories of the sample duration distribution in 2004. *FAS123* takes value 0 for each year until 2005 and value 1 afterwards. Standard errors (reported in parentheses) are clustered at the firm-level. ***, **, and * indicate statistical significance at the 1%-, 5%- and 10%-level.

to their CEOs (baseline specification) or measures the total amount of options granted, both during the pre-reform year 2004. The term δ_c reflects the depreciation for each investment category c. Following the approach used by Garicano & Steinwender (2016) and Fromenteau *et al.* (2019), we either ordinally rank asset categories according to their time to payoff or we directly use the category-specific depreciation rate to distinguish between more long- and more short-term investments.

Importantly, if the revision of FAS 123 induced treated firms to adjust their investment composition towards short-term assets, the coefficient of interest β_1 is expected to be positive. By exploiting the change in incentives triggered by this reform as a quasi-natural experiment, we aim to capture a causal and economically meaningful effect of incentives on within-firm capital (mis)allocation.

The vector $\lambda_{i,t}$ contains fixed effects at the firm-year level. These firm-year fixed effects absorb unobserved time-varying firm-specific factors that can affect investment decisions. Notably, these include demand shocks or technology shocks as long as they do not affect short- and long-term investments differently. Hence, our identification is based on within-firm variation across investment categories for a given time period. The vector $\lambda_{c/t}$ contains either fixed effects for investment categories c or category-year fixed effects $\lambda_{c,t}$. In our baseline specifications, we restrict our sample period to the years around the implementation of FAS 123R. Either we consider a smaller time frame from 2002 to 2007 or a more extended time frame from 2000 to 2014.

Since investments are lumpy in their nature, we transform investment expenditures using the inverse hyperbolic sine function, i.e., $invest_{i,c,t} = \text{arsinh}\left(I_{i,c,t}\right) = \ln\left(I_{i,c,t} + \sqrt{I_{i,c,t}^2 + 1}\right)$, in our baseline estimations. This has the advantage that we include zero investments in our estimations while we get for large investment expenditures $\text{arsinh}\left(I_{i,c,t}\right) \to \ln 2 + \ln I_{i,c,t}$ such that the interpretation is almost identical to a log regression. Alternatively, we also estimate Equation (2.1) with logarithmic transformations or consider the Box-Cox transformation instead of using the inverse hyperbolic sine function.

2.2.3 Main Results

Tables 2.5 to 2.7 show our main results of estimating Equation (2.1). Table 2.5 outlines the results of the regression analysis when we use the option dummy as treatment variable $X_{i,2004}$. This binary treatment divides our sample into two groups: the treatment group of firms with management affected by the reform and the control group whose management should be less affected by the reform. Besides that, our specifications control for ex-ante differences in investments between firms with different compensation practices by interacting the measure of long-term incentives with the depreciation. We include firm-year fixed effects to account for time-varying, firm-level demand and productivity shocks or permanent firm-specific differences in the investment policy. Furthermore, by including category or category-year fixed effects, we keep track of investment-category-specific events which might potentially bias our results. It should be noted that the interaction term of the FAS 123R dummy and the depreciation rate is absorbed by these category-year fixed effects. Standard errors are clustered at the firm-level following Abadie *et al.* (2017).

Table 2.5: Incentives and the Durability of Investments – Option Dummy

	Investments					
	(1)	(2)	(3)	(4)	(5)	(6)
Measure of Depreciation:	*Ordering*		*Depreciation Rate*			
FAS123 × Option-Dummy × Depr	0.0478**	0.0480**	0.595**	0.595**	0.693***	0.537**
	(0.0240)	(0.0239)	(0.232)	(0.231)	(0.252)	(0.235)
Option-Dummy × Depr	0.0135	0.0132	-0.292	-0.294	-0.237	-0.454
	(0.0361)	(0.0361)	(0.355)	(0.355)	(0.356)	(0.350)
FAS123 × Depr	-0.0409**		-0.558***			
	(0.0207)		(0.200)			
Investment FE	×		×			
Investment-Year FE		×		×	×	×
Firm-Year FE	×	×	×	×	×	×
Observations	13,422	13,422	13,422	13,422	33,737	14,200
No. Firms	667	667	667	667	684	721
Sample Period	2002 - 2007	2002 - 2007	2002 - 2007	2002 - 2007	2000 - 2014	2002 - 2007
Sample						incl. fin. & util.

Notes: The Table reports the results on the relationship between managerial incentives and investment decisions. *Option-Dummy* is a dummy that indicates if any options are awarded in 2004. *FAS123* takes value 0 for each year until 2005 and value 1 afterwards. *Depr* is the measure of depreciation, following an ordinal scale in columns 1 and 2, and expressed in absolute depreciation rates in columns 3 to 6. Standard errors (reported in parentheses) are clustered at the firm-level. ***, **, and * indicate statistical significance at the 1%-, 5%- and 10%-level.

In the first two columns, we use a simple ordering of categories as a measure of depreciation, which follows the ordering of depreciation rates and ranges from 1 (land) to 7 (advertising). We are interested in the coefficient outlined in the first row, which is the coefficient of the composite interaction term combining the FAS 123R dummy, the treatment indicator and the depreciation measure. We can infer that our coefficient of interest is positive and significant at the 5%-level in column 1 when we use the ordinal ranking as a measure of asset depreciation. When we include fixed effects at the category-year level in column 2 to control for aggregate trends in certain investment categories, the coefficient of interest hardly changes. In columns 3 to 6, we then assign depreciation rates as a measure of asset depreciation. Again, we estimate a positive coefficient of interest, which is significant at the 5%- or 1%-level.[10] This suggests that reform-induced shifts in incentives cause a relative shift in investments towards more short-term assets. Quantitatively, the coefficient suggests

[10]Results also remain robust to including fixed-effects at the firm-category level.

that treated firms shift about 6% more investment to a category with a 10 percentage point higher depreciation rate compared to non-option paying firms (columns 3 and 4). This result remains robust for an extended time period around the reform between 2000 and 2014 (column 5) or when we include firms from the utility, financial and public administration sectors into the sample (column 6).

Table 2.6: Incentives and the Durability of Investments – Option Share

	Investments					
	(1)	(2)	(3)	(4)	(5)	(6)
Measure of Depreciation:	*Ordering*		*Depreciation Rate*			
FAS123 × Option-Share × Depr	0.0775*	0.0820**	0.711*	0.735*	0.777*	0.678*
	(0.0395)	(0.0395)	(0.391)	(0.391)	(0.417)	(0.385)
Option-Share × Depr	0.0707	0.0682	-0.580	-0.596	-0.508	-0.870
	(0.0613)	(0.0612)	(0.617)	(0.617)	(0.601)	(0.604)
FAS123 × Depr	-0.0315**		-0.353**			
	(0.0160)		(0.158)			
Investment FE	×		×			
Investment-Year FE		×		×	×	×
Firm-Year FE	×	×	×	×	×	×
Observations	13,422	13,422	13,422	13,422	33,737	14,200
No. Firms	667	667	667	667	684	721
Sample Period	2002 - 2007	2002 - 2007	2002 - 2007	2002 - 2007	2000 - 2014	2002 - 2007
Sample						incl. fin. & util.

Notes: The Table reports the results on the relationship between managerial incentives and investment decisions. *Option-Share* is given by the option share in total compensation in 2004. *FAS123* takes value 0 for each year until 2005 and value 1 afterwards. *Depr* is the measure of depreciation, following an ordinal scale in columns 1 and 2, and expressed in absolute depreciation rates in columns 3 to 6. Standard errors (reported in parentheses) are clustered at the firm-level. ***, **, and * indicate statistical significance at the 1%-, 5%- and 10%-level.

Next, we use the option share in total compensation as continuous treatment variable $X_{i,2004}$ in Table 2.6. Also with the continuous treatment, results suggest that more affected firms shift more investment towards short-lived categories after the accounting reform. Furthermore, we group firms into quintile spells based on their respective position in the option share distribution and run bin regressions to capture non-linear effects within $X_{i,2004}$. Results are reported in Table 2.7. Again, our coefficient of interest is positive and significant throughout all specifications. The average investment wedge, measured as shift to a 10 percentage points higher depreciation rate investment category, equals 1.9% for two adjacent quintiles in our most stringent specification (column 4). This result remains robust for different time horizons and sample sizes (column 5 and 6).

Table 2.7: Incentives and the Durability of Investments – Option Quintiles

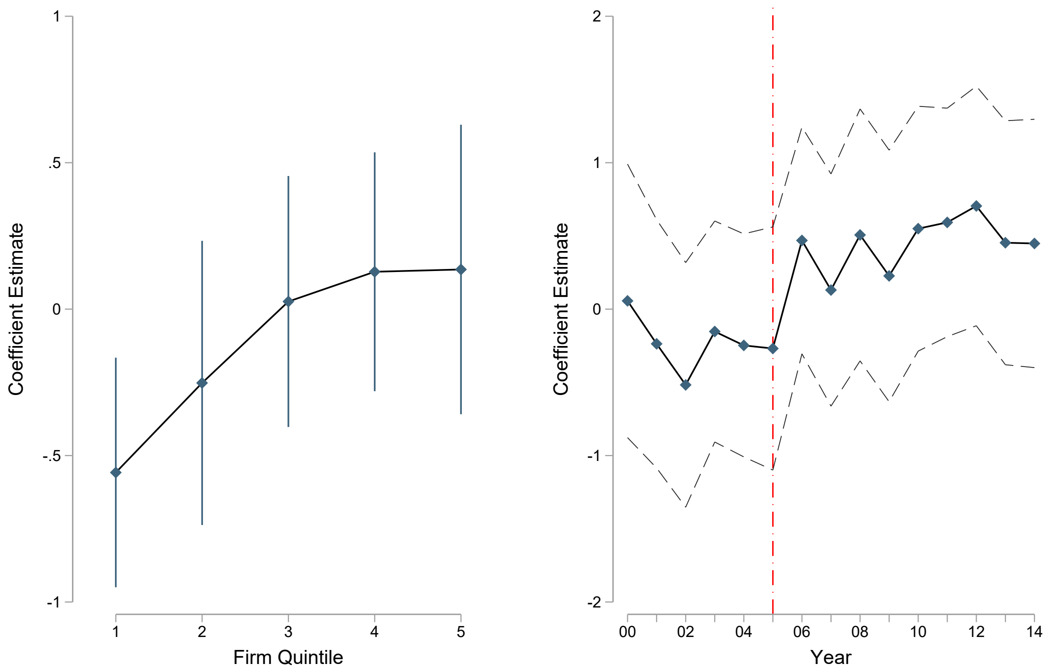
	Investments					
	(1)	(2)	(3)	(4)	(5)	(6)
Measure of Depreciation:	*Ordering*		*Depreciation Rate*			
FAS123 × Option-Quintile × Depr	0.0185**	0.0193***	0.180**	0.185**	0.195**	0.168**
	(0.00718)	(0.00719)	(0.0718)	(0.0718)	(0.0781)	(0.0715)
Option-Quintile × Depr	0.0125	0.0121	-0.0926	-0.0954	-0.0772	-0.150
	(0.0112)	(0.0112)	(0.113)	(0.113)	(0.111)	(0.111)
FAS123 × Depr	-0.0604***		-0.650***			
	(0.0230)		(0.228)			
Investment FE	×		×			
Investment-Year FE		×		×	×	×
Firm-Year FE	×	×	×	×	×	×
Observations	13,422	13,422	13,422	13,422	33,737	14,200
No. Firms	667	667	667	667	684	721
Sample Period	2002 - 2007	2002 - 2007	2002 - 2007	2002 - 2007	2000 - 2014	2002 - 2007
Sample						incl. fin. & util.

Notes: The Table reports the results on the relationship between managerial incentives and investment decisions. *Option-Quintile* is the quintile of the option share distribution in 2004. *FAS123* takes value 0 for each year until 2005 and value 1 afterwards. *Depr* is the measure of depreciation, following an ordinal scale in columns 1 and 2, and expressed in absolute depreciation rates in columns 3 to 6. Standard errors (reported in parentheses) are clustered at the firm-level. ***, **, and * indicate statistical significance at the 1%-, 5%- and 10%-level.

To provide evidence that the sign of the average effect is not driven by skewness or outliers of a specific quintile, we also estimate the impact of FAS 123R on the investment mix for each quintile separately by interacting the FAS 123R dummy and the depreciation rate measure with a set of five dummy variables (one for each quintile of $X_{i,2004}$). The left graph in Figure 2.1 plots these five coefficients and illustrates that the distortion towards more short-lived investment categories increases monotonically across quintiles. We can also reject the null hypothesis that the coefficient estimate for the first and the fifth quintile are similar at the 5%-significance-level. Overall, by exploiting the accounting reform, we are able to document that exogenous increases in short-termist incentives induce more short-termist oriented investment decisions.

As a next step, we are going to study if the common trend assumption is likely fulfilled in

Figure 2.1: Investment Wedges by Treatment Quintiles and Years



Notes: The left graph in the Figure plots jointly estimated quintile-specific coefficients when investments are regressed on the FAS 123R dummy interacted with quintile dummies and depreciation rates. Firm-year and category fixed effects are included, standard errors are clustered at firm-level. Dashed lines illustrate 95% confidence intervals. The null hypothesis of coefficient equality at the bottom and the top quintile can be rejected at the 5%-level ($p = 0.032$). The right graph in the Figure plots time-specific coefficients when investments are regressed on the interaction between an option dummy with year dummies and depreciation rates. Firm-year and category-year fixed effects are included, standard errors are clustered at firm-level. Dashed lines illustrate 95% confidence intervals. The null hypothesis of coefficient equality before versus after the reform can be rejected at the 1%-level ($p = 0.008$).

our empirical setting. If option-paying and non-option-paying firms experience different time trends in their investments even without the accounting reform, we would wrongly attribute the observed investment wedge to the exogenous accounting reform. To rule this out, we regress investment expenditures on the interaction between annual dummies, depreciation rates and the option dummy. The right graph in Figure 2.1 plots the coefficient estimates for each triple interaction and shows that there is a distinct and permanent jump in the investment wedge in the year after the reform. Until 2005, the coefficient of the investment wedge is relatively constant and close to zero, which suggests that investment patterns did not systematically differ across treatment and control firms. After 2005, the coefficients then unambiguously shift into positive terrain, remaining at that positive level until the end of our sample. The slight fluctuations between 2007 and 2010 are likely to be driven by turmoils around the Global Financial Crisis. Overall, we can strongly reject the null hypothesis that the pre-FAS-123R average coefficients equals the post-FAS-123R averages at the 1%-level.

Table 2.8: Incentives and Capital Stocks

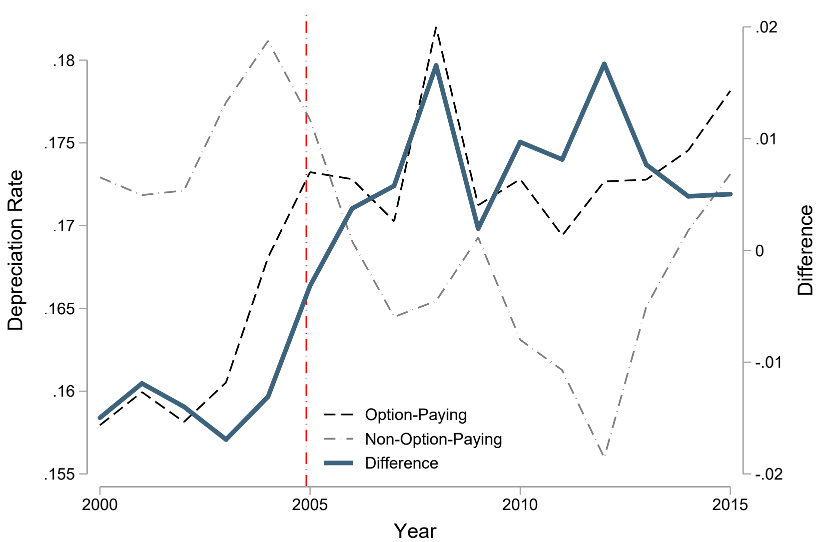
	Capital Stocks					
	(1)	(2)	(3)	(4)	(5)	(6)
Measure of Depreciation:	*Ordering*		*Depreciation Rate*			
FAS123 × Option-Dummy × Depr	0.0403*	0.0404*	0.513**	0.518**	0.780***	0.438*
	(0.0223)	(0.0224)	(0.224)	(0.225)	(0.288)	(0.226)
Option-Dummy × Depr	-0.0128	-0.0130	-0.472	-0.475	-0.509	-0.551
	(0.0356)	(0.0355)	(0.374)	(0.374)	(0.368)	(0.367)
FAS123 × Depr	-0.0437**		-0.572***			
	(0.0203)		(0.202)			
Investment FE	×		×			
Investment-Year FE		×		×	×	×
Firm-Year FE	×	×	×	×	×	×
Observations	12,690	12,690	12,690	12,690	31,784	13,415
No. Firms	663	663	663	663	681	710
Sample Period	2002 - 2007	2002 - 2007	2002 - 2007	2002 - 2007	2000 - 2014	2002 - 2007
Sample						incl. fin. & util.

Notes: The Table reports the results on the relationship between managerial incentives and capital stocks. As dependent variable, the natural logarithms of the respective capital stocks are used. Physical capital stocks are directly obtained from Factset. Intangible capital stocks (R&D and Advertising) are determined the following: Initial capital stock of category c equals $k_{c,0} = \frac{Invest_{c,0}}{\delta_c}$, and the subsequent values are constructed iteratively, where the capital stock of category c at time t equals $k_{c,t} = k_{c,t-1}(1-\delta_c) + Invest_{c,t}$. *Option-Dummy* is a dummy that indicates if any options are awarded in 2004. *FAS123* takes value 0 for each year until 2005 and value 1 afterwards. *Depr* is the measure of depreciation, following an ordinal scale in columns 1 and 2, and expressed in absolute depreciation rates in columns 3 to 6. Standard errors (reported in parentheses) are clustered at the firm-level. ***, **, and * indicate statistical significance at the 1%-, 5%- and 10%-level.

Since we considered gross investments as dependent variable so far, the observed relative increase in short-term investments could principally be partly absorbed by the faster depreciation of these investments, such that a reallocation towards a shorter-lived capital stock within the firm does not take place in the end. To explicitly test for the effects on capital reallocation, we construct logarithmized category-specific capital stocks and include them as an alternative dependent variable in our baseline regressions. Physical capital stocks are directly obtained from Factset and intangible capital stocks are determined based on a perpetual inventory method. The results from Table 2.8 demonstrate that the introduction of FAS 123R led indeed to substantial reallocation of capital within firms. On average, option-paying firms increased the stock of a capital category with a 10 percentage point higher depreciation rate by 5.2% compared to non-option-paying firms.

Related to that, we further provide evidence that the firm-specific depreciation rate of treated firms went up by the introduction of FAS 123R. To assess this, we construct a depreciation rate for each firm-year based on the relative size of each firm's category-specific capital stocks. Figure 2.2 plots the mean depreciation rate for option-paying firms, non-option-paying firms as well as their difference. While depreciation rates move in parallel until 2004, depreciation rates of option-paying firms fall less than those of non-option-paying firms do, leading to a non-trivial difference between those two groups of firms. Comparing the pre- with the post-FAS-123R depreciation rates suggests that the difference in depreciation rates increased by about 2 percentage points.

Figure 2.2: Average Firm-Specific Depreciation Rates over Time



Notes: The Figure plots the evolution of firm-specific mean depreciation rates for option-paying firms (black), non-option-paying firms (gray) and their difference (bold blue, right axis). Firm-specific depreciation rates are calculated as a weighted mean of category-specific depreciation rates, where the weights are the firm's capital stocks in the respective categories.

We then use these firm-year-specific depreciation rates as the dependent variable and run firm-level difference-in-differences regressions. The results in Table 2.9 reveal a substantial cut in the durability of the capital stock for treated firms. Quantitatively, the depreciation rate of the average capital stock of option-paying firms increased by 1.58 percentage points compared to the control group. Ceteris paribus, this decrease in the durability of the capital stock imposes substantial costs on the affected firms. Besides the risk that these firms might suffer from productivity losses due to suboptimal factor composition, firms would have to spend more to retain the same level of capital stock as before the reform.[11] We quantify these extra cost burdens by calculating the additional financing costs required to match the level of the pre-FAS-123R capital stock. Materialized in additional interest payments, we obtain an amount of USD 15.29 per USD 1,000 invested for the affected firms.[12]

Table 2.9: Incentives and Capital Stock Depreciation

	Average Depreciation Rate			
	(1)	(2)	(3)	(4)
FAS123 × Option-Dummy	0.0158***	0.0165***	0.0189***	0.0163***
	(0.00549)	(0.00568)	(0.00590)	(0.00584)
Option-Dummy		-0.0118		
		(0.00964)		
Year FE	×	×	×	×
Firm FE	×		×	×
Observations	4,118	4,118	10,261	4,877
No. Firms	700	700	701	831
Sample Time	2002 - 2007	2002 - 2007	2000 - 2014	2002 - 2007
Sample				incl. fin. & util.

Notes: The Table reports the results on the relationship between managerial incentives and investment decisions. We use the firms' average depreciation rates weighted by capital stocks in the individual asset categories as the dependent variable. For each firm i with depreciation-specific capital stocks C in year t, the capital-stock-weighted depreciation rate $\delta_{i,t}$ equals $\sum_{c=1}^{C} \delta_c \times \frac{cap-stock_{i,t,c}}{\sum_{c=1}^{C} cap-stock_{i,t,c}}$. *Option-Dummy* takes 1 if any options are awarded in 2004, and zero otherwise. *FAS123* takes 0 for each year until 2005, 1 afterwards. Standard errors (reported in parentheses) are clustered at the firm-level. ***, **, and * indicate statistical significance at the 1%-, 5%- and 10%-level.

In Table B.6 of the Appendix, we also report empirical evidence on the misallocation effect of incentives based on a model-derived measure of short-term incentives as an alternative to the reduced-form estimates presented here.

[11] Given that FAS 123R affects investment decisions via distorted managerial incentives and has no direct impact on the production side of the firm, we argue here that this shift exacerbated effective factor usage.

[12] See Appendix B1.2 for details on the calculations.

2.2.4 Alternative Channels and Robustness Checks

CEO Turnover: In general, it might be possible that investment decisions are CEO-specific, so we would wrongly attribute changes in the investment mix to changes in the compensation scheme whenever a new CEO enters the firm. We show in Appendix B1 (Table B.2) that our results are not driven by CEO turnover. Focusing on a subsample that includes only firms with a unique CEO, we are able to rule out that channel. The results in Table B.2 indicate that the effect is even more pronounced when we exclude firms where CEO turnover occurred. The coefficient of interest almost doubles in size and is estimated with higher precision.

Measurement of Investments: Additionally, we provide empirical evidence that our results do not depend on a specific transformation of the explained investment variable $invest_{i,c,t}$. Instead of applying the inverse hyperbolic sine function to investment expenditures, we run regressions using a log and a Box-Cox transformation. Table B.3 in Appendix B1 reveals similar results. We also run robustness checks where we either include negative investments in the analysis or set them to zero. The results remain qualitatively the same, the effect becomes even stronger when we include negative investments (Table B.4).

Firm Size: We also illustrate that the change in investment behavior was particularly caused by differences in managerial incentives and not by potential confounding factors like firm size. In principle, larger firms might compensate their CEOs in a different way than their smaller counterparts. In case there is an event in 2006 which affects the investment policy of large firms only, we would run into an omitted variable problem and fail to identify the true relationship between managerial incentives and investment decisions. By explicitly controlling for firm size, we are able to rule out that additional channel. We run regressions where we allow for two groups of interaction terms, one including the treatment variable $X_{i,2004}$ and the other including a measure of firm size. As proxies for firm size, we use either the log number of employees or the log value of total assets. The results in Table B.5 show that the described additional channel via differences in firm size might not be in place. The triple interaction term with firm size hardly explains any variation in the data and is insignificant for either proxy of firm size, employment or assets. We can further see that the coefficient estimate of our original interaction term of interest keeps more or less the same size. The original point estimate of 0.595 (Table 2.5, column 4) falls slightly to 0.564 when considering employment and to 0.586 when considering assets, leaving similar levels of significance.

2.3 Quantitative Analysis

We now present a model of firm investments that rationalizes how the shift in compensation structure towards more bonus payments and away from equity ownership affects investments. Our starting point is a standard neoclassical dynamic investment model, where firms combine capital and labor to produce output. We extend this model in the following ways. First, we assume that decisions are made by a risk-neutral manager, who maximizes the present value of her compensation package. This distorts investment decisions away from those predicted by a standard neoclassical model, where the manager acts to maximize the value of equity and thus makes decisions that are completely congruent to shareholder interests. Similar to Nikolov & Whited (2014), we consider compensation packages that are composed of a fixed salary, a bonus based on current profits and a share of total equity. The larger is the equity share of firm value that accrues to the manager, the more managerial and shareholder incentives are aligned. Second, we introduce two types of capital that differ in their durability in the spirit of Aghion *et al.* (2010) or Rampini (2019), measured by their depreciation rates. Both types of capital are subject to convex capital adjustment costs.

2.3.1 Model

Production: Consider a firm that uses a set of two capital inputs $\mathbf{K}_t = [K_{l,t}, K_{s,t}]$ and labor inputs N_t. Importantly, we assume that the two capital goods differ in their depreciation rates $\delta_l < \delta_s$ such that capital inputs $K_{l,t}$ are more durable than capital inputs $K_{s,t}$. The firm uses these inputs to produce output Q_t according to a simple Cobb-Douglas production function

$$Q_t = \widetilde{Z}F(\mathbf{K}_t, N_t) = \widetilde{Z}\left(K_{l,t}^{\nu}K_{s,t}^{1-\nu}\right)^{\alpha} N_t^{1-\alpha}, \tag{2.2}$$

where $\widetilde{Z}$ measures the firm's productivity. The firm faces isoelastic demand for its product with elasticity ε:

$$Q_t = BP_t^{-\varepsilon}, \tag{2.3}$$

where B is a demand shifter. Combining the production function with the demand curve yields the following revenue production function:

$$R_t = P_tQ_t = Z^{1-a-b}\left(K_{l,t}^{\nu}K_{s,t}^{1-\nu}\right)^{a} N_t^{b}, \tag{2.4}$$

where we substitute $Z^{1-a-b} \equiv B^{1/\varepsilon}\widetilde{Z}^{1-1/\varepsilon}$ such that Z captures the firm's overall business conditions. We define the terms $a \equiv \alpha(1-1/\varepsilon)$ and $b \equiv (1-\alpha)(1-1/\varepsilon)$ for tractability.

Furthermore, each type of capital is subject to quadratic adjustment costs:[13]

$$\frac{\gamma}{2}\left(\frac{K_{j,t+1}}{K_{j,t}}-1\right)^2 K_{j,t}, \quad j \in \{l,s\}.$$

That is, using a current capital mix of $\mathbf{K}_t$ and acquiring a future capital mix of $\mathbf{K}_{t+1}$ gives total capital-related costs of

$$C_t^K = \sum_{j \in l,s}\left[\gamma\left(\frac{K_{j,t+1}}{K_{j,t}}-1\right)^2 K_{j,t} + q_j\left(K_{j,t+1}-(1-\delta_j)K_{j,t}\right)\right], \tag{2.5}$$

with q_j as the unit price of capital good j.

Since we will perform partial-equilibrium analyses in what follows, we treat aggregate variables as constant and also set $q_l = q_s = 1$. Furthermore, we abstract from uncertainty regarding $\widetilde{Z}$ and B. The variable factor labor only causes variable costs of wN_t such that overall profits from the operations of the firm in period t are given by

$$\Pi_t = R_t - C_t^K - wN_t. \tag{2.6}$$

Compensation and Incentives: In this model, we focus on firms with owner-manager separation. As in Nikolov & Whited (2014), we do not derive the form of optimal compensation contracts but instead approximate contracts that we actually observe in the data without making a statement about their optimality.[14] This approach allows us to identify the effects of changing contractual features on firms' investment policies, the allocation of capital and economic activity. Specifically, we assume the following remuneration structure for the manager: total remuneration Γ_t is the sum of a fixed salary w_t^f, a bonus b_t that is some proportional share of current profits $b_t = \eta_b \Pi_t$ and equity grants E_t^m proportional to total equity E_t, such that $E_t^m = \eta_e E_t$:

$$\Gamma_t = w_t^f + b_t + E_t^m. \tag{2.7}$$

[13]Empirical adjustment costs are likely neither quadratic nor fully symmetric across different types of capital. In the calibrated version of our model, we have also examined versions with partially irreversible investment and different adjustment cost parameters γ for different capital goods. These variations do not affect our calibration results in a qualitatively meaningful way. Two additional dimensions excluded from the analysis that are potentially important are *i.* to what extent different capital goods can serve as collateral for loans and *ii.* to what extent capital goods can be rented without actually appearing on the firm's balance sheet.

[14]See Murphy (1999) for an empirical survey on CEO compensation packages.

This particular structure of remuneration packages highlights the core mechanism at hand: a part of remuneration depends on current (short-term) profits, while another part is linked to long-term value. To keep the model tractable, we follow Glover & Levine (2015) in assuming that contracts only last for one period and that the manager does not start out with any pre-existing holdings of equity.[15] For future reference, it is opportune to denote managers of the firm by the period t that they are in charge of steering the firm.

Assuming a complete financial market in the background, the market value of equity E_t is given by the discounted stream of expected future cash flows. After taking into account salaries and bonuses for management, the total amount available for dividend payments in each period is given by $(1-\eta_b)\Pi_t - w_t^f$. Furthermore, we let capital markets anticipate that similar remuneration schemes may exist in the future. Hence, if the manager in charge during period $t+1$ is also expected to be awarded a share η_e of equity, shareholders in period t anticipate that the share of future total market capitalization they hold shrinks by a factor of $1-\eta_e$, leading to share dilution.[16] With complete markets and rational expectations, equity then is valued as

$$E_t = (1-\eta_b)\Pi_t - w_t^f + \frac{1}{1+r}\mathbb{E}_t\left\{(1-\eta_e)E_{t+1}\right\}, \tag{2.8}$$

where r is the relevant market interest rate. After recursive substitution, this becomes

$$E_t = (1-\eta_b)\left[\Pi_t + \sum_{\tau=1}^{\infty}\left(\frac{1-\eta_e}{1+r}\right)^{\tau}\mathbb{E}_t\left\{\Pi_{t+\tau}\right\}\right] - \sum_{\tau=0}^{\infty}\left(\frac{1-\eta_e}{1+r}\right)^{\tau}\mathbb{E}_t\left\{w_{t+\tau}^f\right\}. \tag{2.9}$$

Using Equation (2.9), we can rewrite the value of the manager's remuneration package as

$$\Gamma_t = w_t^f - \eta_e\sum_{\tau=0}^{\infty}\theta^{\tau}\mathbb{E}_t\left\{w_{t+\tau}^f\right\} + \varphi\left[\Pi_t + \beta\sum_{\tau=1}^{\infty}\theta^{\tau}\mathbb{E}_t\left\{\Pi_{t+\tau}\right\}\right], \tag{2.10}$$

[15] Considering multi-period contracts between managers and owners quickly complicates matters a lot and requires a substantial amount of further structural assumptions. These include *i.* managers' preference relation regarding payoffs at different points in time, *ii.* managers' ex-ante exposure to the firm's performance via preexisting holdings of equity, *iii.* a process linking managers' probability of staying with the firm to firm performance and *iv.* uncertainty about future remuneration packages. All these assumptions on their own would have important consequences regarding the overall term-structure of the managers' decision problem.

[16] The fact that equity-based compensation can lead to share dilution is a well known fact in finance (e.g., Asquith & Mullins 1986, Huson *et al.* 2001, Core *et al.* 2002). In the model context, this implies that managers' overall share in market capitalization would converge to 100% eventually if they were to remain employed infinitely by the firm. This aspect counteracts discounting and could lead to non-trivial time preferences.

where we define

$$\begin{aligned}
\varphi &:= \eta_b + \eta_e(1-\eta_b), && (2.11)\\
\beta &:= \frac{\eta_e(1-\eta_b)}{\eta_b + \eta_e(1-\eta_b)}, && (2.12)\\
\theta &:= \frac{1-\eta_e}{1+r}. && (2.13)
\end{aligned}$$

The term $w_t^f - \eta_e \sum_{\tau=0}^{\infty} \theta^\tau \mathbb{E}_t \left\{ w_{t+\tau}^f \right\}$ captures the manager's fixed wage and the wage payments of her successors. This term is exogenous to the manager's decision problem such that we may ignore it in the following. This simplifies the model further such that we can consider managers' remuneration packages given by

$$\Gamma_t = \varphi \left[\Pi_t + \beta \sum_{\tau=1}^{\infty} \theta^\tau \mathbb{E}_t \left\{ \Pi_{t+\tau} \right\} \right]. \tag{2.14}$$

Decision-Making: As the remuneration package is represented in Equation (2.14), an interesting property becomes apparent. The payout profile resembles the preferences that a risk-neutral agent with quasi-hyperbolic time preferences for profits would have. In other words, incentivizing managers with a combination of both, bonuses on current profits and equity payouts induces decision-making that is present biased. Furthermore, managers' optimization problem in period t_0 inherently depends on the expected behavior of their successors in future periods, and the behavior of a current manager directly affects the feasible set of outcomes of its immediate successor. Essentially, different generations of managers play a dynamic game with one another: each manager chooses a factor mix $(\mathbf{K}_{t+1}, N_t)$ to maximize her own remuneration taking into account previous managers' decisions and expectations regarding future behavior. We focus on Markov-perfect equilibria with stationary, smooth strategies, where each manager's decision only depends on her inherited capital stock.

Deriving the demand for the freely adjustable factor labor is straightforward and yields

$$N_t = \left(\frac{b Z^{1-a-b} \left(K_{l,t}^{\nu} K_{s,t}^{1-\nu} \right)^a}{w} \right)^{\frac{1}{1-b}}. \tag{2.15}$$

Equation (2.15) gives a standard labor demand relation equating marginal costs and the marginal revenue product of labor.

In the presence of capital adjustment costs, it is not possible to analytically solve for the policy functions regarding the capital goods. However, we can implicitly characterize a time-invariant policy function, assuming that the policy functions of all managers just depend on the current capital goods and on expectations that future managers will behave in the same way. We denote this function as $\mathcal{K}(\mathbf{K}) = (\mathcal{K}_l(\mathbf{K}), \mathcal{K}_s(\mathbf{K}))$. Here, $\mathcal{K}_j(\mathbf{K})$ is the policy function for capital good $j \in \{l, s\}$. I.e., in period t a manager whose firm starts with capital stocks $\mathbf{K}_t = (K_{l,t}, K_{s,t})$ chooses $K_{j,t+1} = \mathcal{K}_j(\mathbf{K}_t)$. The function $\mathcal{K}(\cdot)$ is then the solution to the manager's first-order conditions. Hence, with a slight abuse of notation, in period t, the policy function will be the solution $\mathbf{K}_{t+1}$ of the following self-referencing characterization for j:[17]

$$0 = \frac{\partial \Pi_t}{\partial K_{j,t+1}} + \beta\theta \frac{\partial \Pi_{t+1}}{\partial K_{j,t+1}} + \theta(1-\beta) \sum_{k=l,s} \frac{\partial \mathcal{K}_k(\mathbf{K}_{t+1})}{\partial K_j} \frac{\partial V(\mathcal{K}(\mathbf{K}_{t+1}))}{\partial K_k}. \tag{2.16}$$

Here, the term $V(\cdot) := [\Pi_t + \theta V(\mathcal{K}(\mathbf{K}_t))]|_{\mathbf{K}_t}$ represents a recursive continuation value, conditional on the current choice of capital inputs. This capital-specific Euler equation (2.16) takes into account the strategic dependence of future behavior on current decisions. The first two elements are fairly standard: the first element incorporates the current costs of investment (including the unit prices of capital goods and the marginal costs of adjusting the respective capital stocks), the second term represents the marginal returns in the next period, discounted by $\beta\theta$, adjusted for depreciation. The final term is a peculiarity of our model and other models with quasi-hyperbolic time preferences. This term captures the marginal effect on equity via changes in future investment behavior. Both, the unknown gradients of the capital policy functions $\frac{\partial \mathcal{K}_k(\mathbf{K}_{t+1})}{\partial K_j}$ for $j, k \in \{l, s\}$ as well as the unknown gradient of the continuation-value function $V(\cdot)$ are relevant to evaluate the effects of future investment on equity value. Whenever managers are compensated with a combination of bonuses and equity (which implies that $\beta \neq 1$), this last term does not cancel out such that this cannot be solved analytically and requires to be approximated numerically within the calibration exercise.

Discussion: The direct effects of managerial incentives on corporate investments modeled in this study are captured by the terms β and θ introduced by the compensation package. The investment policy of a decision-maker that maximizes the long-term firm value corresponds to terms $\beta = 1$ and $\theta = \frac{1}{1+r}$. Intuitively, the term $\beta < 1$ induces the manager to behave as if she was solving some quasi-hyperbolic optimization problem. This behavior arises from the fact that the compensation structure in Equation (2.7) causes a short-term bias for the manager since current profits are rewarded by both, equity ownership and bonus payments. Increasing the bonus share η_b and lowering the equity share η_e decreases β and increases her bias towards optimizing current profits. Furthermore, the term $\theta < 1$ incorporates a

[17] The derivation of the optimality condition (2.16) is relegated to Appendix B2.

dilution factor arising from the manager taking into account that her equity ownership will be diluted by future managers that will also be incentivized with equity. With equity-based remuneration, share dilution affects long-term investors' holdings of the firm's stock. This implies that for any $\eta_e > 0$, future income streams are more strongly discounted than purely at the market interest rate since $\theta < \frac{1}{1+r}$.

While our model allows for fairly rich dynamics on investment patterns and firms' capital stocks, it still is a fairly stylized simulation since we abstract from other factors that typically vary over time and affect investment decisions as well. One of these abstractions is risk-aversion. While being difficult to measure the extent of an individual manager's risk-aversion, a risk-averse decision-maker could likely have an even stronger preference to tilt the within-firm capital allocation further towards short-term assets as these assets expose the decision-maker to less risk. In that sense, the results that we obtain from the counterfactual analysis of the calibrated model could be seen as some lower bound of reform-induced capital misallocation. Furthermore, we neglect the role of convexity in compensation schemes and the behavior associated with it. While this simplifies our quantitative analysis, Hayes *et al.* (2012) provide empirical evidence that the reform-induced change in convexity had little impact on CEOs' risk-taking behavior.[18] Another aspect that we abstract from in the baseline quantification is the consideration of general-equilibrium effects. Since factor prices could adjust in general equilibrium, this would explicitly allow for feed-back effects into other decision-makers' investment decisions even though their incentives might have remained unchanged. As a robustness check, we study a general-equilibrium extension of the model that takes price effects into account. This general-equilibrium extension, however, comes at the cost that we have to abstract from aggregate dynamics such that we only compare steady-state equilibria.

2.3.2 Model Quantification

Equipped with our model, we aim to quantify the effects of the introduction of FAS 123R on the capital allocation of firms and economic outcomes. In order to do that, we calibrate it to match certain features of public US companies and industry characteristics before the reform. We then assume that there is an unexpected shock to β in a way consistent with what we observe in the data around the reform.[19] Industry-specific information is obtained from the US files of the EU KLEMS database for 2003-2005, for firm-level remuneration data

[18] Bebchuk & Fried (2010) discuss how equity-based compensation packages can be designed to achieve strong ties to long-term results.

[19] In this exercise, we do not alter θ to focus ideas purely on the effect of a relative shift in the duration structure of managers' remuneration. That is, in terms of the model we effectively consider a shock to η_b.

we rely on Execucomp and Coles *et al.* (2006).[20]

We consider a sample of 1,000 firms that draw a pre- and a post-FAS-123R value for β that match the observed distributions of β in the years 2005 and 2007 from a discretized distribution taking observed transition probabilities into account. We classify the distribution of β into ten bins varying from 0.75 to 1.0 in steps of size 0.025. Table 2.11 provides the observed transition probabilities across bins, the changing distribution of β is plotted in Figure 2.3. The histograms illustrate the shift of compensation packages away from equity around the reform: drawing a large value for β became less likely after the reform. However, the transition matrix also suggests that there is substantial path-dependency as the diagonal elements (i.e., the probabilities of remaining within a certain bin) show values between 63.60% and 90.15%. Path dependency seems to matter in particular at the outer bounds of the distribution as the probability of remaining within a bin is highest for the bottom and the top bin. Overall, the sample mean value for β falls by about 2.8 percentage points from 0.918 to 0.890. This decline in β is driven by both a reduction in the share of equity compensation η_e and an increase in the average bonus share η_b. Moreover, 69.4% of firms remain in the same bin for β, while 19.7% move to a bin with a higher value for β and 10.9% enter a lower β-bin. Thus, the incentive structure of managers has shifted only slightly, but noticeably in the period around the reform.

We assign each firm of our random sample to a specific industry taking the size composition of industries in the US according to OECD data on the number of firms by sector into account. We assume that the measure for firm's overall business conditions Z is composed of an industry-wide demand condition $B = B^{ind}$ and a firm-specific TFP $\tilde{Z} = Z^{firm}$ according to

$$Z = (B^{ind})^{\frac{1}{\varepsilon}} (Z^{firm})^{\frac{\varepsilon-1}{\varepsilon}}.$$

For each industry, we use the values for value added as a proxy for the revenue of the firm,[21] the total stock of both types of capital, average depreciation rates for both types of capital, the average wage paid to employees and the number of employees. For information on the industries used and the corresponding values for the variables, we refer to Table 2.10. Each firm is characterized by a vector of three i.i.d. random draws, which determine Z^{firm}, the manager's incentive structure determined by β and the equity ownership share η_e. The wage rate and the depreciation rates for short- and long-term capital goods are directly inferred from the industry draw. We use standard values from the literature for the adjustment-cost

[20] See Table 2.10 for an industry overview and Appendix B3 for a detailed description on the construction of firm-specific compensation packages.

[21] We could, of course, explicitly consider a production function with intermediate inputs, but this would complicate the analysis without materially affecting the mechanism studied here.

Table 2.10: Industry-Level Variables

Code	Industry Description	Probability Weight (in %)	Value Added (in Mio USD)	Wage Bill (in Mio USD)	Employment (in Thd)	Wages (in Thd USD)	Depr Rates s	Depr Rates l	Capital Stock (in Mio USD)	$\frac{K_l}{K_s+K_l}$ (in %)
A	Agriculture, forestry and fishing	1.972	138,161	36,249	1,278	28.4	0.13	0.02	462,506	58.02
B	Mining and quarrying	0.332	260,953	62,677	552	113.5	0.14	0.02	1,481,196	92.88
C	Total manufacturing	7.883	1,726,301	930,930	16,226	57.4	0.11	0.03	2,794,956	47.38
D, E	Electricity, gas and water supply	0.563	288,219	90,943	1,566	58.1	0.10	0.02	1,665,872	78.54
F	Construction	12.575	748,735	458,619	8,903	51.5	0.16	0.03	228,765	31.76
G	Wholesale and retail trade	22.269	1,777,411	961,865	19,776	48.6	0.15	0.03	1,367,003	71.11
H	Transportation and storage	3.054	472,378	317,617	5,525	57.5	0.14	0.03	1,051,537	60.11
I	Accommodation and food service activities	7.907	414,118	256,740	8,885	28.9	0.14	0.03	466,458	78.35
J	Information and communication	0.397	698,043	325,449	4,865	66.9	0.13	0.04	1,374,041	70.97
K	Financial and insurance activities	5.023	930,028	505,515	6,637	76.2	0.18	0.04	925,047	61.75
M, N	Other business services	17.840	1,343,732	874,366	10,753	81.3	0.15	0.04	1,056,987	50.14
Q	Healthcare	9.033	929,544	767,055	15,756	48.7	0.15	0.03	940,826	76.25
R, S	Arts, entertainment and recreation	11.153	510,096	332,260	8,142	40.8	0.15	0.05	743,230	84.53

Notes: Industry-specific probability weights are based on the number of enterprises across sectors from the OECD Structural Statistics of Industry and Services database for the year 2005. Other industry-level information is based on U.S. 2003–2005 files from EU KLEMS data. Wage bill is obtained by multiplying the number of people employed times the wage. Depr rate s displays the depreciation rate of the short-term capital stock, which is given by the capital stock-weighted depreciation rates of telecommunication equipment (N11322G), computer hardware (N11321G), transport (N1131G) and other machinery equipment and weapons (N11OG). Accordingly, depr rate l is the industry-specific long-term depreciation rate, that is directly provided by EU KLEMS (depreciation rate for other buildings and structures, N11OG). The last column displays the share of long-term capital in total capital.

Table 2.11: Transition Matrix β before and after FAS 123R

	β post-FAS-123 in 2007									
β pre-FAS-123 in 2005	I 0.75-0.775	II 0.775-0.8	III 0.8-0.825	IV 0.825-0.85	V 0.85-0.875	VI 0.875-0.9	VII 0.9-0.925	VIII 0.925-0.95	IX 0.95-0.975	X 0.975-1
I 0.75-0.775	**90.15**	1.01	1.55	0.97	1.35	1.21	0.53	0.58	0.19	2.46
II 0.775-0.8	13.46	**67.01**	1.92	2.56	1.92	2.88	2.56	1.92	0.96	4.81
III 0.8-0.825	10.59	1.81	**69.00**	3.10	3.36	2.07	2.07	3.62	1.55	2.84
IV 0.825-0.85	7.04	1.85	3.70	**66.67**	3.89	4.44	3.70	3.15	1.30	4.26
V 0.85-0.875	6.98	1.67	2.12	2.73	**67.69**	4.25	5.61	4.10	1.21	3.64
VI 0.875-0.9	5.29	1.53	2.82	2.23	4.35	**65.92**	6.11	5.64	2.35	3.76
VII 0.9-0.925	3.39	1.45	1.36	3.19	3.10	4.94	**63.60**	7.74	6.00	5.23
VIII 0.925-0.95	3.19	0.94	1.38	2.25	2.39	3.41	5.66	**66.06**	7.76	6.96
IX 0.95-0.975	1.80	0.50	0.87	1.49	1.61	3.10	4.34	9.06	**65.32**	11.91
X 0.975-0.1	2.29	0.45	0.58	0.81	1.16	1.81	1.42	3.42	6.93	**81.13**

Notes: The Table reports transition probabilities for FAS-123R-induced changes in β. We group betas into ten bins each ranging 2.25 percentage points. Data is left-censored at 0.75, which applies to 14.39% of the observations. Row i displays for a β grouped in bin i the probabilities of being in bins 1-10 after the reform. Therefore, rows sum up to 100%. Diagonal entries indicate the probabilities for β being unchanged after the reform.

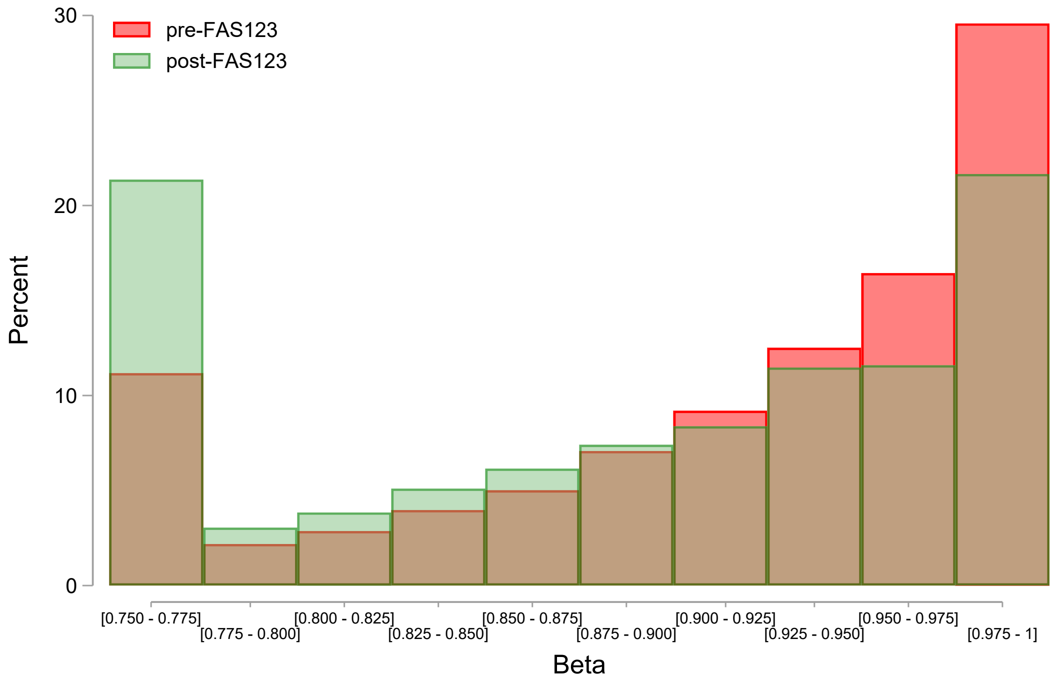
parameter γ and the interest rate r.[22]

The scale parameter B^{ind}, the factor shares a and b for capital and labor, and the long-term capital share ν have to be calibrated. Here, we adopt the following approach and calibrate these values to the benchmark case $\beta = 1$.[23] Then, the steady-state version of the

[22] For γ we follow Bloom (2009, Table III) and choose 4.844. The interest rate r is set to 2.98%. A detailed discussion can be found in Section B3.2 in the Appendix.

[23] This approach implies that the simulated sample is not exactly representative of the empirical sample because the observed average of the firms' β is below 1. However, this is the only way of calibrating the parameters analytically. Also the relative size of the effects is not altered in a materially important way by this strategy.

Figure 2.3: Changing Incentives around FAS 123R



Notes: The Figure depicts the empirical distribution of the β parameter before (red) and after (green) FAS 123R. Distribution overlap is illustrated by the brown area. We group βs into ten bins each ranging 2.25 percentage points. Data is left-censored at 0.75, which applies to 14.39% of the observations.

Euler equation (2.16) can be simplified to

$$1 = \theta\left(MPK_j + 1 - \delta_j\right), \quad j = l, s, \tag{2.17}$$

where the marginal products of capital are given by

$$MPK_l = a\nu Z^{1-a-b} K_l^{a\nu - 1} K_s^{a(1-\nu)} N^b \tag{2.18}$$

$$MPK_s = a(1-\nu) Z^{1-a-b} K_l^{a\nu} K_s^{a(1-\nu)-1} N^b. \tag{2.19}$$

The steady-state version of (2.15) is given by

$$wN = bZ^{1-a-b} K_l^{a\nu} K_s^{a(1-\nu)} N^b. \tag{2.20}$$

Conditions (2.17)–(2.20), together with the revenue function (2.4) can be used to pin down four parameters: the revenue productivity shifter Z, the capital share α, the share of durable capital goods in total capital ν and the demand elasticity ε. For the calibration, we use the average firm in an industry with $Z^{firm} = 1$. Using this, we can reformulate the steady-state conditions (2.17)–(2.20) as well as Equation (2.4) in the following way:

$$\begin{aligned}
R &= \left(B^{ind}\right)^{1-a-b} K_l^{a\nu} K_s^{a(1-\nu)} N^b \\
1 &= \theta \left(a\nu \frac{R}{K_l} + 1 - \delta_l \right) \\
1 &= \theta \left(a(1-\nu) \frac{R}{K_s} + 1 - \delta_s \right) \\
b &= \frac{wN}{R}.
\end{aligned}$$

We then calibrate the parameters $B^{ind}, \alpha, \nu, \varepsilon$ such that the values for the labor-to-output ratio $\frac{wN}{R}$, the share of long-term capital in total capital $\frac{K_l}{K_s+K_l}$, the capital-to-output ratio $\frac{K_l+K_s}{R}$ and the overall scale of operations R match those of the respective sector in the data.[24]

The individual scaling factor Z^{firm} is drawn from an idiosyncratic distribution, where we assume the logarithm of Z^{firm} to be normally distributed around a zero mean and a standard deviation of 0.52, which is what İmrohoroğlu & Şelale Tüzel (2014) find for the productivity dispersion in Compustat data.

We then solve the model for each firm individually. Since the incentive structure in the model features a present-bias ($\beta < 1$) and decision-makers face capital adjustment costs ($\gamma > 0$), our model resembles a quasi-hyperbolic discounting problem such that solving it involves similar challenges as those documented in previous papers on neoclassical growth models with quasi-geometric discounting (e.g., Krusell & Smith 2003, Maliar & Maliar 2016).[25] In particular, as the generalized Euler equation for capital does not have a specific closed-form solution, we resort to numerical methods. Since Euler-equation methods are likely to fail (Maliar & Maliar 2016), we use a version of the endogenous gridpoint method first introduced by Carroll (2006). This method works similar to backward induction: For a fixed number of possible future stocks of both types of capital, one solves the managers' optimality conditions for current stocks. This procedure essentially constructs inverted policy functions

[24] Note, that we use a sector's value added as a proxy for R. Also, remember: $a \equiv \alpha(1 - 1/\varepsilon)$ and $b \equiv (1 - \alpha)(1 - 1/\varepsilon)$.

[25] In the case without adjustment costs ($\gamma = 0$), a simple equilibrium is straightforward: Since managers' utility is modeled as linear and markets are complete, the choice of $\mathbf{K}_t$ by manager $t-1$ only acts as a level shift to current profits. Hence, manager t's marginal calculations are separate from the current state of the capital stock. As such, the manager could simply choose an arbitrary value of $\mathbf{K}_{t+1}$ irrespective of $\mathbf{K}_t$. If all managers follow such a strategy, the gradients of the policy function are zero everywhere. In anticipation of this, future behavior cancels out of the model equations and the optimality conditions (2.16) for each capital good $j \in \{l, s\}$ simplifies to

$$1 = \beta\theta \left[\frac{\partial R(K_{l,t}, K_{s,t}, N_t,)}{\partial K_{j,t}} + (1 - \delta_j) \right].$$

from which we can back out the dynamics for each firm.

2.3.3 Results

Relation to the Empirical Estimates: We begin by replicating the reduced-form regressions based on our simulated data. Table 2.12 reports estimates using the simulated sample of firms. Note that in contrast to the empirical sample, these data only contain two distinct types of capital. Furthermore, the treatment indicators used in the estimations here is either a dummy indicating whether the firm experienced a reduction in β or the continuous value of β in the pre-reform period. Even though we did not target the coefficient estimates in the parameterized version of the model, we find the magnitude of the reform-induced investment distortion to be very similar compared to the empirical counterparts. When using the dummy as treatment indicator in columns 1 and 2 of Panel A, we obtain a coefficient of 0.426, which almost equals the counterpart based on the empirical sample (0.595 in columns 3 and 4 of Table 2.5). In the two subsequent columns of Panel A, we consider the respective capital stocks as dependent variable and thereby replicate the reduced-form regressions from Table 2.8 (columns 3 and 4). The coefficients of interest from both regressions are of similar magnitude here as as well. In columns 1 and 2 of Panel B, we then use the continuous treatment variable and again find coefficients of similar size compared to the empirical counterparts given in Table 2.6 (columns 3 and 4). Given this relatively close replication of the empirical estimates, we feel confirmed that our calibration approach is suitable to quantify the effects of the accounting reform on production, investment and capital misallocation. As an alternative to the reduced-form estimates, we also report evidence on the misallocation effect using empirical variation in β. Results are presented in Table B.6 of the Appendix.

Within-Firm Adjustments: In a next step, we use our simulated firm panel to analyze the dynamic within-firm adjustments in response to the reform. These are depicted in Figure 2.4. The upper graphs in the Figure plot investments into short- and long-term capital goods, normalized by their respective capital stocks. Firms respond to the reform with a short-run drop in investments in both capital goods. This cut in investments is consistent with the empirical findings by Ladika & Sautner (2019), who report a reform-induced investment cut in the years directly following the introduction of FAS 123R. As expected, the results show that this cut in investments is asymmetric across investment goods. Our results deviate from the previous literature in this respect since our model captures heterogeneity in investment categories. Consistent with our empirical findings presented in Section 2.2 before, the reform causes a distortion in investments across assets with different life spans. While short-term investments are reduced by about 0.5% on average, the drop in long-term invest-

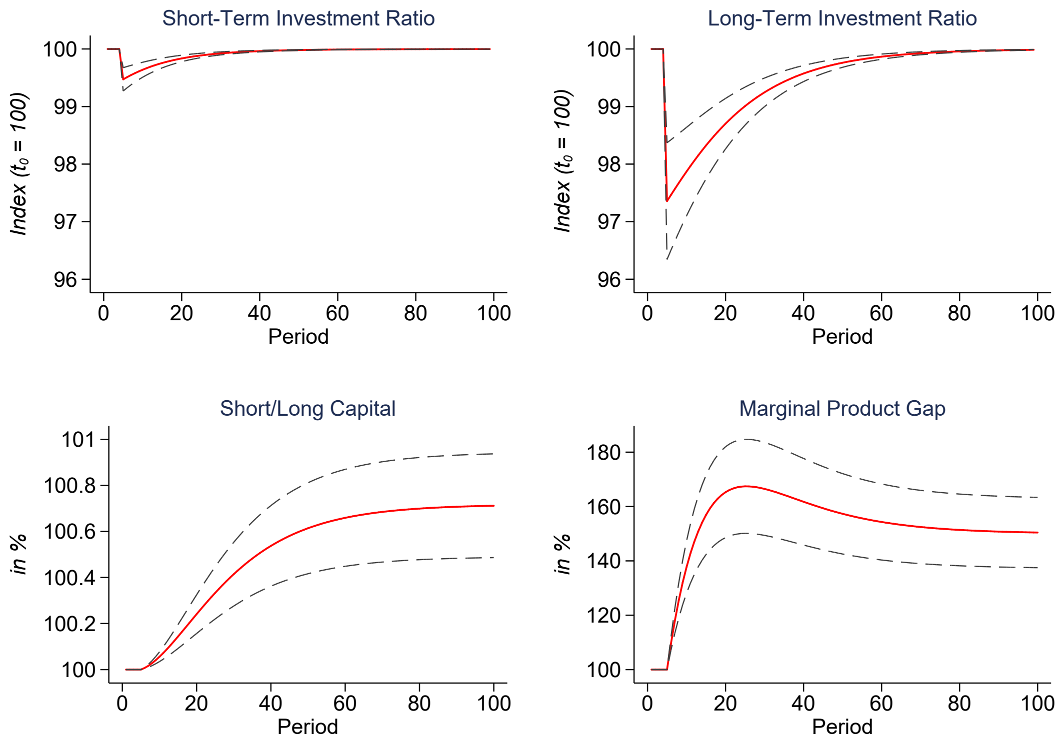
Table 2.12: Simulated Firms – Regression Results

	Investment		*Capital Stock*	
	(1)	(2)	(3)	(4)
Panel A: Interaction with Pre-FAS123 Option Dummy				
FAS123 × Option-Dummy × Depr	0.426***	0.426***	0.400***	0.400***
	(0.0231)	(0.0231)	(0.0199)	(0.0199)
Option-Dummy × Depr	0.651	0.651	0.0341	0.0341
	(0.594)	(0.594)	(0.540)	(0.540)
FAS123 × Depr	-0.0327***		-0.0380***	
	(0.00375)		(0.00458)	
Panel B: Interaction with Pre-FAS123 Option Share				
FAS123 × Option-Share × Depr	0.716***	0.716***	0.744***	0.744***
	(0.0918)	(0.0918)	(0.0993)	(0.0993)
Option-Share × Depr	-7.420**	-7.420**	-8.018***	-8.018***
	(3.093)	(3.094)	(2.878)	(2.879)
FAS123 × Depr	-0.605***		-0.641***	
	(0.0831)		(0.0917)	
Investment FE	×		×	
Investment-Year FE		×		×
Firm-Year FE	×	×	×	×
Observations	4,000	4,000	4,000	4,000
No. Firms	1,000	1,000	1,000	1,000

Notes: This Table reports the results on the relationship between managerial incentives and investment decisions for our simulated panel of 1000 firms. We collapse the data into a pre- and post-reform era, where *FAS123* is a dummy variable indicating the latter period. *Option-dummy* is defined as binary variable, which is 1 if a firm experience an actual reduction in its firm-specific β after the reform, and 0 otherwise. Accordingly, *Option-share* is proxied by the firm-specific β in the pre-reform period. *Depr* is the measure of depreciation for the two capital goods, which is 3.28 percent for long-term capital and 14.48 percent for short-term capital. Standard errors (reported in parentheses) are clustered at the firm-level. ***, **, and * indicate statistical significance at the 1%-, 5%- and 10%-level.

ments appears substantially larger around 2.6%. This heterogeneous response in investments results in a shift of the within-firm capital stock towards relatively more short-term capital. This can be observed in the lower left graph of Figure 2.4, which depicts the share of short-term capital in percent of long-term capital goods. On average this fraction is 82.3% in t_0 and increases about 0.7 percentage points in response to the reform.

Figure 2.4: Within-Firm Adjustments to FAS 123R



Notes: The Figure depicts the dynamic adjustment process for short-term investment (top-left), long-term investment (top-right), the capital ratio (bottom-left) and the marginal product gap (bottom-right). Short- and long-term investments are normalized by their respective capital stocks. For each firm, we normalize each of the responses with respect to their pre-FAS-123R values. The average adjustment is illustrated by the solid red line, dashed black lines depict 95% confidence intervals.

In order to make a statement on the economic relevance of such a relatively mild shift in the within-firm capital stock composition, we compute the distortion of marginal revenue products across investment categories within firms, inspired by Hsieh & Klenow (2009). Specifically, we define the marginal product gap within a firm as

$$MPG_t = |MPK_{s,t} - MPK_{l,t}|, \tag{2.21}$$

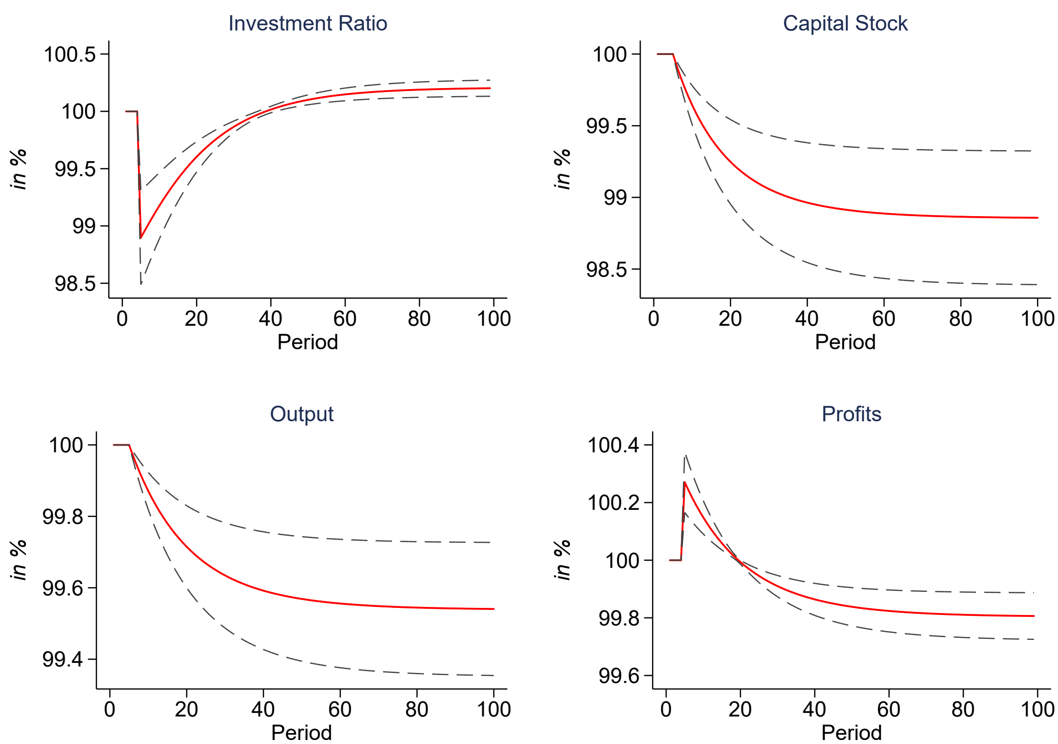
where $MPK_{j,t},\ j \in \{l, s\}$ is the sum of the marginal revenue product of a capital good and its resale value $(1 - \delta_j)$ such that the marginal product gap MPG_t captures the wedge in the different rates of return across capital goods within firms. The graph at the lower right of Figure 2.4 plots this measure of within-firm misallocation of capital. It shows that the relatively moderate shift in the composition of capital stocks triggered by the rather small reform-induced shift in incentives causes a very substantial rise in within-firm capital misallocation. Since short-term capital goods have higher depreciation rates, those capital goods can adjust relatively faster, which explains the spike in the marginal product gap followed by a slight reduction afterwards. This can also be seen in the change of the curvature of the relative capital stocks from convex to concave (lower left graph). The marginal product gap increases in the long-run by 50.4% on average. This increase corresponds to an average wedge in the rates of return across capital goods that is equal to about 3.7 basis points.

Firm-Level Effects: Next, we consider the firm-level effects of the reform, which we illustrate in Figure 2.5. The upper left graph in the Figure depicts total gross investment normalized by the total capital stock. Again, one can observe the immediate reduction in the investment ratio (by about 1.1%) directly after the reform that already became apparent in the graphs showing investment into individual capital goods. Interestingly, the long-run steady state level of total gross investment relative to the capital stock slightly *increases* compared to pre-reform levels. This higher investment ratio in the long-run is driven by the within-firm reallocation of capital. Since the capital composition shifts towards short-term capital goods and these deplete faster, the average depreciation rate of capital increases. Consequently - in relative terms - larger re-investments are necessary. Nevertheless, gross investment falls in the aggregate leading to a reduction in the firms' total capital stock by around 1.1% on average, which is illustrated in the upper right graph in Figure 2.5.

We then quantify the effects of the within-firm capital misallocation channel on economic output and profits. Based on the underlying Cobb-Douglas production function (2.2), economic output falls by about 0.5% on average. Due to the homogeneity of the production function, the partial-equilibrium decline in employment is similar to the output change. When considering profit changes in the graph at the lower right, a short-run spike in profits by about 0.3% on average becomes evident. This short-run profit spike is driven by the sudden cut in investments. Profits then decline in the long-run by 0.2% on average as the within-firm capital stocks and the capital mix shift away from the social optimum. The finding that the motive to raise short-term profits at the expense of long-run macroeconomic growth matters in the aggregate is also in line with Terry (2015), who finds that short-termist incentives cost 6% of output in the long-run. Compared to this finding, the impact of the FAS 123 reform on output is indeed substantial, even though its direct effect on incentives has been moderate.

Capital Misallocation across Firms: Finally, we use our model to analyze the effects of the reform on misallocation across firms. Since the FAS 123 reform only affects incentives

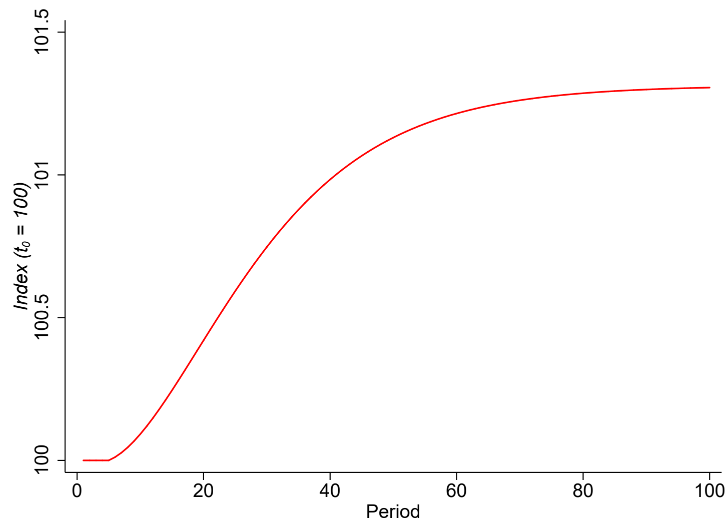
Figure 2.5: Firm-Level Effects of FAS 123R



Notes: The Figure depicts the dynamic adjustment process for the total investment ratio (top-left), the capital stock (top-right), output (bottom-left) and profits (bottom-right). For each firm, we normalize each of the responses with respect to their pre-FAS-123R values. The average adjustment is illustrated by the solid red line, dashed black lines depict 95% confidence intervals.

and investment choices of some managers while other firms remain unaffected, the change in accounting rules is likely to raise misallocation across firms. In Figure 2.6, we plot the cross-firm dispersion in the capital mix of short- relative to long-term capital by normalizing the standard deviation of the capital ratio across firms with the initial standard deviation before the reform. It is evident that the cross-firm dispersion in the capital ratio increases by about 1.3% after the reform, speaking to the fact that firms become more heterogeneous in terms of factor endowment. Given that FAS 123R has no direct effect on the marginal productivity of capital goods, such a reallocation of capital across firms should not have been taken place from a social-planner point of view. We therefore interpret this increase in firm heterogeneity with respect to capital endowment as indirect evidence for more cross-firm capital misallocation as, ceteris paribus, firms are more unevenly endowed with short- and long-term capital after the reform.

Figure 2.6: Effects of FAS 123R on Capital Misallocation across Firms



Notes: The Figure plots the dynamic adjustment in the cross-firm dispersion of the capital ratio. For each period, we calculate the standard deviation of the capital ratio over our firm-sample and normalize the respective value with the pre-FAS-123R standard deviation.

Robustness to General-Equilibrium Effects: We next study to what extent the previous partial-equilibrium results are robust once we account for general-equilibrium effects. When the reform increases firms' demand for short-term capital goods, some parts of the within-firm misallocation of capital could be mitigated by increases in factor prices. Furthermore, when firms produce at higher marginal costs due to a sub-optimal capital mix, final-good prices might increase leading to lower welfare. At the same time, demand shifts away from short-termist firms because consumers can substitute towards cheaper goods. To study these effects, we use the same sample of firms as before but endogenize factor markets and demand for final goods. In this (pseudo-)general-equilibrium extension, goods produced by the firms within each sector are combined into a CES bundle. The various sectoral bundles are then combined into an aggregate Cobb-Douglas final good. Regarding factor markets, we assume that all costs related to gross investments are created from using labor and we impose factor-market clearing by equating aggregate labor demand with a fixed labor endowment. The demand shifter B^{ind} now becomes an endogenous equilibrium object and we use labor as the numéraire such that the wage rate is normalized to 1 and homogeneous across sectors. Compared to the partial-equilibrium analyses, the disadvantage of this approach is that we can only compare implied aggregate steady states before and after the reform and thus neglect dynamic adjustments around the reform. Details on the treatment of the general-equilibrium effects can be found in Appendix B2.2.[26]

As before, firms differ along the following dimensions: each firm is assigned to one out of 13 sectors, which determines most model parameters and the CES basket into which the firm's output is included. Additionally, each firm draws an idiosyncratic TFP, as well as their own β, η_e and η_b, where we use the same transition of firm-specific βs as in the partial-equilibrium setting before.

In Table 2.13, we present the counterfactual effects of our simulated reform on a set of aggregate variables. In each case, the presented numbers are relative changes compared to the steady-state value before the reform. Remember that the shock on managerial incentives induced by FAS 123R has been rather moderate with an average decline in β by roughly 2.8 percentage points (about 1 percentage point if we consider the discretized distribution of β). In the previous partial-equilibrium exercise, this shock was associated with a substantial gap in the marginal products of capital causing a drop in output, capital stocks and a relative shift in investment from long-term to short-term capital goods.

Table 2.13: General Equilibrium Effects: Aggregate Results from Counterfactual Reform

Variable	Change (%)	Variable	Change (%)
Output	-0.08	Price level	0.17
Long-term investment	-0.88	Short-term investment	-0.46
Long-term capital stock	-0.97	Short-term capital stock	-0.51
Overall investment	-0.59	Overall capital stock	-0.81

Notes: The Table shows the effects of the simulated reform on a set of aggregate variables. For each variable, the effect is measured as the percentage change of the steady-state value after the reform relative to the steady-state value before the reform.

These findings carry through to our general-equilibrium analysis here, albeit the effects are quantitatively smaller due to the counteracting general-equilibrium adjustments. Aggregate output drops by about 8 basis points (compared to 50 basis points in the partial-equilibrium setting). However, there are two issues that prevent us from a direct comparison to the previous results. First, the partial-equilibrium analyses use data on sectoral wages, while there is a uniform numéraire wage in general equilibrium. Second, the partial-

[26] In this extension, we abstract from firm entry and exit and still assume managers' remuneration packages as exogenously given. As such, we denote this extension a pseudo-general-equilibrium framework.

equilibrium analyses plot means of normalized firm values, which cannot be used for the aggregate adjustments in general equilibrium, since here the size differences across firms matter as well.[27] Thus, the behavior of the normalized aggregate variables presented in Table 2.13 rather resembles the one of a normalized mean *across* firms in the economy. To isolate the general-equilibrium feedback, we therefore also consider a scenario where we shock the βs but keep B^{ind} constant such that we are still in a partial-equilibrium setting but with homogeneous wages fixed at 1. If we apply this to our sample and consider the same output measure as in the partial-equilibrium setting from before, firms' output shrinks by 0.61% on average, which is substantially closer to the 0.50% obtained in the partial-equilibrium analysis with sectoral wage data. In general equilibrium, this overall effect on average firm output is then mitigated in absolute terms due to factor-market competition. Here, firms' output shrinks on average by 0.29% due to the reform. In contrast, if we take size differences across firms into account, the (fictitious) average firm sees its output decrease by 0.42% in the partial-equilibrium setting, whereas the average firm in general equilibrium has an output decrease of 12 basis points. The general-equilibrium effects at the aggregate level are thus broadly in line with the behavior of the fictitious average firm that we studied in partial equilibrium. However, since consumers substitute demand away from short-termist firms, the effect on aggregate output is about one third smaller (8 versus 12 basis points) compared to the output change for the average firm.

If we compare the change in aggregate capital stocks, we also see that the general-equilibrium change is about one third smaller than the partial-equilibrium change: while the capital stock falls by 0.81% in general equilibrium, it falls by 1.1% in partial equilibrium. Furthermore, the reduction of total investments is somewhat smaller (-0.59%) than the drop in the overall capital stock as firms need to reinvest more frequently due to the shift in the capital mix away from more durable capital goods. This shift can also be observed in the larger decline in long-term investments compared to the decline in short-term investments.

Lastly, the general-equilibrium exercise allows us to determine the effects of the reform on the aggregate price level of the final good and hence on the real wage and thus welfare in the economy. Here, we observe an increase in the price level of about 17 basis points, which translates to an equally sized decline in the real wage caused by the reform.

[27] Aggregate output changes presented in Table 2.13 correspond to changes in the final consumption bundle $\mathcal{Q}$. See Appendix B2.2 for details.

2.4 Conclusion

In this study, we analyze how short-termist managerial incentives affect the allocation of capital inside firms. Using the 2005 revision of the FAS 123 accounting statement as a quasi-natural experiment, we provide empirical evidence showing that affected firms systematically shifted investment expenditures towards less durable assets in response to a shift towards more short-term managerial incentives. To quantify the impact of such incentive distortions on output, investment and capital (mis)allocation, we then calibrate a dynamic model of firm investments in which managers determine investment policies and face typical incentive contracts.

Our results indicate that even relatively small deviations in incentives away from long-term compensation schemes, like those induced by the accounting reform, can cause substantial economic distortions. Firms cut their investments into long-term assets, and within-firm capital misallocation increased due to a mismatch in decision-makers' private marginal products of capital and social marginal products of capital, causing a fall in output, capital stocks and real wages. The results imply that corporate decision-makers' incentives are very crucial when designing economic policies – such as the considered accounting reform – as managers react very sensitively to changes in their incentive schemes. Disregarding those aspects in policy reforms can substantially affect economic welfare.

There are several future directions for this work to reduce the adverse economic effects of managerial short-termism. One direction could be to study the scope of income taxation to incentivize managers to act more long-term. Another direction of research could be to study the role of employment duration in compensation contracts to guide managerial behavior.

Chapter 3

The Role of Capital Durability for the Investment Response under Uncertainty*

*I would like to thank Jan Fritsche, Sebastian Horn, Franziska Hünnekes, Gerhard Illing, Dominik Sachs, Alexander Schwemmer, Jan Schymik and Peter Zorn for helpful comments.

3.1 Introduction

Reviewing 25 years of empirical research on the relationship between investments and uncertainty, there is overwhelming evidence that higher levels of uncertainty lead to a slowdown in corporate investments (e.g, Leahy & Whited 1996, Guiso & Parigi 1999, Bloom *et al.* 2007, Julio & Yook 2012, Gulen & Ion 2015, Alfaro *et al.* 2018). In this chapter, I give a more nuanced view on the negative investment-uncertainty relationship: I show that long-term investments, such as buildings and machinery investments, are particularly affected by changes in uncertainty, while short-term investments, such as advertising and IT investments, react less sensitively. In response to an uncertainty shock, firms cut long-term investments more strongly than short-term investments, which effectively decreases the durability of the capital stock used in production. I rationalize my empirical findings by embedding them into the existing theory on real options. In the presence of uncertainty over future business conditions, making an irreversible investment creates additional costs for the firm as it gives up the opportunity to receive new information.[1] This foregone *option value of waiting* is particularly high for long-term investments since they are tied to the firm's capital stock for a long period of time. In contrast to that, short-term investments deplete much faster and therefore give the firm more flexibility in tracking the optimal capital stock level when future business conditions are uncertain.

The first part of this chapter provides causal empirical evidence how uncertainty affects investments with different durabilities. Heterogeneity in investment goods regarding their degree of durability allows me to identify the pure composition effect within the firm while holding fixed all observed and unobserved (possibly) time-varying firm-specific factors.[2] I construct an annual firm-investment category panel for publicly traded US firms in the period

[1]See, e.g., Bernanke (1983), Pindyck (1988), Caballero (1991), Pindyck (1993) for a theoretical discussion on the negative investment response under uncertainty. Specifically, Caballero (1991) shows that partial irreversibilities and imperfect competition or decreasing-returns-to-scale production are sufficient conditions to generate a negative investment-uncertainty relationship. In contrast to that, Hartman (1972) and Abel (1983) demonstrate that under perfect competition or constant-returns-to-scale production uncertainty actually *increases* investments. Furthermore, see Dixit & Pindyck (1994) for a textbook discussion. An illustrative summary of the underlying mechanism can be found on page 3: "The reason is that a firm with an opportunity to invest is holding an *option* analogous to a financial call option – it has the right but not the obligation to buy an asset at some future time of its choosing. When a firm makes an irreversible investment expenditure, it exercises, or *kills*, its option to invest. It gives up the possibility of waiting for new information to arrive that might affect the desirability or timing of the expenditure; it cannot disinvest should market conditions change adversely. This lost option value is an opportunity cost that must be included as part of the cost of the investment. As a result, the NPV rule 'invest when the value of a unit of capital is at least as large as its purchase and installation cost' must be modified. The value of the unit must exceed the purchase and installation cost, by an amount equal to the value of keeping the investment option alive."

[2]This is by including firm-year fixed effects.

between 1995 and 2016. For these firms, I obtain firm-specific uncertainty shocks by computing annual volatilities of daily stock price returns (Leahy & Whited 1996, Bulan 2005). My constructed measure of uncertainty exhibits considerable time and cross-sectional variation, and tracks, on average, measures of aggregate uncertainty reasonably well. To mitigate endogeneity concerns regarding stock prices, I follow Alfaro *et al.* (2018) and instrument firm-specific stock price volatility with sources of aggregate uncertainty (i.e., fluctuations in oil prices, exchange rates, treasury bill prices and policy uncertainty). My empirical results indicate that relative to a baseline category firms cut investment goods with a 10 percentage point lower depreciation rate by 8.1% more when firm-specific uncertainty doubles. This effect is very unlikely to be driven by specific categories or possible confounding factors (e.g., irreversibility), as it turns out to be (almost) monotone over a sample of seven broad investment categories that differ in their degree of durability. Furthermore, the effect persists when controlling for first-moment shocks. In further analyses, I study the implications for the firms' total investment responses in the cross section. For each firm, I compute the average depreciation rate of the capital stock and group firms along this measure. Firm-level regressions reveal that firms with more durable capital cut *total* investments more strongly when hit by an uncertainty shock. A 1-standard-deviation increase in capital stock durability leads to an additional decline in total investments by 3.4% when firm-specific uncertainty doubles. Therefore, heterogeneity in asset durability is an important determinant for the firm's investment response under uncertainty.

In the second part of this chapter, I study the empirical relationship found in the first part through the lens of the canonical dynamic investment model, where investments are subject to a rich mix of nonconvex adjustment costs.[3] I modify this baseline model in two ways. First, following Bloom *et al.* (2007) and Bloom (2009), I introduce firm-specific uncertainty as Markov-switching regime changes in the dispersion of the firm's business conditions. Second, output is produced by combining two types of capital goods that differ in their degree of durability as in Barrero *et al.* (2017) and Rampini (2019). I show numerically that the model generates investment dynamics that are qualitatively consistent with the patterns found in the empirical part. Following an unexpected and permanent increase in uncertainty, firms decrease investments into long-term capital by more than investments into short-term capital, such that the capital mix used for production is shifted towards less durable capital goods. I rationalize this finding by analyzing the investment policy functions of capital goods with different durabilities. Simulation-based results reveal that more durable investment goods have, ceteris paribus, larger investment inactivity areas, which are responsible for the more reluctant investment response under uncertainty. When uncertainty raises, the option value

[3] See, e.g., Chapter 8 in Adda & Cooper (2003) for further details.

of waiting increases by more for the durable than for the non-durable investment good since investments into the first good require a higher commitment as they are longer tied to the capital of the firm.

Literature Review: While most of the theoretical and empirical literature has focused on the effects of uncertainty on aggregate investments or on the differential effects on investments with different degrees of irreversibilities (e.g., Guiso & Parigi 1999, Gulen & Ion 2015, Kim & Kung 2016, Schauer (neé Klepsch) 2019), the role of capital durability for the investment response under uncertainty has not received much attention yet. To the best of my knowledge, only Barrero *et al.* (2017) stress, among other factors, the importance of capital durability for the investment response under uncertainty in a related setting. The authors decompose uncertainty into a short-run and long-run component, and find that *long-run* uncertainty reduces capital investments more strongly than hiring. They show that a model that includes joint differences in durability and irreversibility, but is otherwise fairly similar to my model, is able to explain these different dynamics in investments and hiring. In further empirical analyses, Barrero *et al.* (2017) focus on heterogeneity in capital investments and show that industries with particularly low capital depreciation rates cut total investments more strongly in response to changes in *long-run* uncertainty. My analysis sets apart from their study in the following respect: I provide empirical evidence that this result also holds for changes in the *overall* level of uncertainty as it holds when running firm-level regressions (and thereby improving identification). Moreover, the availability of granular investment category data at the firm-level allows me to estimate a pure composition effect of uncertainty on investments with different durabilities within the firm.

Furthermore, my study relates to the literature that analyzes the effects of uncertainty on key macroeconomic variables other than investments (e.g., consumption). Romer (1990) studies the effects of uncertainty over future income on consumption spending on durable and non-durable goods. Approximating income uncertainty through stock market variability, Romer (1990) finds that higher stock market fluctuations markedly decrease the production of durable consumption goods, while the output of perishable consumption goods is hardly affected.[4]

More broadly, this chapter also relates to the literature that analyzes the determinants of corporate short-termism. In this literature, a number of factors which induce firms to shift

[4]There is the same mechanism at work as in my analysis: in the presence of uncertainty, there is a trade-off between buying consumer durables and postponing the purchase. While the purchase of durables instantly generates utility for the consumer, the consumer may choose a quality level that is either too high or too low compared to his future (uncertain) income. As uncertainty rises, the option value of waiting increases, leading to a more reluctant spending behavior on consumer durables.

their investment expenditures towards less durable capital goods have already been outlined. Among other factors, such investment behavior could be driven by financial frictions and credit constraints (e.g., Garicano & Steinwender 2016, Rampini 2019, Aghion *et al.* 2010), tighter competition (e.g., Fromenteau *et al.* 2019), investor pressure (e.g., Terry 2015) or managerial incentives (e.g., Schramm *et al.* 2021). I contribute to this debate by proposing an additional channel, which fosters corporate short-termism: higher uncertainty induces firms to reduce long-term investments by more than short-term investments, which effectively decreases the durability of the firm's capital stock in production.

The remainder of this chapter is structured as follows. In the next Section 3.2, I present empirical evidence on the relationship between uncertainty and investments with different durabilities. Section 3.3 outlines the simulation exercise that is used to rationalize the investment dynamics found in the empirical part of this chapter. Finally, Section 3.4 concludes.

3.2 The Empirical Relationship between Capital Durability and Uncertainty

The following section describes the constructed data set and the empirical strategy that is used to estimate the causal relationship between uncertainty and investments with different durabilities. Finally, results are reported.

3.2.1 Data

I construct an annual firm-investment category panel for publicly traded US industrial companies for the period between 1995 and 2016. As it is standard in the empirical literature on business investments, I exclude the financial sector, utilities and public administration firms (e.g., Ottonello & Winberry 2018, Clementi & Palazzo 2019). Furthermore, firm-year observations with either negative assets, employment or sales are excluded from the analysis. I collect data on the firms' investment decisions for seven categories that differ along their degree of durability. Ranked from the most to the least durable investment category, these are investments into land, buildings, machinery, transport, R&D, computers and advertising. The FactSet Fundamentals Global Databases provide annual firm-level information on the capital stock of Property, Plant & Equipment including land, buildings, machinery, transport and IT investments. I use a perpetual inventory method to transform stock values into gross investment flows. Furthermore, annual expenditures on R&D and advertising are obtained from Compustat North America. I assign depreciation rates that are consistent with the existing literature (e.g., Garicano & Steinwender 2016, Fromenteau *et al.* 2019), an overview can be found in Table 3.1.

Table 3.1: Assigned Depreciation Rates

Category	*Land*	*Buildings*	*Machines*	*Transport*	*R&D*	*Computer*	*Advertising*
Depreciation	0%	3%	12%	16%	20%	30%	60%

Notes: Assigned category-specific depreciation rates following Garicano & Steinwender (2016) and Fromenteau *et al.* (2019).

Finding an adequate measure of uncertainty is not straightforward, as uncertainty can result from multiple sources. At the firm-level, these can be changes in taxation or regulatory practices, fluctuations in interest or exchange rates, or technological progress. In the literature, two different concepts to uncover firm-specific uncertainty exist. One approach relies on survey-based methods, where executives or managers are questioned about their expectations regarding future firm-specific outcomes. Here, uncertainty is measured either directly by the managers' subjective probability distributions (e.g., Guiso & Parigi 1999, Altig *et al.* 2020b) or by the degree of disagreement across executives/financial analysts (e.g., Bond & Cummins 2004, Bachmann *et al.* 2013). Potential drawbacks of this approach are the lack of detailed adequate survey data and the focus on specific questions/outcome variables in the survey. An alternative, that captures the nature of uncertainty more broadly and that I will use in my empirical analysis, is the concept of stock price volatility. Here, the underlying assumption is that all information that market participants consider relevant to the firm's future business conditions is reflected in the firm's share price. Therefore, large fluctuations in the firm's current share price indicate high uncertainty over future firm-specific business conditions. The general availability of stock market data for publicly listed firms at a high frequency allows me to obtain a quite detailed firm-specific measure of uncertainty for a very large set of firms. Following Leahy & Whited (1996) and Bulan (2005), I compute firm-specific uncertainty as the annual standard deviation of the firm's daily stock returns. To limit the impact of general stock market rallies and bubbles which are not related to firm's fundamentals, I also use the firm's daily excess returns with respect to the S&P500 as input for the standard deviation.

CRSP US Stock Databases provide detailed information on the daily stock prices of publicly listed US firms. I merge this information with annual balance sheet and investment data obtained from Compustat and FactSet.[5] The final sample comprises information for

[5] Annual stock price volatilities are merged with annual balance sheet information. Importantly, since firms differ regarding the starting month of their fiscal year, I can exploit this additional time dimension when constructing firm-specific uncertainty shocks. E.g., a firm with fiscal year going from March to February is merged with the standard deviation of its stock price returns in exactly that period.

1,142 distinct firms for the time period between 1995 and 2016. Table 3.2 gives an overview of selected firm characteristics. The median firm maintains assets valued at USD 1.24 bn and employs about 5,500 workers. Annual sales are in a similar order of magnitude as total assets, median cash holdings amount to USD 87m. The bottom part of Table 3.2 summarizes the firms' investment decisions. On average, firms spend most of their resources on machinery (USD 349m), R&D (USD 260m) and advertising (USD 225m), but investments into other categories also play a non-negligible role. The occurrence of zero investments at the 10th percentile indicates lumpy investment decisions at the firm-level (e.g., Doms & Dunne 1998).

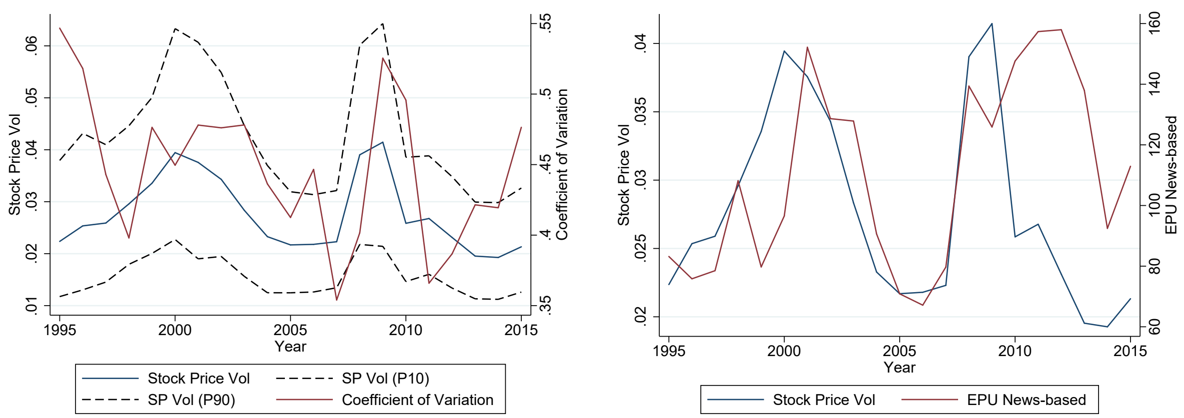
Table 3.2: Summary Statistics – Firm Characteristics

	Mean	P10	P50	P90	Std. Dev.	N
Assets (in 10^6 USD)	7165.0	160.11	1243.0	14543.4	23944.3	20,260
Employment (in 10^3)	23.337	0.5240	5.5000	54.353	76.984	20,153
Sales (in 10^6 USD)	6643.1	155.16	1294.8	13409.4	22306.7	20,259
Cash (in 10^6 USD)	512.82	6.3660	86.977	1048.4	1730.0	20,048
Stock Price Volatility	0.02751	0.01378	0.02392	0.04518	0.01498	20,239
Investments (in 10^6 USD)						
Advertising	225.31	1	26.958	521.03	647.68	8,762
Buildings	81.280	0	7.2420	140.77	377.10	15,396
Computer	96.508	1.5718	18.471	173.25	379.59	4,143
Land	18.760	0	0.03400	17.100	348.88	13,297
Machines	348.71	1.0530	44.052	686.76	1800.1	15,014
R&D	259.72	0	23.387	449.23	991.44	13,552
Transport	93.008	0	0.6893	69.160	521.30	2,821

Notes: Annual firm characteristics (row 1-4) are obtained from Compustat North America. Data on stock price volatilities (row 5) are received from CRSP US Stock Databases. Investment expenditures are displayed in the bottom part of this Table. Advertising and R&D investments are obtained from Compustat North America, data on the remaining categories are provided by FactSet Fundamentals Global Databases.

Figure 3.1a plots the average stock price volatility for the sample firms over time. During the sample period, there were at least two major events where uncertainty increased markedly. The first spike around 2001 coincided with the 9/11 terrorist attack, the second spike can be clearly attributed to the outbreak of the Global Financial Crisis (GFC) in 2008. Before, in between and after these two events, however, there were periods of extremely low levels of uncertainty, which indicates substantial variation in uncertainty over time. Moreover, there were also significant differences in the cross-sectional dimension. This can be seen by the large gap between the stock price volatility of the 10th and the 90th percentile, and by the large fluctuations in the coefficient of variation over time (which is the ratio between the standard deviation and the mean, and is illustrated by the red line). In particular the latter one implies that there were times when firm-specific uncertainty evolved quite uniformly followed by periods of strongly diverging patterns (such as during the GFC in 2008). In summary, there seems to be sufficient time and cross-sectional variation in the constructed uncertainty measure that can be exploited to identify the effects of uncertainty on corporate investment decisions. Figure 3.1b confirms that the average volatility of firm-specific stock returns does indeed reflect (at least to some extent) aggregate uncertainty and is therefore an appropriate measure for uncertainty in the economy. In this Figure, I additionally plot a news-based Economic Policy Uncertainty (EPU) index for the US over time and compare the evolution of both indicators. The EPU indicator was introduced by Baker *et al.* (2016) and measures economic policy uncertainty based on newspaper coverage.[6] Figure 3.1b demonstrates that both indicators track each other reasonably well.[7]

Figure 3.1: Stock Price Volatility as Measure of Uncertainty



(a) (Cross-sectional) Variation over Time (b) Compared to Aggregate Uncertainty (EPU)

Notes: Figure 3.1a plots the average stock price volatility (blue) and the corresponding 10th and 90th percentile (gray dashed) in the sample over time. The red line displays the coefficient of variation in stock price volatility in the sample over time (right y-axis). It is computed by dividing the standard deviation by the corresponding mean. In Figure 3.1b, the blue line indicates the average stock price volatility in the sample over time, the red line plots the EPU News-based indicator obtained from Baker *et al.* (2016).

3.2.2 Empirical Strategy

The empirical strategy is based on three types of regression equations. The first set of regressions identifies the composition effect on investments with different durabilities within

[6]The authors construct this index by scanning large US newspapers for terms related to economic and policy uncertainty. In particular, they search for articles containing the term 'uncertainty' or 'uncertain', the terms 'economic' or 'economy' and one or more of the following terms: 'congress', 'legislation', 'white house', 'regulation', 'federal reserve' or 'deficit'.

[7]There are some deviations in recent years, where economic policy uncertainty prevailed at high levels while stock price volatility settled down in the aftermath of the GFC.

the firm using ordinary least squares (OLS). The second set addresses possible endogeneity concerns with respect to stock price volatility using instrumental variable (IV) regressions. This comes at the cost of having a shorter estimation period due to data limitations. Therefore, IV regressions are mainly used to validate the baseline results while further robustness checks are performed with OLS. The final set of regressions examines differential effects of uncertainty on total corporate investments across firms.

Within-Firm In order to identify the causal impact of uncertainty on investments with different durabilities, I regress firms' investment decisions on firm-specific uncertainty shocks. These shocks are obtained by calculating the percentage change in the firm's stock price volatility over two consecutive periods. Specifically, the uncertainty shock faced by firm i at year t equals $\Delta\sigma_{i,t} = \frac{\sigma_{i,t}-\sigma_{i,t-1}}{\sigma_{i,t-1}}$.[8] To limit the impact of contemporaneous confounding factors and to account for time-to-build delays, I use lagged uncertainty shocks in the baseline specifications.[9] Heterogeneity in investments allows me to identify the pure composition effect within the firm while holding fixed all time-varying, firm-specific factors. Taking all this into account, I estimate the following specification:

$$invest_{i,c,t} = \beta_1 \times \delta_c \times \Delta\sigma_{i,t-1} + \lambda_{i,t} + \lambda_{c,t} + \lambda_{i,c} + \varepsilon_{i,c,t}, \tag{3.1}$$

where $invest_{i,c,t}$ denotes the amount a firm i invests into category c at year t.[10] I interact lagged uncertainty shocks $\Delta\sigma_{i,t-1}$ with a measure of depreciation δ_c, which is either the actual depreciation rate or a simple ordering of the categories (from land $=1$ to advertising $=7$), such that β_1 is the coefficient of interest and indicates how firms adjust their investment mix in response to an uncertainty shock. A positive β_1 implies that firms shift expenditures from more durable to less durable investment categories when facing increased uncertainty. To improve identification, I include the full set of two-dimensional fixed effects that absorb all the remaining variation in the data that does not help to identify β_1. These are firm-year fixed effects $\lambda_{i,t}$, that capture all firm-specific (possibly time-varying) factors such as demand or productivity shocks, which affect all investment categories to the same extent. Furthermore, the inclusion of category-year fixed effects $\lambda_{c,t}$ captures time-varying demand

[8] In robustness checks, I also use the level of volatility $\sigma_{i,t}$ or, following Alfaro *et al.* (2018), $\Delta\sigma_{i,t} = \frac{\sigma_{i,t}-\sigma_{i,t-1}}{\frac{1}{2}\sigma_{i,t}+\frac{1}{2}\sigma_{i,t-1}}$ as shock variable. Results are not materially affected (results on the latter specification can be found in column 7 of Table 3.4).

[9] In the Appendix, I also estimate local projections, where I allow the shock to affect investments over a 10-year horizon. Results are displayed in Figure C.1.

[10] In order to account for lumpiness in investments and therefore to be able to include zero observations, I transform investment expenditures using the inverse hyperbolic sine function $invest_{i,c,t} = \arcsin(I_{i,c,t}) = Log\left(I_{i,c,t} + \sqrt{I_{i,c,t}^2 + 1}\right)$. In robustness checks, I also re-estimate Equation 3.1 using a logarithmic transformation (see column 1 and 2 of Table 3.4).

changes for specific investment categories.[11] To control for structural differences in firm-specific investment mixes, I saturate Equation 3.1 with firm-category fixed effects $\lambda_{i,c}$. In an alternative specification, I replace firm-year fixed effects with the level of the uncertainty shock and lagged time-varying firm characteristics.[12] This modification allows me to increase the number of identifying observations in the sample and to obtain an average effect of uncertainty on business investments.[13] Following Abadie *et al.* (2017), standard errors in these and the subsequent regressions are clustered at the firm-level.

IV Approach Despite the use of lagged uncertainty shocks, there is the risk of running into a simultaneity problem in Equation 3.1 as the stock market is by nature forward-looking. Since stock prices might be to some extend determined by expectations over future investment opportunities, causality could go the other way round, i.e., fluctuations in stock returns are driven by expectations over certain investment policies. In order to shut down this channel, I decompose the firm's stock price volatility into an aggregate and a firm-specific component. This is done by instrumenting firm-specific uncertainty with different sources of aggregate uncertainty taking into account industry-specific elasticities.[14] This instrumentation strategy was first proposed by Alfaro *et al.* (2018) and I follow their setting very closely. To measure aggregate uncertainty, I use annual volatilities of oil prices, exchange rates, treasury bill prices and the EPU indicator.[15] In order to account for the relative importance of these aggregate sources for each firm, I weight each aggregate volatility with the exposure of the firm's industry to these categories. Therefore, the instruments are constructed in a 3-step process. First, daily firm-specific stock price returns $r_{i,t}^{SP}$ are regressed on the daily changes of each of the ten aggregate categories[16] r_t^{agg} and on a vector of 3-digit SIC industry dummies λ_j (see Equation 3.2). Due to data limitations, the sample period covers the time from 2005 to

[11] Leaving these fixed effects out could lead to a substantial bias in the estimated coefficient. For example, due to the digital revolution, IT investments increased steadily over the sample period. At the same time, in particular the recent years have been characterized by a high level of uncertainty. Thus, a positive effect would be measured here, although it is based on a pure spurious correlation (assuming that digitalization is not a consequence of growing uncertainty).

[12] These firm controls comprise total assets, cash holdings and annual sales.

[13] Note that in Equation 3.1, all firm-year observations where a firm invests only into a single category are absorbed by the firm-year fixed effect as is the average effect of the firm-specific uncertainty shock.

[14] Therefore, I obtain a set of industry-specific instruments, where industries are based on SIC-3-digits.

[15] I use exchange rates with respect to the following six currencies: AUD, CAD, CHF, EUR, GBP, JPY, SEK. According to the the Federal Reserve, these currencies are widely traded and are defined as 'major' currencies, see `http://www.federalreserve.gov/pubs/bulletin/2005/winter05_index.pdf`. Moreover, for the EPU indicator, I compute the annual mean instead of the volatility.

[16] These are the oil price, the treasury bill price, the EPU and the seven currency pairs outlined in Footnote 15.

2016.[17] To limit the impact of idiosyncratic firm events, sensitivities $\widehat{\beta_j^{\text{agg}}}$ are estimated at the industry-level j. In a second step, I weight the estimated sensitivities by their statistical power (t-stat), where elasticities with a t-stat $< |1.96|$ obtain a zero weight.[18] Finally, I multiply the absolute values of the estimated elasticities with the aggregate volatilities and end up with the final vector of industry-specific instruments Z_{jt} (see Equation 3.3).

$$r_{i,t}^{SP} = \sum_{\text{agg}=1}^{10} \beta_j^{\text{agg}} \times r_t^{\text{agg}} + \lambda_j + \varepsilon_{i,t} \tag{3.2}$$

$$Z_{j,t} = |\widehat{\beta}_j^{\text{weighted,agg}}| \times \Delta\sigma_t^{\text{agg}} \qquad \text{for} \;\; \text{agg} = 1, ..., 10 \tag{3.3}$$

With the industry-specific instruments $Z_{j,t}$ at hand, I then estimate the following IV regressions, where the first stage is given by Equation 3.4:

$$\begin{aligned} interact_{i,c,t} = \beta_{\text{1st stage}} \times \delta_c \times Z_{j,t} + \lambda_{i,t} + \lambda_{c,t} + \lambda_{i,c} + \varepsilon_{i,c,t} \\ \text{with} \;\; interact_{i,c,t} = \delta_c \times \Delta\sigma_{i,t}. \end{aligned} \tag{3.4}$$

Again, δ_c is the measure of depreciation and $\Delta\sigma_{i,t}$ denotes the annual change in firm-specific stock price volatility. The specification is saturated with the full set of two-dimensional fixed effects $\lambda_{i,t}$, $\lambda_{c,t}$ and $\lambda_{i,c}$. The second stage follows Equation 3.5:

$$invest_{i,c,t} = \beta_{IV} \times \widehat{interact}_{i,c,t-1} + \lambda_{i,t} + \lambda_{c,t} + \lambda_{i,c} + \varepsilon_{i,c,t}, \tag{3.5}$$

where $invest_{i,c,t}$ is the amount a firm i invests into category c at year t, and $\widehat{interact}_{i,c,t-1}$ are the lagged fitted values obtained from estimating Equation 3.4.

In order to identify a causal effect, it is required that the constructed instruments are valid, i.e., they are relevant and exogenous. The relevance condition is fulfilled if there is a (sufficiently) strong correlation between endogenous regressors and exogenous instruments. For this reason, it is particularly useful to weight the different sources of aggregate uncertainty by their relative importance for the firm's industry as this increases the correlation in the first stage regression. For example, an industry composed of firms that are predominantly active in the domestic market and have local supply chains should not be much affected by exchange rate fluctuations. Instead of estimating a weak correlation between these firms'

[17] Following Alfaro *et al.* (2018), I calculate implied volatilities for oil, the treasury bill and the 7 currencies using data on futures from Thomson Reuters Eikon. For oil and the treasury bill, these time series start in 2005.

[18] This is, $\widehat{\beta}_j^{\text{weighted,agg}} = \frac{\text{t-stat}_j^{\text{agg}}}{\sum_{d=1}^{10} \text{t-stat}_j^{d}} \times \widehat{\beta}_j^{\text{agg}}$.

stock price volatilities and volatilities in exchange rates, the estimated sensitivities already limit (or even eliminate) the weak impact of the exchange rates in the first stage, thereby increasing the explanatory power in the first stage regression.

Regarding the exclusion restriction, the situation is somewhat more involved. This condition states that the instruments have an influence on the dependent variable only through their impact on the regressors. In my setting, the constructed set of instruments falls into the general class of *shift-share instruments*, where aggregate volatilities represent the *shifts* and the estimated sensitivities characterize the *shares*.[19] The existing literature has formulated two scenarios under which shift-share instruments are exogenous. This is the case if either shares are exogenous and shifts are endogenous (Goldsmith-Pinkham *et al.* 2020), or if shifts are exogenous and shares are endogenous (Borusyak *et al.* 2018).[20] The first scenario (random shares, non-random shifts) is very unlikely to hold in my setting as there might be omitted industry-specific factors that simultaneously impact the firm's investment decision and affect the dependence of the firm's business model on specific external factors, i.e., the estimated elasticities (*shares)*. For example, higher industry competition could lead to more short-term investments while firms might focus increasingly on exchange rate fluctuations to decrease production costs.[21] The second scenario (random shifts, non-random shares), however, seems to be more likely to hold. According to Borusyak *et al.* (2018), shift-share instruments are valid if the shifts are as-good-as-randomly assigned to the firms, even if the shares are endogenous. Since in my setting the shifts correspond to uncertainty shocks stemming from external factors, as-good-as-random assignment seems to be quite plausible. Given that an individual firm is too small to affect aggregate outcomes, i.e., firms are atomistic, a single firm should not be able to impact exchange rates, monetary policy or oil prices. Therefore, the external uncertainty shocks should not be affected by unobserved firm-specific factors and each firm is confronted with the same external shock.[22]

Across Firms After analyzing the role of asset durability for the composition of investments within firms, the final part of this section considers whether there are any heterogeneous effects on total investments across firms. Is there just a composition effect at work,

[19]See Bartik (1991), Blanchard & Katz (1992), Autor *et al.* (2013) for other examples of shift-share instruments in the literature.

[20]Needless to say, that if both shifts and shares are exogenous, the instrument is also exogenous.

[21]It should be noted that firm-specific omitted factors (like agency frictions or managerial incentives) should be less of a concern here since elasticities are estimated at the industry-level (assuming firms to be atomistic).

[22]As an example where this assumption would be violated, Borusyak *et al.* (2018) state a labor supply regression where labor growth is instrumented by import tariffs. If these import tariffs only apply to some firms/industries and these firms/industries experience different labor supply trends, the assumption of (as good as) random assignment of shifts would not hold.

where firms change the ratio of long- to short-term investments but total investments decline for all firms to the same extent, or do firms with different degrees of asset durability differently adjust total investments in response to uncertainty? In order to comment on that question, I construct a firm-specific measure of asset durability $\delta_{i,t}$, which is for each firm i at year t the capital-stock-weighted depreciation rate.[23] As dependent variable, I use the log of total firm-specific investments $I_{i,t}$, which is obtained by summing up the amount of all category-specific investments during a particular year. I then estimate the following firm-level regression, where $\textit{firm-controls}_{i,t}$ is a vector of time-varying firm characteristics comprising assets, cash holdings and annual sales, and $\lambda_{i/t}$ are firm and calendar-year fixed effects:

$$\begin{aligned} \textit{Log}\,(I_{i,t}) =& \beta_1 \times \delta_{i,t-1} \times \Delta\sigma_{i,t-1} + \beta_2 \times \Delta\sigma_{i,t-1} + \beta_3 \times \delta_{i,t-1} \\ &+ \beta_4 \times \textit{firm-controls}_{i,t-1} + \lambda_i + \lambda_t + \varepsilon_{i,t} \end{aligned} \tag{3.6}$$

The coefficient of interest is β_1. It indicates if and how predetermined, firm-specific asset durability $\delta_{i,t-1}$ matters for the investment response under uncertainty. A positive β_1 would imply that firms which employ a relatively high share of long-term capital in production reduce total investments more strongly than firms with a relatively low share.

3.2.3 Empirical Results

Within-Firm Table 3.3 shows the main results from estimating Equation 3.1. Column 1 is the baseline specification, where I include the full set of two-dimensional fixed effects, stock price volatility is based on excess returns and the measure of depreciation is the actual depreciation rate. In column 2, I replace firm-year fixed effects with lagged firm characteristics and the uncertainty shock. This increases the number of firms in the sample by 45. Column 3 uses absolute instead of excess stock price returns, and column 4 takes a simple ordering of the investment categories by their depreciation rates as measure of depreciation. Before I analyze the composition effect on investments, which is illustrated by the coefficient of the interaction term outlined in the first row, I focus on the average effect on investments first. It is given by the point estimate in the second row of column 2. The coefficient of -0.137 implies that average investment declines by 10.5% when firm-specific volatility doubles.[24] This corresponds to a 2.9-standard-deviation uncertainty shock. This is fairly in line with

[23]I.e., $\delta_{i,t} = \sum_{c=1}^{7} \frac{\text{Cap-Stock}_{i,t,c}}{\text{Total Cap-Stock}_{i,t}} \times \delta_c$.

[24]Here, the average depreciation rate is set to 10.9%, which is the sample average of the firm-specific (tangible-)capital-stock-weighted depreciation rate.

Alfaro *et al.* (2018), who find an average decline in tangible investments by 12.9% in response to a 3.3-standard-deviation uncertainty shock. A shock of this size would correspond to an annual investment decline of 11.9% for my estimations. Besides the reduction in average investments, there is an additional composition effect at work. The positive coefficient of the interaction term indicates that more durable investments are reduced more strongly in response to an uncertainty shock. When uncertainty doubles, investments into a category with a 10 percentage point lower depreciation rate are cut by 2.8% more. This implies that, on average, land investments are cut by 16.8% more than investments into advertising. Hence, increased uncertainty is leading firms to tie their capital less strongly to long-term capital.

Table 3.3: Baseline Results – OLS

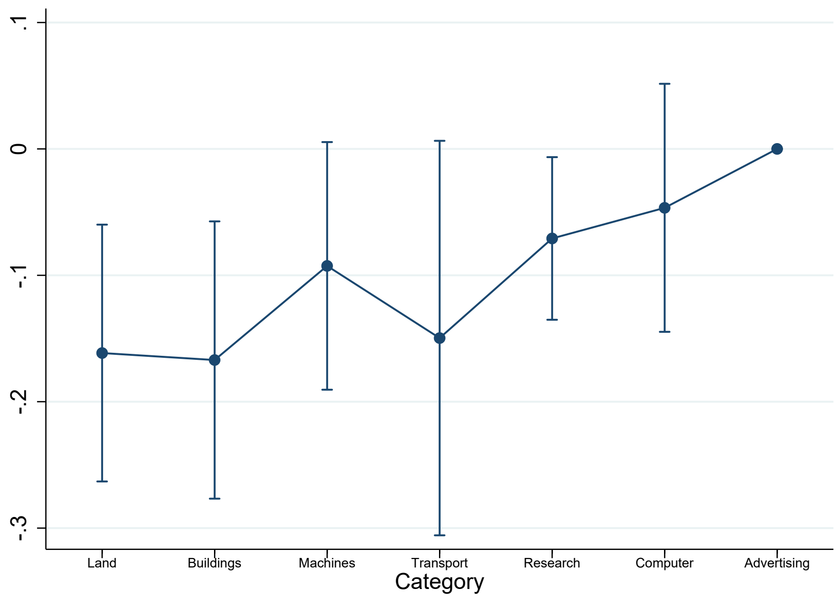
VARIABLES	(1) Inv	(2) Inv	(3) Inv	(4) Inv
Uncertainty-Shock × Depreciation	0.284***	0.290***	0.236***	0.0268***
	(0.0836)	(0.0671)	(0.0837)	(0.00849)
Uncertainty-Shock		-0.137***		
		(0.0285)		
Assets		0.206***		
		(0.0364)		
Cash		0.0308***		
		(0.00853)		
Sales		0.323***		
		(0.0422)		
Observations	61,688	62,566	61,688	61,688
R-squared	0.895	0.817	0.895	0.895
Firm x Time FE	×		×	×
Investment x Time FE	×	×	×	×
Firm x Investment FE	×	×	×	×
Time	1995 - 2016	1995 - 2016	1995 - 2016	1995 - 2016
Depr Rate	Percent	Percent	Percent	Ordering
Volatility	Ex Ret	Ex Ret	Stock Ret	Ex Ret
Clustering	Firm	Firm	Firm	Firm
Nr. of Firms	1031	1076	1031	1031

Notes: Table 3.3 estimates the effect of uncertainty on investments with different durabilities within the firm. Column 1 includes the full set of two-dimensional fixed effects, stock price volatility is based on excess returns and the measure of depreciation is the actual depreciation rate. In column 2, firm-year fixed effects are replaced by firm characteristics and the uncertainty shock (both lagged). Column 3 uses absolute instead of excess stock price returns, and column 4 takes a simple ordering of the investment categories by their depreciation rates as measure of depreciation. ***, **, and * indicate statistical significance at the 1%-, 5%- and 10%-level.

However, it could be the case that the observed effect is driven by a few categories only and that no systematic relationship between capital durability and uncertainty exists. To rule out that possibility, I estimate category-specific coefficients and plot them in Figure 3.2.

The estimated coefficients are measured relative to a baseline category, which is advertising. It is evident that there is an almost monotone relationship between capital durability and investment cuts, which makes the existence of any confounding factors driving the results from Table 3.3 very unlikely.[25] Therefore, these results confirm that capital durability matters for the investment response under uncertainty.

Figure 3.2: The Effect of Uncertainty on Investments across Categories



Notes: Figure 3.2 plots category-specific coefficients when investments are regressed on the interaction between uncertainty shocks and investment category dummies. The full set of two-dimensional fixed effects is included, standard errors are clustered at firm-level. Investment categories are ordered from the most durable (left) to the least durable good (right). Vertical lines depict 95% confidence intervals.

Table 3.4 provides further robustness checks for the baseline results on the composition effect. In column 1 and 2, I take a log instead of an inverse hyperbolic sine transformation of the dependent variable and insert a zero when investment in the data is zero. Column 3 and 4 repeat the estimations from column 1 and 2 using net investments as dependent variable.[26] The coefficient on the interaction term is still positive and significant. Column 5 controls for an additional channel that might have an effect on the investment composition and that is based on different degrees of asset tangibility. In principle, tangible assets can be used for purposes other than production, e.g., as collateral, and could therefore be valued differently by firms if uncertainty increases. At the same time, tangibility is highly correlated with

[25] It is only the transport category that falls out of line, but given the wide confidence bands, the existence of this outlier should not be overrated.

[26] I obtain these investments by applying the following formula: $I^{\text{net}} = I^{\text{gross}} - \text{Depr-Rate} \times \text{Capital-Stock}$

durability, i.e., the two intangible assets, R&D and advertising, have substantially higher depreciation rates than all other categories. To explicitly control for that channel, I additionally interact the uncertainty shock with an intangible dummy, that is one for the two intangible categories listed above, and zero otherwise. The estimated coefficient of that interaction term is insignificant and close to zero, while the coefficient of the original interaction term remains significant and hardly changes. In column 6, I control for first-moment effects by additionally interacting the measure of depreciation with the lagged change in annual stock price returns. While this coefficient is almost zero and insignificant, the effect of uncertainty does not alter by the inclusion of this additional interaction term. In the last column, I normalize the shock variable in line with Alfaro *et al.* (2018). Results do not change.

Table 3.4: OLS Results – Robustness

VARIABLES	(1) Inv	(2) Inv	(3) Net-Inv	(4) Net-Inv	(5) Inv	(6) Inv	(7) Inv
Uncertainty-Shock × Depr	0.207**	0.223***	0.268*	0.348***	0.254***	0.283***	0.318***
	(0.0866)	(0.0697)	(0.142)	(0.119)	(0.0888)	(.0836)	(0.0946)
Uncertainty-Shock		-0.114***		-0.209***			
		(0.0277)		(0.0424)			
Uncert.-Sh. × Intangible					0.0170		
					(0.0345)		
Return × Depr						0.00028	
						(0.00040)	
Observations	61,688	62,566	61,688	62,566	61,688	61,689	61,688
R-squared	0.889	0.819	0.728	0.574	0.895	0.895	0.895
Firm Controls		×		×			
Firm x Time FE	×		×		×	×	×
Investment x Time FE	×	×	×	×	×	×	×
Firm x Investment FE	×	×	×	×	×	×	×
Time	1995 - 2016	1995 - 2016	1995 - 2016	1995 - 2016	1995 - 2016	1995 - 2016	1995 - 2016
Volatility	Ex Ret	Ex Ret	Ex Ret	Stock Ret	Ex Ret	Ex Ret	Ex Ret
Shock	Percent	Percent	Percent	Percent	Percent	Percent	Normalized
Dep Var	log w/ zero	log w/ zero	log w/ zero	log w/ zero	arcsin	arcsin	arcsin
Clustering	Firm	Firm	Firm	Firm	Firm	Firm	Firm
Nr. of Firms	1031	1076	1031	1076	1031	1031	1031

Notes: Column 1 and 2 use a logarithmic transformation of the dependent variable, where in column 1, the full set of two-dimensional fixed effects is included and in column 2, firm-year fixed effects are replaced by firm controls (assets, sales, cash) and the uncertainty shock (both lagged). Column 3 and 4 use net investments as dependent variables and follow otherwise the same specification as in column 1 and 2. Column 5 additionally interacts an *Intangible*-Dummy with the uncertainty shock. *Intangible* equals one if the investment category is R&D or advertising, and zero otherwise. In column 6, I control for first-moment effects by additionally interacting the measure of depreciation with the lagged change in annual stock price returns. In column 7, uncertainty shocks are obtained by following formula: $\Delta\sigma_{i,t} = \frac{\sigma_{i,t}-\sigma_{i,t-1}}{\frac{1}{2}\sigma_{i,t}+\frac{1}{2}\sigma_{i,t-1}}$. ***, **, and * indicate statistical significance at the 1%-, 5%- and 10%-level.

Durable vs Irreversible Investments In this subsection, I will argue that my empirical findings are very unlikely to be driven by differences in asset irreversibilities. The existing literature has already highlighted the role of partial irreversibilities for the investment response under uncertainty, where firms cut under uncertainty more strongly investment categories which are more difficult to reverse (e.g., Guiso & Parigi 1999, Gulen & Ion 2015, Kim & Kung 2016, Schauer (neé Klepsch) 2019). Therefore, if there is a systematic correlation between capital depreciation rates and asset irreversibilities, there is the risk of running into an omitted variable problem.

In general, the lack of adequate data on asset-specific irreversibilities makes a comprehensive answer to this issue quite challenging. Nonetheless, it should be noted that durability and irreversibility are two different concepts that should not be mixed up. While the former makes a statement about how long a unit of capital can be used in production, the latter says something about how easy a unit of used capital can be resold on the secondary market. The degree of firm-specificity is thereby the predominant factor that explains the degree of asset irreversibility (e.g., Ramey & Shapiro 2001). Based on this, it is not apparent why more durable investment goods should be more firm-specific, i.e., resulting in a positive correlation between durability and irreversibility and therefore biasing my results.[27] Figure 3.2 shows that the *durability*-effect is (almost) monotone over a sample of seven broad investment categories, which makes the explanation of correlated irreversibilities quite unlikely. Moreover, column 5 of Table 3.4 demonstrates that the durability-effect is still there when controlling for investment categories that are particularly difficult to reverse (i.e., intangible assets).

IV Approach Table 3.5 presents the results when estimating the relationship using an IV approach (see Equation 3.4 & 3.5). Due to data limitations, the sample covers the period from 2005 to 2016. Again, column 1 shows the baseline specification with the full set of two-dimensional fixed effects, volatility based on excess returns and the actual rate as measure of depreciation. For comparison, column 2 shows the same specification with OLS.[28] In column 3, firm-year fixed effects are replaced by the uncertainty shock and time-varying firm controls (both lagged). Column 4 uses actual instead of excess stock price returns, and column 5 takes a simple ordering of the investment categories by their depreciation rates as measure of depreciation. It is worth mentioning that throughout all specifications the Kleibergen-Paap F-statistics are sufficiently strong (exceeding the Stock-Yogo critical values

[27]If there is a correlation at all, the opposite direction might rather be the case: while durable goods (such as land or buildings) might have fairly low resale losses because they are marketable, short-term investments (such as IT systems and research expenditures) tend to be more company-specific. In this case, I would even underestimate the role of capital durability for the investment response under uncertainty.

[28]That is, to better compare coefficients as the results from Table 3.3 are based on a longer sample period.

at the 5%-level), rejecting a weak correlation between regressors and instruments. At the same time, the p-values of the Hansen J-statistics demonstrate that the null hypothesis that the instruments are valid, i.e., uncorrelated with the error terms, does not need to be rejected. Again, the coefficient of the interaction term is positive and highly significant throughout all specifications, indicating a shift in the investment decisions towards less durable capital goods in response to higher uncertainty.

Table 3.5: Baseline Results – IV

VARIABLES	(1) Inv	(2) Inv	(3) Inv	(4) Inv	(5) Inv
Uncertainty Shock × Depreciation	0.814**	0.275***	0.565**	0.524**	0.0807**
	(0.322)	(0.0953)	(0.251)	(0.214)	(0.0353)
Uncertainty Shock			-0.417***		
			(0.110)		
Observations	40,054	40,054	40,624	40,054	40,054
R-squared	-0.001	0.906	0.017	-0.000	-0.001
Firm Controls			×		
Firm x Time FE	×	×		×	×
Investment x Time FE	×	×	×	×	×
Firm x Investment FE	×	×	×	×	×
Time	2005 - 2016	2005 - 2016	2005 - 2016	2005 - 2016	2005 - 2016
Depr Rate	Percent	Percent	Percent	Percent	Ordering
Volatility	Ex Ret	Ex Ret	Ex Ret	Stock Ret	Ex Ret
Clustering	Firm	Firm	Firm	Firm	Firm
Nr. of Firms	1014	1014	1064	1014	1014
Model	IV	OLS	IV	IV	IV
Kleibergen-Paap Wald rk F stat	37.58		22.03	100.3	44.39
Hansen J stat p-val	0.829		0.375	0.759	0.875

Notes: Table 3.5 estimates the effect of uncertainty on investments with different durabilities using IV regressions. Column 1 includes the full set of two-dimensional fixed effects, stock price volatility is based on excess returns and the measure of depreciation is the actual depreciation rate. Column 2 estimates the specification from column 1 with OLS. In column 3, firm-year fixed effects are replaced by firm characteristics (assets, sales, cash) and the uncertainty shock (both lagged). Column 4 uses absolute instead of excess stock price returns, and column 5 takes a simple ordering of the investment categories by their depreciation rates as measure of depreciation. ***, **, and * indicate statistical significance at the 1%-, 5%- and 10%-level.

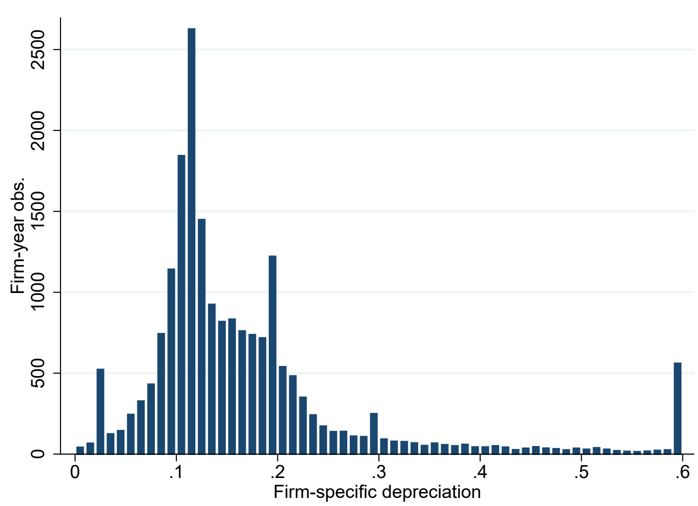
When comparing the coefficients from the first two columns, it is noticeable that the effect in the IV specification is almost three times larger than the OLS estimates.[29] Possible explanations for this difference could be the existence of shocks that downward-bias the OLS estimates. For example, a positive productivity shock that increases R&D expenditures (more short-term investments) and decreases firm-specific uncertainty might bias in that direction. Alternatively, more favourable demand conditions might also downward-bias

[29] Alfaro *et al.* (2018) also obtain a factor of 3 when comparing IV with OLS estimates in univariate regressions.

OLS estimates as they reduce firm-specific uncertainty while leading firms to expand their marketing and advertising expenditures to meet the additional demand. Given that in the IV specification any endogenous variation in stock price movements is removed from the uncertainty measure, I interpret column 1 as the *causal effect* of uncertainty on investments with different durabilities. A 2.9-standard-deviation uncertainty shock reduces investments with a 10 percentage point lower depreciation rate by 8.1% more. Taking actual instead of excess stock price volatility (column 4), the effect is somewhat muted and amounts to 5.2%. The effect persists when I use a simple ordering of the investment categories by their depreciation rates as measure of depreciation (column 5).

Across Firms After the previous analysis focused on composition changes in investments within firms, I now examine whether there are any cross sectional differences in the firms' total investment responses. Figure 3.3 plots the distribution of firm(-year)-specific depreciation rates. The average depreciation rate in the sample equals 16.9%, the median corresponds to 13.3%. The majority of firm-year observations are bunched around the median ($P_{25} = 10.7\%$ and $P_{75} = 19.7\%$), yet there is considerable variation in firm-specific durability, particularly on the right side of the distribution. The bunching of observations at specific rates can be explained by the fact that some firms only invest into a single category in given year. For example, the maximum depreciation rate of 60% occurs quite frequently as companies in these cases have only invested in advertising during a particular year.

Figure 3.3: Firm Heterogeneity in Asset Durability



Notes: Figure 3.3 plots the distribution of firm-specific depreciation rates $\delta_{i,t}$. It is calculated by taking a capital-stock-weighted average of investment-category-specific depreciation rates ($\delta_{i,t} = \sum_{c=1}^{7} \frac{\text{Cap-Stock}_{i,t,c}}{\text{Total Cap-Stock}_{i,t}} \times \delta_c$).

Table 3.6 shows the results when estimating Equation 3.6. In column 1, I take the actual depreciation rate δ_{it}, which is computed as outlined in Footnote 23 and illustrated in Figure 3.3, as firm-specific measure for capital durability. In column 2, I use the simple ordering of the investment categories by their depreciation rates instead of the actual depreciation rates for the calculation of firm-specific capital durability. Column 3 groups firms into quintiles based on their respective position in the distribution of durability (Figure 3.3) and runs a bin regression. In column 4, the grouping is based on deciles.

Table 3.6: Firm Heterogeneity and Total Investment Response

VARIABLES	(1) Log(Inv)	(2) Log(Inv)	(3) Log(Inv)	(4) Log(Inv)
Uncertainty-Shock × Firm-specific Depr	0.295*	0.0372**	0.0335***	0.0162**
	(0.160)	(0.0162)	(0.0128)	(0.00658)
Uncertainty-Shock	-0.122***	-0.210***	-0.170***	-0.160***
	(0.0405)	(0.0720)	(0.0521)	(0.0500)
Firm-specific Depr	1.117***	0.154***	0.153***	0.0807***
	(0.387)	(0.0384)	(0.0246)	(0.0136)
Observations	17,257	17,257	17,257	17,257
R-squared	0.866	0.867	0.867	0.868
Firm Controls	×	×	×	×
Firm FE	×	×	×	×
Time FE	×	×	×	×
Time	1995 - 2016	1995 - 2016	1995 - 2016	1995 - 2016
Firm-specific Depr	Percent	Ordering	Quintiles	Deciles
Volatility	Ex Ret	Ex Ret	Ex Ret	Ex Ret
Clustering	Firm	Firm	Firm	Firm
Nr. of Firms	1068	1068	1068	1068

Notes: In column 1, capital durability $\delta_{i,t}$ is based on the firm-specific, capital-stock-weighted depreciation rate, i.e., $\delta_{i,t} = \sum_{c=1}^{7} \frac{\text{Cap-Stock}_{i,t,c}}{\text{Total Cap-Stock}_{i,t}} \times \delta_c$. In column 2, a simple ordering of investment categories is used instead of the actual capital depreciation rates for the calculation of firm-specific capital durability. Column 3 groups firms into quintiles based on their respective position in the δ-distribution (Figure 3.3). In column 4, the grouping is based on deciles. All specifications include lagged time-varying firm controls (assets, sales, cash). ***, **, and * indicate statistical significance at the 1%-, 5%- and 10%-level.

Before focusing on the coefficient of interest outlined in the first row, it is worth mentioning two other findings. First, the average effect of uncertainty on total investments is still negative and highly significant. This is in line with the existing empirical literature that finds a negative investment-uncertainty relationship, and provides additional evidence in favor of this hypothesis. Second, firms with lower levels of asset durability (high-δ firms) generally invest more. This latter result is not surprising as faster depreciation requires more investments to maintain the capital of the firm. Turning now to the interaction term of durability and uncertainty, the estimated coefficient is positive and significant in all specifications. Firms with more durable capital cut total investments more strongly in response to increased uncertainty. Quantitatively, firms with a 1-standard-deviation higher capital stock durability (0.1136) cut total investments by 3.4% more when uncertainty doubles. This is also the average differential effect for firms located in two adjacent quintiles (column 3). When using a more refined classification, where firms are grouped based on deciles, the positive differential effect remains significant (column 4).[30]

3.3 Modeling the Impact of Uncertainty on Investments with Different Durabilities

This section outlines how I model investment decisions in capital goods with different durabilities under uncertainty. The starting point is the standard textbook dynamic investment model (Adda & Cooper 2003, Ch. 8), which is extended in two ways: first, firm-specific uncertainty is integrated as Markov-switching regime changes in the dispersion of firm-specific business conditions (Bloom *et al.* 2007, Bloom 2009). Second, output is produced by combining two types of capital goods that differ in their degree of durability (Barrero *et al.* 2017, Rampini 2019).

3.3.1 Model Setup

I consider a firm i that combines two types of capital, K_s and K_l, to produce in each period t output Q with the following Cobb-Douglas decreasing-returns-to-scale production function

$$Q_{i,t}(Z_{i,t}, K_{s,i,t}, K_{l,i,t}) = Z_{i,t} K_{s,i,t}^{\alpha_s} K_{l,i,t}^{\alpha_l}, \tag{3.7}$$

where $\alpha_{s/l} > 0$ (with $\alpha_s + \alpha_l < 1$) reflect the corresponding capital shares in production and $Z_{i,t}$ is firm-specific total factor productivity. For the sake of simplification, I set the output price $P_{i,t}$ equal to one, such that output $Q_{i,t}$ equals revenues $R_{i,t}$.[31] Importantly, $Z_{i,t}$ is stochastic and follows an AR(1) process, which is specified in logs:

$$\ln Z_{i,t} = z_{i,t} = \rho_z z_{i,t-1} + \sigma_{i,t}\epsilon_{i,t} \quad \text{with} \quad \epsilon_{i,t} \sim N(0,1). \tag{3.8}$$

[30] In further analyses, I split the sample into low-δ firms (i.e., firms located in the two bottom quintiles) and high-δ firms (i.e., firms located in the two top quintiles), and estimate the effect of uncertainty on investments separately for each group. While high-δ firms reduce total investments by only 1.9%, low-δ firms cut investments by 12.0% when uncertainty doubles.

[31] In Appendix C2, I show that this revenue function is consistent with a particular parameterization of the firm's profit maximization problem, where the firm employs labor as additional production input and faces an isoelastic demand curve.

Time-varying, firm-specific volatility is captured by $\sigma_{i,t}$, which switches between two uncertainty regimes, σ_H and σ_L with $\sigma_H > \sigma_L$, where transition probabilities are given by $Pr(\sigma_{t+1} = \sigma_y | \sigma_t = \sigma_x) = \pi_{xy}$.[32]
Each type of capital evolves according to

$$K_{j,i,t+1} = I_{j,i,t} + (1 - \delta_j) K_{j,i,t} \quad \text{with} \quad j \in \{s, l\}. \tag{3.9}$$

I assume that K_l is more durable than K_s, i.e., it holds that $\delta_l < \delta_s$. Capital investments are subject to nonconvex adjustment costs.[33] These include partial irreversibilities, which imply a positive price gap between the purchase (p_p) and resale (p_s) price of capital. These costs capture the idea that capital is firm-specific and account for adverse selection and transaction costs in the market for used capital.[34] Moreover, nonconvex adjustment costs are comprised of fixed investment costs F, which always occur as soon as a non-zero amount is (dis)invested. The cost function of the firm can be summarized by following expression:

$$C^K_{i,t} = \sum_{j \in \{s,l\}} q(K_{j,i,t+1} - (1 - \delta_j) K_{j,i,t}) + \sum_{j \in \{s,l\}} \mathbb{1}_{\{I_{j,i,t} \neq 0\}} F, \tag{3.10}$$

with

$$q = \begin{cases} p_p & \text{if } K_{j,i,t+1} \geq (1 - \delta_j) K_{j,i,t} \\ p_s < p_p & \text{if } K_{j,i,t+1} < (1 - \delta_j) K_{j,i,t} \qquad \text{for} \quad j \in \{s, l\}. \end{cases} \tag{3.11}$$

It should be noted that the cost function is assumed to be fully symmetric across capital goods. Both long- and short-term investments are subject to the same capital adjustment costs. This is needed in order to study solely the role of capital durability for the investment response to uncertainty. Moreover, the empirical results from the first part of this chapter revealed that there is a quite monotonic relationship between uncertainty and investments with different durabilities (recall Figure 3.2), and this relation does not vanish once capital-specific factors other than durability (e.g., tangible vs intangible investment) are controlled for (recall column 3 of Table 3.4).
Combining revenues (Equation 3.7) and costs (Equation 3.10), one-period profits $\Pi_{i,t}$ are

[32]Importantly, I follow Khan & Thomas (2008), Bachmann *et al.* (2013), Bloom *et al.* (2018) and introduce uncertainty as *uncertainty over total factor productivity* in the model. As an alternative, uncertainty can also enter the model as *uncertainty over demand conditions* (e.g., Bloom 2009).

[33]As convex adjustment costs do not directly interact with uncertainty and thereby do not change the model results in a meaningful way, they are not included in the baseline model. This is mainly done to improve on computational speed. Including these costs would require a much more refined capital grid, which drastically increases the running time of the solution method.

[34]E.g., Abel & Eberly (1994), Abel & Eberly (1996). In addition, see Ramey & Shapiro (2001) for an empirical assessment of the market for used capital.

obtained:

$$\Pi_{i,t} = R_{i,t} - C^K_{i,t} \tag{3.12}$$

Given the stochastic process for total factor productivity including the time-varying process for uncertainty $\sigma_{i,t}$ and the current capital endowment, the firm i maximizes the sum of current and expected future discounted profits by choosing a sequence of optimal capital mixes, $\{K_{s,i,t+j+1}, K_{l,i,t+j+1}\}_{j=0}^{\infty}$, i.e.,

$$V(Z_{i,t}, K_{s,i,t}, K_{l,i,t}, \sigma_{i,t}) = \max_{\substack{\{K_{s,i,t+j+1},\\ K_{l,i,t+j+1}\}_{j=0}^{\infty}}} \sum_{j=0}^{\infty} \left(\frac{1}{1+r}\right)^j \mathbb{E}_t\Big[\Pi_{i,t+j}(Z_{i,t+j}, K_{s,i,t+j}, K_{l,i,t+j}, \sigma_{i,t+j})\Big], \tag{3.13}$$

where the market interest rate is constant and given by r.

3.3.2 Model Solution

In the presence of adjustment costs, the stated maximization problem does not allow for an analytical solution. Therefore, I rely on numerical methods to characterize the solution of the model.[35] Equation 3.13 can be restated in recursive formulation:

$$\begin{aligned} V(Z_t, K_{s,t}, K_{l,t}, \sigma_t) = \max_{K_{s,t+1}, K_{l,t+1}} & \Pi_t(Z_t, K_{s,t}, K_{l,t}, \sigma_t) + \\ & \frac{1}{1+r}\mathbb{E}_{Z_{t+1},\sigma_{t+1}|Z_t,\sigma_t}\Big[V(Z_{t+1}, K_{s,t+1}, K_{l,t+1}, \sigma_{t+1})\Big] \end{aligned} \tag{3.14}$$

Based on this functional equation, I use the algorithm proposed by Barrero *et al.* (2017) for the solution routine, which is a hybrid of grid-based policy and value function iteration. Starting with an initial guess V_0, I solve for the initial capital policy functions, $K_{s,t+1} = g_0(Z_t, K_{s,t}, K_{l,t}, \sigma_t)$ and $K_{l,t+1} = h_0(Z_t, K_{s,t}, K_{l,t}, \sigma_t)$. Given these policy functions, I iterate

[35] As the solution routine is the same for each firm, I leave out the firm index i for the remainder of this section. Furthermore, I discretize the AR(1) process for firm-specific productivity using Tauchen's Method. Since Z_t follows a log-normal distribution, the conditional mean of Z_t depends on the variance of the shock σ. This is a property of the log-normal distribution. However, this implies that an uncertainty shock $\sigma_{H/L}$ would not be a mean preserving spread but also changes the expected level of productivity, which contrasts the idea of a pure second moment shock. In order to fix that, I follow the literature and apply the Jensen correction to the conditional mean of Z, i.e., $\mathbb{E}_{t-1}[Z_t] = \rho_z Z_{t-1} - \frac{\sigma_t}{2}$.

on the value function for 300 times[36], i.e.,

$$\begin{aligned}V_{0,i+1}(Z_t, K_{s,t}, K_{l,t}, \sigma_t) = \Pi_t(Z_t, K_{s,t}, g_0(Z_t, K_{s,t}, K_{l,t}, \sigma_t), K_{l,t}, h_0(Z_t, K_{s,t}, K_{l,t}, \sigma_t), \sigma_t) + \\ \frac{1}{1+r}\mathbb{E}_{Z_{t+1},\sigma_{t+1}|Z_t,\sigma_t}\Big[V_{0,i}(Z_{t+1}, g_0(Z_t, K_{s,t}, K_{l,t}, \sigma_t), h_0(Z_t, K_{s,t}, K_{l,t}, \sigma_t), \sigma_{t+1})\Big] \\ \text{with} \quad i = 1, ..., 300.\end{aligned} \tag{3.15}$$

Once the iteration terminates, $V_{0,300}$ is used to solve for the new set of policy functions, $g_1(.)$ and $h_1(.)$. Finally, I set $V_{0,300}$ equal to $V_{1,0}$ and repeat the iteration procedure outlined in Equation 3.15, now evaluated with the new set of policy functions, $g_1(.)$ and $h_1(.)$. The optimal solution of the model is obtained once the policy functions do not update anymore, i.e., $g_n(.) = g_{n+1}(.)$ and $h_n(.) = h_{n+1}(.)$.

For the exogenous model parameters, I choose conventional and widely-used values from the literature. Table 3.7 gives an overview of the different model parameters each with a brief description.

Table 3.7: Parameter Selection

Parameter	Description	Value	Rationale
$\alpha_{s/l}$	Capital shares	0.40	Bloom *et al.* (2007), Barrero *et al.* (2017)
$p_p - p_s$	Partial irreversibilites	0.30	Bloom (2009) (0.339), Bloom (2007), Barrero *et al.* (2017) (0.25)
F	Investment fixed costs	0.01	Barrero *et al.* (2017)
δ_s	Durability of short-term capital	0.25	Captures roughly R&D (20%), IT (30%) and Advertising (60%)
δ_l	Durability of long-term capital	0.10	Captures roughly Land (0%), Buildings (3%), Machines (12%) and Transport (16%)
r	Interest rate	0.05	Conventional value
ρ_z	Persistance of productivity	0.95	Khan & Thomas (2008)
π_{ii} $i = L, H$	Persistance of volatility process	0.90	Barrero *et al.* (2017): use 0.85 for short-run and 0.95 for long-run volatility
σ_L	Low volatility state	0.24	Barrero *et al.* (2017)
σ_H	High volatility state	$1.33 \times \sigma_L$	Std. Dev. of empirical shock (34.4%)

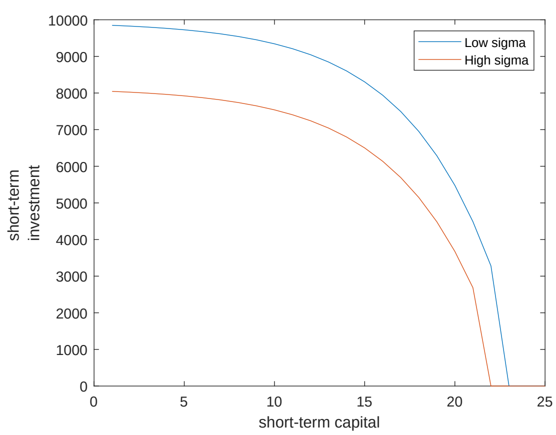
Notes: Table 3.7 gives an overview of the parameters used in the model. A brief justification for each choice is provided in the right column.

Equipped with the parameterized model, I run the policy iteration outlined above on a state space for (Z, K_s, K_l, σ) of $(5, 65, 65, 2)$. Figure 3.4 displays the investment policy

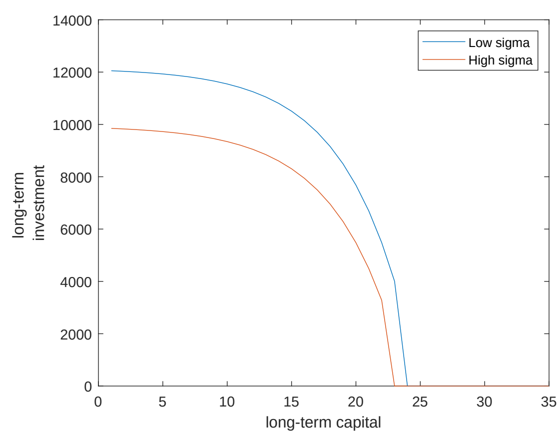
[36] This additional iteration step is crucial for improving the updating process of the policy functions. When this step is included, the full maximization routine converges within 22 seconds (13 policy function iteration steps) on a state space for (Z, K_s, K_l, σ) of $(5, 65, 65, 2)$. For comparison, if one would omit this additional iteration routine, the full program would run around 17 minutes and would converge after 1038 iterations.

functions for each type of capital.[37] Both policy functions display the typical investment behavior in the presence of nonconvex adjustment costs (e.g., Bloom *et al.* 2007, Bloom 2009). When confronted with a stochastic future, these costs generate investment inactivity areas, where it is optimal for the firm to *wait-and-see* and do *nothing*. Technically speaking, nonconvex adjustment costs create real option values of waiting that induce firms to delay investment decisions. In Figure 3.4, these investment inactivity areas are illustrated by the horizontal lines at the origin of the y-axis. When uncertainty over future business conditions increases, the option value of waiting increases as well. This is a results of basic option theory: as tail events become more likely now while the option-holder/the firm is insured against left-tail events (simply by not exercising the option/ not investing) and fully benefits from a right-tail event (by exercising the option/investing), having the opportunity to invest becomes more valuable. Therefore, higher uncertainty also increases the size of inactivity areas leading to a more reluctant investment behavior. This is depicted in Figure 3.4, where the horizontal range widens for both types of capital once volatility is set to the high uncertainty regime.

Figure 3.4: Policy Functions for Short- and Long-Term Investments



(a) Short-term



(b) Long-term

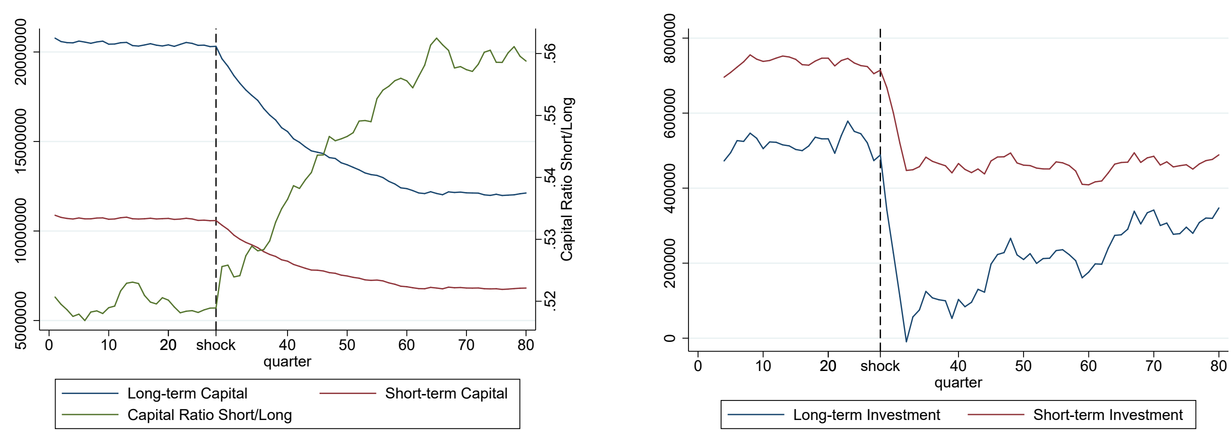
Notes: Figure 3.4 plots the investment policy functions for short-term (left) and long-term (right) investments. They are evaluated at the central gridpoint for productivity ($Z = 1$) and at the 30th gridpoint for K_l (left) and K_s (right), respectively. The blue and red lines indicate the optimal investment behavior under the low (blue) and high (red) uncertainty regimes. For illustration purpose, investment responses are restricted to non-negative investments.

[37]Strictly speaking, the policy functions in the model are 5-dimensional objects, which makes the graphical illustration quite challenging. Therefore, the functions displayed in Figure 3.4 are reduced to three dimensions, where I evaluated them at the central gridpoint for productivity, where $Z = 1$, and the 30th gridpoint for K_l (Figure 3.4a) and K_s (Figure 3.4b), respectively. For illustration purpose, investment policy functions are restricted to the non-negative investment range.

3.3.3 Simulation Results

To obtain a better understanding of how firms adjust their investment behavior in response to an uncertainty shock, I run the following simulation exercise. There are 1000 firms, each with firm-specific, time-varying productivity, all initially operating in the low uncertainty regime that lasts for 28 quarters.[38] However, there is no perfect foresight, i.e., firms only observe the current volatility state and form expectations about future states according to the transition probabilities. After seven years, volatility switches from the low to the high uncertainty regime that lasts until the end of the simulation. This change happens for all firms at the same time in an unexpected way. On the one hand, this setting allows me to compare steady-state investment behaviors in both uncertainty regimes. In addition, I can gain valuable insights how firms adjust during the transition path from the low to the high uncertainty regime.

Figure 3.5: Simulated Capital Stocks and Investments



(a) Long- and Short-Term Capital Stocks

(b) Long- and Short-Term Investments

Notes: Figure 3.5 plots average capital stocks (Panel (a), left y-axis), the ratio between short- and long-term capital (Panel (a), right y-axis) and the investment behavior (Panel (b)) in response to increased uncertainty. For the first 28 quarters, the economy is in the low uncertainty regime σ_L. From the 29th quarter, uncertainty is set to the high regime σ_H, which persists until the end of the simulation.

Figure 3.5 shows the average investment behavior and the resulting capital stocks at the firm-level for the time span of the simulation. When focusing on the capital stock dynamics outlined in Panel 3.5a, it can be seen that firms maintain higher levels of long-term capital for the entire simulation period.[39] The left side of the dashed vertical line depicts the low

[38] Although the volatility process is set to be firm-specific, volatility states are synchronized across firms for this simulation exercise. This is done in order to study the impact of an uncertainty shock on the whole economy.

[39] After all, this is not surprising since, all other things being equal, long-term capital is more valuable

uncertainty environment ($\sigma_L = 0.24$). Here, the ratio between short- and long-term capital is around 52%, illustrated by the green line. After seven years, uncertainty suddenly jumps to $\sigma_H = 0.32$, which corresponds to an increase of 33%.[40] As a response to that, firms immediately begin reducing both types of capital until, after a while, the capital stocks converge to the new desired levels. Importantly, the reductions in the capital stocks take place in an asymmetric manner, where long-term capital is decreased more strongly than short-term capital. Overall, this leads to an increase in the capital ratio[41] by around 4 percentage points, indicating that firms use relatively more short-term capital in production now. The underlying dynamics are also reflected in Panel 3.5b, where the investment behavior is plotted. Due to the higher depreciation rate, short-term capital requires more investments to keep the capital stock constant. When the uncertainty shock hits the economy, investments in both types of capital decline. However, long-term investments almost pause, which leads to a much faster depletion of the long-term capital stock. To summarize, this very stylized model is able to capture the investment dynamics found in the empirical part of this chapter in a qualitatively consistent way: uncertainty shocks reduce long-term investments more strongly than short-term investments.

3.3.4 The Option Value of Durable Investments

In a next step, I analyze the underlying mechanism in the model that leads to this asymmetric cut in investments. The literature (e.g., Bloom *et al.* 2007, Bloom 2009) has already highlighted the role of nonconvex adjustment costs for the responsiveness of total investments under uncertainty. In particular, model-based simulations have shown that in the presence of nonconvex adjustment costs, higher uncertainty increases the option value of waiting, which results in a cutback of total corporate investments.[42] This insight is also reflected in Figure 3.4, where higher uncertainty leads to broader inactivity areas for both types of capital investments.

However, the simulation exercise from the previous section has demonstrated that long-term investments decrease more strongly both in absolute and in relative terms compared to short-term investments (recall Figure 3.5b). This result indicates that uncertainty affects the inactivity areas of both investment functions *differently* – and this holds true under

for the firm as it is productive over a longer time period compared to short-term capital, which depletes faster. One can also infer this directly from the ratio of first-order conditions for capital in steady-state: $\frac{K_s}{K_l} = \frac{p_p - p_s(1-\delta_l)}{p_p - p_s(1-\delta_s)} < 1$ since $\delta_l < \delta_s$.

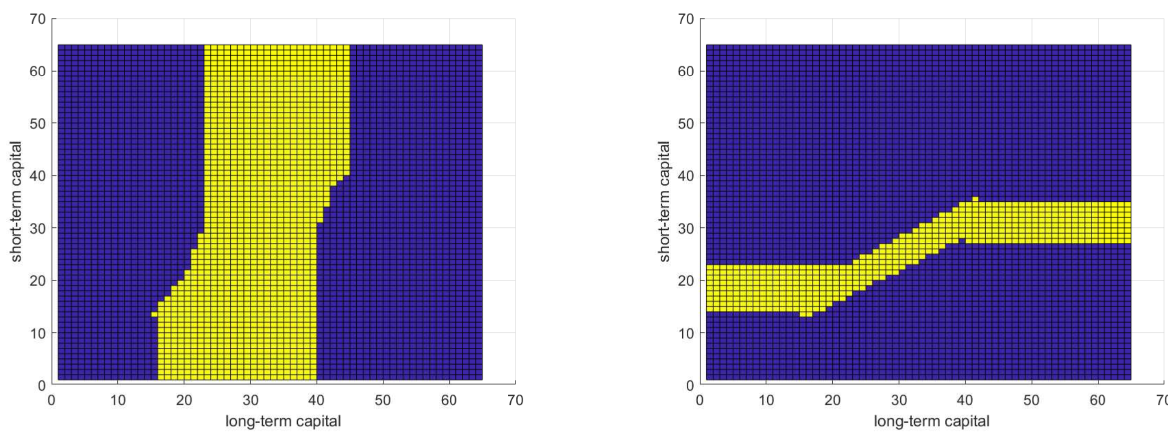
[40] This increase is roughly equivalent to a 1-standard deviation uncertainty shock in the empirical data.

[41] The capital ratio is defined as ratio of short- relative to long-term capital.

[42] See Bloom (2009), page 625: "[...] investment rates fall dramatically in the 4 months after the shock because higher uncertainty increases the real-option value to waiting, so firms scale back their plans."

the assumption of fully *symmetrical* nonconvex adjustment costs across both capital goods. Specifically, as long-term investments are cut back more strongly, higher uncertainty might have relatively increased the inactivity area of those investments. Figure 3.6 illustrates the investment policy functions under the high uncertainty regime for long-term (Panel 3.6a) and short-term (Panel 3.6b) investments. The yellow area marks all combinations of long- and short-term capital where the optimal investment response for the respective capital good is zero (implying a *wait-and-see* investment policy). In contrast to that, blue-shaded areas indicate all capital combinations that imply a flexible (non-zero) investment response. Comparing the investment policy functions of both capital goods, it is apparent that long-term investments are determined by much larger areas of inactivity. For these investments, a policy of *doing nothing* (or *wait-and-see*) is beneficial for much more combinations of capital, while short-term investments tend to be adjusted more frequently and flexibly. The larger inactivity area for long-term investments then generates the more reluctant response in these investments under uncertainty.

Figure 3.6: Inactivity Areas for Long- and Short-Term Investments



(a) Long-Term Investment

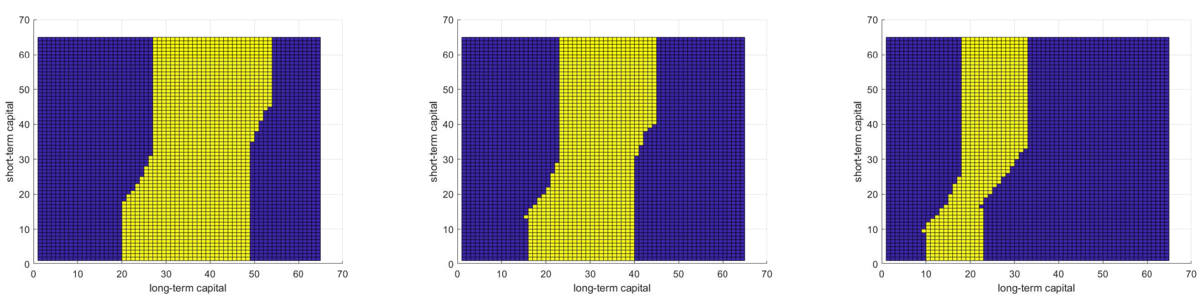
(b) Short-Term Investment

Notes: Figure 3.6 plots the policy functions for long-term (left) and short-term (right) investments on the two-dimensional capital grid for the high-uncertainty regime when productivity is set to one. The yellow area marks all combinations of long- and short-term capital where the optimal investment response for the respective capital good is zero. Accordingly, blue-shaded areas illustrate non-zero investments.

Based on these insights, it can be summarized that capital durability interacts with nonconvex adjustment costs in a very meaningful way: more durable investments are determined by larger areas of investment inactivity. To analyze this more formally, I now vary the durability of long-term capital in the model while holding fixed the depreciation rate of the short-term good (at $\delta_s = 0.25$). Results for different values of δ_l are displayed in

Figure 3.7. The Figure shows that there is indeed a systematic relationship between capital durability and the size of the investment inactivity area. A lower capital depreciation rate is associated with a larger investment inactivity area. The more durable an investment good is, the higher is the option value of waiting under uncertainty. In general, this result is quite intuitive. Since both investment goods are equally costly to revert, expected resale losses are higher for long-term investments, as they are tied to the firm's capital stock for a longer period of time and are therefore more likely to be resold when the chosen capital level turns out to be too high. In that sense, short-term capital provides the firm with a higher degree of flexibility under uncertainty because these capital goods deplete much faster in the form of natural value losses and hence have a lower risk of bearing resale losses. In anticipation of the higher expected resale losses on long-term investments, firms behave more cautiously with these investments and scale them back more strongly when uncertainty increases.

Figure 3.7: Investment Inactivity Areas for Different Degrees of Asset Durability



(a) $\delta_l = 0.05$ (b) $\delta_l = 0.10$ (c) $\delta_l = 0.20$

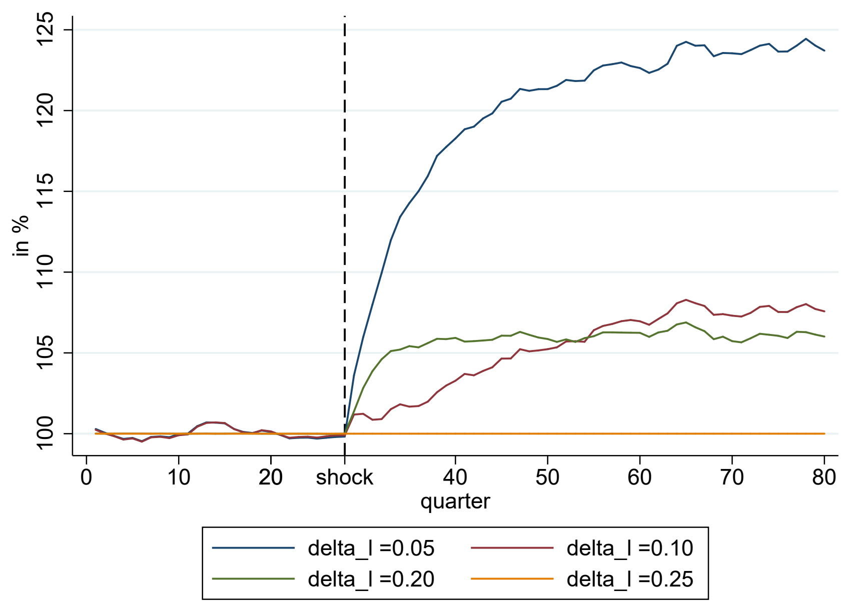
Notes: Figure 3.7 plots the policy function for long-term investments under varying degrees of durability. In Panel (a), δ_l is set to 0.05, Panel (b) shows the baseline calibration with $\delta_l = 0.10$ and is therefore similar to Figure 3.6a, in Panel (c), δ_l is set to 0.20. The depreciation rate of short-term capital is fixed at $\delta_s = 0.25$ and productivity is set to one. The yellow areas mark all combinations of long- and short-term capital where the optimal investment responses are zero. Accordingly, blue-shaded areas illustrate non-zero investments.

In a final step, it is examined whether it is indeed the different sizes in the inactivity areas that generate the asymmetric investment behavior. In order to do that, I repeat the simulation exercise from Section 3.3.3 and vary again δ_l. Figure 3.8 plots for each simulation run the ratio of short- to long-term capital over time. To better compare adjustment processes taking place on different levels, I normalize the capital ratios with respect to their pre-shock levels.[43] The results show that the greater the difference in the depreciation rates of both capital goods is, the more asymmetrically is the investment response to an uncertainty shock. When the difference in depreciation rates is 20 percentage points (i.e., $\delta_l = 0.05$

[43]These are the capital ratios used in the low uncertainty era.

and $\delta_s = 0.25$), the ratio of short- to long-term capital increases by almost 25% (blue line) in response to a persistent increase in uncertainty. Once the difference in depreciation rates becomes smaller, the positive change in the capital ratio decreases as well. A depreciation rate of 10% for long-term capital increases the capital ratio by only 8% in the long run (red line). This number corresponds to the increase of the capital ratio from 52% to 56% that has been illustrated in Figure 3.5a. When δ_l is set to 20%, the change in the capital ratio further diminishes. According to the green line in Figure 3.8, short- relative to long-term capital increases by only 6%. In the scenario where both depreciation rates are equalized, the yellow line indicates that there is no asymmetric investment behavior anymore. Both capital goods are reduced by exactly the same amount and proportion.

Figure 3.8: Simulated Capital Ratios for Different Degrees of Durability



Notes: Figure 3.8 plots the average ratio of short- relative to long-term capital for varying degrees of durability in long-term capital ($\delta_l = 0.05$ blue, $\delta_l = 0.10$ red, $\delta_l = 0.20$ green, $\delta_l = 0.25$ yellow). The depreciation rate of short-term capital is fixed at $\delta_s = 0.25$. For the first 28 quarters, the economy is in the low uncertainty regime σ_L, while afterwards uncertainty is set to the high regime σ_H, which persists until the end of the simulation. Capital ratios are normalized by their respective pre-shock averages.

3.4 Conclusion

This chapter studies the role of capital durability for the investment response under uncertainty. Using within-firm variation in the holdings of capital goods with different durabilities, I find that durable investments are reduced more strongly than short-term investments in response to firm-specific uncertainty shocks. In addition to this shift in the within-firm investment composition, I also find implications for aggregate investments: when firm-specific uncertainty increases, firms with more durable capital cut total investments more strongly than firms that employ more short-term capital in production.

I then rationalize these findings by studying the investment response of capital goods with different durabilities through the lens of the canonical dynamic investment model. In response to an unexpected and permanent increase in the level of uncertainty, firms in the model cut long-term investments more strongly than short-term investments (i.e., in a way that is qualitatively consistent with my empirical findings), which leads effectively to a decline in the durability of the firms' capital stock in production. It is important to note that this result holds under the assumption of symmetrical nonconvex adjustment costs. Hence, in addition to the degree of investment irreversibilities, their durability is another important determinant for the investment behavior under uncertainty. Simulation-based results reveal that the option values of waiting of capital investments monotonically decrease in the size of their depreciation rates.

There are several avenues for future research. An interesting direction could be to study the degree of substitutability between short- and long-term capital in production and to examine possible implications for the investment response under uncertainty. If more durable capital goods can be easily replaced by short-term investments, this might mitigate the decline in aggregate investments. But if long-term capital tends to behave in a complementary way to short-term investments, this could lead to particularly severe consequences for economic output and aggregate growth. Quantifying these long-run costs of the uncertainty-induced decline in capital durability would therefore be another fruitful direction for future academic research.

Appendix A

Appendix to Chapter 1

A1 Web-Based Matching Procedure

Given the absence of common identifier between Dealogic Loanware and SNL Financial, we have to match the two data sets based on the name of the bank. In doing so, we have to deal with the 'classical' string match problem, where the name of the same banks in the two data sets may be different in its spelling. For example, the Bavarian state bank is listed as "BayernLB" in Dealogic Loanware and as "Bayerische Landesbank AöR" in SNL Financial. In addition, complex ownership structures and the existence of holding companies can further complicate the matching (e.g., Dealogic Loanware provides syndicated loan data for NatWest Markets, which is the investment banking arm of The Royal Bank of Scotland (RBS), whereas in SNL Financial only information for RBS is available). In both of the examples mentioned, traditional methods of fuzzy string matching would lead to a poor result.

Against this background, we apply the following matching algorithm: in a first round, we match banks by their punctuation-free names. This traditional method already gives us 441 matches between the two data sets. In further rounds, we match banks based on common URL addresses. That is, we collect the URLs of the top 5 hits when running an internet search engine with the bank's name and look for cases where cleaned URL addresses coincide. We consider a bank pair as matched when at least one particular combination of the top 5 URLs matches. In this manner, we are able to match an additional amount of 242 banks. In a last step, we check all matches for plausibility by hand.

A2 Classification of Borrower Risk

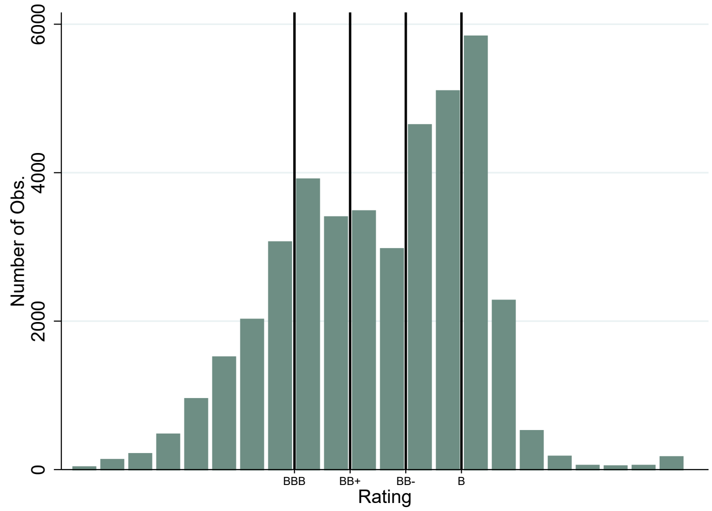
For the baseline specification on borrower risk, we divide the sample into five risk classes based on the borrowers' credit rating. This is done in a way that captures the distribution of credit ratings in our sample, which is quite uneven across the Standard & Poor's rating scale (recall Figure 1.2; e.g., 84 percent of all companies share a rating between *BBB+* and *B-*). An overview of the allocation of ratings into the five risk classes is provided in Table A.1. Reflecting the thinner tails of the distribution, the top and and bottom eight rating bins in the Standard & Poor's rating scale are assigned to the best- and worst-rated risk classes, respectively. The remaining six rating bins are assigned to the inner three risk classes, with each of these classes including two bins. Notably, our classification captures the cut-off between investment grade (*BB+* or higher) and non-investment grade (*BBB-* or lower) ratings, which is between buckets 3 and 4, and also forms the basis for the sample splits in Tables 1.4 and 1.8. Figure A.1 displays the distributions of observations across the five risk classes. In order to show that our results do not depend on the specific classification of the rating variable that is outlined above, we provide results for alternative specifications in Section 1.6.

Table A.1: Classification of the Five-Bin Rating Scale

Five-bin scale	Standard & Poor's scale
5	AAA, AA+, AA, AA-, A+, A, A-, BBB+
4	BBB, BBB-
3	BB+, BB
2	BB-, B+
1	B, B-, CCC+, CCC, CCC-, CC, C, D

Notes: Table A.1 summarizes the classification of the individual rating classes into five general categories.

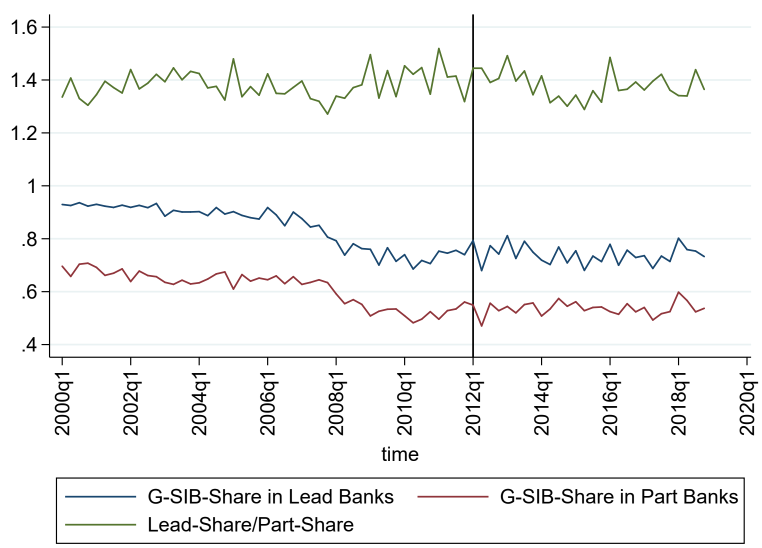
Figure A.1: Number of Observations by Credit Rating



Notes: This figure plots a histogram with respect to the credit rating. Each bar represents one of 22 rating bins ranging from AAA to D. The vertical lines indicate the four cut-off points for the own-created five-bin rating scale.

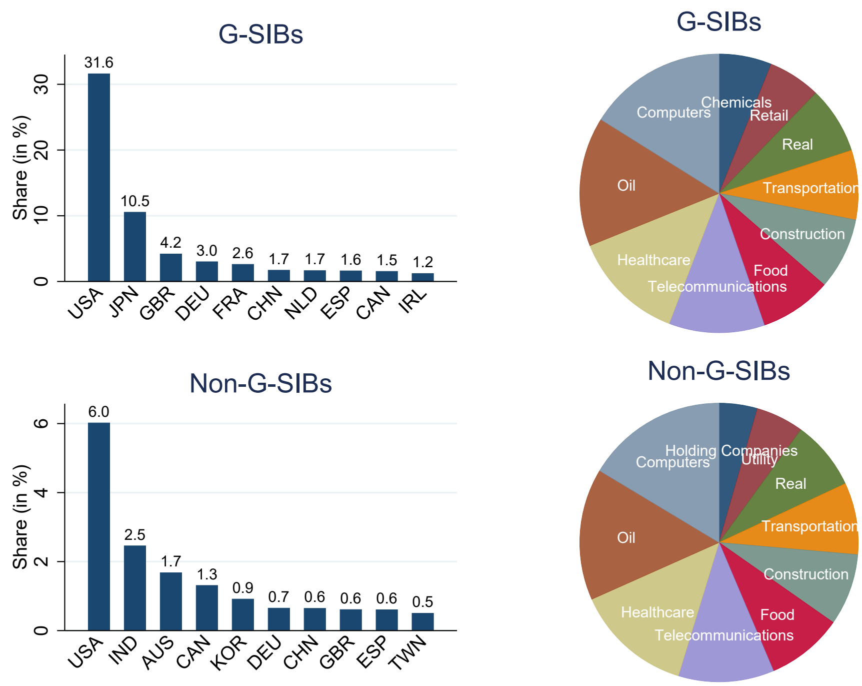
A3 Additional Figures and Tables

Figure A.2: Average G-SIB Share over Time



Notes: For each quarter, we calculate the share of the lending volume originated by G-SIBs in the total number of leading banks (blue) and participating banks (red). The green line indicates the ratio between the two lines.

Figure A.3: Geographical and Industry Breakdown of Lending Volume



Notes: The left panel aggregates lending volumes by the country of the respective borrowing party for G-SIBs (top) and Non-G-SIBs (bottom) for the period 2010 - 2018. The right panel illustrates lending volumes by borrowing industry for G-SIBs (top) and Non-G-SIBs (bottom) for the same period. For illustration purposes, we focus on the 10 largest countries/industries in each panel.

Table A.2: Credit Supply – Alternative Specifications

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Log(Lending)	Log(Lending)	Log(Lending)	Log(Lending)	Log(Lending)	Lending Volume
Post2012 × GSIB	-0.0223	0.00121	-0.00740	-0.243*	-0.137	0.124
	(0.133)	(0.161)	(0.131)	(0.130)	(0.137)	(0.143)
Post2012 × Assets					0.0752*	
					(0.0424)	
Post2012 × ROAA					-0.00732	
					(0.0338)	
Post2012 × CET1					1.674	
					(1.555)	
Observations	585,376	493,240	924,532	1,069,880	693,996	344,762
R-squared	0.232	0.253	0.203	0.215	0.212	
Bank Controls	×	×	×	×	×	×
Bank FE	×	×	×	×	×	×
Qtr x Ctr x Ind FE	×	×	×	×	×	×
Firms	Priv Sec Ind	Priv Sec Ind	All	Priv Sec Ind	Priv Sec Ind	Priv Sec Ind
Time	2010 - 2018	2010 - 2018	2010 - 2018	2000 - 2018	2010 - 2018	2010 - 2018
Control Group	USD 100 bn	BCBS sample	baseline	baseline	baseline	baseline
Clustering	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Ctr x Qtr
Margin	Int & Ext	Int & Ext	Int & Ext	Int & Ext	Int & Ext	Int & Ext
Model	OLS	OLS	OLS	OLS	OLS	PPML
Frequency	Quarterly	Quarterly	Quarterly	Quarterly	Quarterly	Quarterly
Unit of Obs	Bank x Qtr x Ctr x Ind	Bank x Qtr x Ctr x Ind	Bank x Qtr x Ctr x Ind	Bank x Qtr x Ctr x Ind	Bank x Qtr x Ctr x Ind	Bank x Qtr x Ctr x Ind
Nr. of Banks	169	77	598	542	541	477
Pseudo R2						0.427

Notes: Table A.2 estimates the effect on lending volumes. Column 1 includes only banks with total assets larger than USD 100 bn, while column 2 considers only banks that are included in the Basel Committee on Banking Supervision's G-SIB assessment sample. In column 3, we include all borrowing parties in the sample, column 4 extends the pre-treatment period to 2000. In column 5, we additionally interact the reform dummy with bank controls. In column 6, we estimate the relationship using a Poisson Pseudo-Maximum Likelihood (PPML) Estimator. ***, **, and * indicate statistical significance at the 1%-, 5%- and 10%-level.

Table A.3: Portfolio Riskiness – Alternative Specifications

VARIABLES	(1) Log(Lending)	(2) Log(Lending)	(3) Log(Lending)	(4) Log(Lending)	(5) Sec Dummy	(6) Sec Dummy	(7) Log(Lending)	(8) Log(Lending)
Post2012 × GSIB × Rat	0.512**	0.115*	0.219**	0.179				
	(0.239)	(0.0646)	(0.0977)	(0.109)				
Post2012 × GSIB × Sec							0.184*	0.315***
							(0.0970)	(0.114)
Post2012 × GSIB					0.134***	0.671***		
					(0.0500)	(0.246)		
Observations	8,911	7,129	9,480	9,147	64,695	64,362	25,866	22,821
R-squared	0.845	0.837	0.851	0.856	0.248		0.718	0.719
Bank & Tranche Controls					×	×		
Bank x Time FE	×	×	×	×			×	×
Rat x Ctr x Time FE	×	×	×	×				
Bank x Rat x Ctr FE	×	×	×	×				
Sec x Ctr x Time FE							×	×
Bank x Sec x Ctr FE							×	×
Bank FE					×	×		
Quarter FE					×	×		
Control Group	baseline	baseline	USD 100 bn	BCBS sample	baseline	baseline	USD 100 bn	BCBS sample
Clustering	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Ctr x Qtr
Frequency	Quarterly	Yearly	Quarterly	Quarterly	-	-	Quarterly	Quarterly
Rating	Binary	Deciles	Five-bin scale	Five-bin scale	-	-	-	-
Unit of Obs	Bank x Qtr x Rat x Ctr	Bank x Qtr x Rat x Ctr	Bank x Qtr x Rat x Ctr	Bank x Qtr x Rat x Ctr	Bank x Tranche	Bank x Tranche	Bank x Qtr x Sec x Ctr	Bank x Qtr x Sec x Ctr
Model	OLS	OLS	OLS	OLS	LPM	Logit	OLS	OLS
Nr. of Banks	65	67	57	50	271	194	111	71

Notes: Table A.3 estimates the effect on portfolio riskiness. Columns 1-4 study the effect with respect to borrower risk. In column 1, we use a binary risk classification (IG vs. non-IG) as rating variable, in column 2 the rating classification is based on deciles. Column 3 includes only banks with total assets larger than USD 100 bn, while column 4 considers only banks that are included in the Basel Committee on Banking Supervision's G-SIB assessment sample. In columns 5-8, we investigate the effect on secured lending. In columns 5 and 6, we use the information whether a tranche is secured or not as dependent binary variable and estimate tranche-level regressions (LPM in column 5 and Logit in column 6). In columns 7 and 8, we apply similar restrictions to the control group as in columns 3 and 4. ***, **, and * indicate statistical significance at the 1%-, 5%- and 10%-level.

Table A.4: Pricing of Tranches – Alternative Specifications

VARIABLES	(1) Log(Marg)	(2) Log(Marg)	(3) Log(Marg)	(4) Log(Marg)	(5) Log(Marg)	(6) Log(Marg)	(7) Log(Marg)
Post2012 × GSIB	0.0633**	0.0855**	0.0844*				
	(0.0318)	(0.0332)	(0.0430)				
Post2012 × GSIB × Rat				0.0598***	0.118***	0.0735***	0.0905***
				(0.0177)	(0.0427)	(0.0242)	(0.0296)
Observations	24,337	24,880	23,541	23,504	24,524	24,055	22,800
R-squared	0.722	0.747	0.750	0.779	0.713	0.795	0.796
Bank Controls	×	×	×				
Tranche Controls	×	×	×	×	×	×	×
Bank x Quarter FE				×	×	×	×
Rat x Ctr x Qtr FE				×	×	×	×
Bank x Rat x Ctr FE				×	×	×	×
Bank FE	×	×	×				
Qtr x Ctr FE	×	×	×				
Firms	Priv Ind	Priv Ind	Priv Ind	Priv Ind	Priv Ind	Priv Ind	Priv Ind
Time	2010 - 18	2010 - 18	2010 - 18	2010 - 18	2010 - 18	2010 - 18	2010 - 18
Control Group	baseline	USD 100 bn	BCBS sample	baseline	baseline	USD 100 bn	BCBS sample
Clustering	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Ctr x Qtr	Bank & Ctr x Qtr
Unit of Obs	Tranche x Bank	Tranche x Bank	Tranche x Bank	Tranche x Bank	Tranche x Bank	Tranche x Bank	Tranche x Bank
Margins	incl Base -Rate	excl Base -Rate	excl Base -Rate	incl Base -Rate	excl Base -Rate	excl Base -Rate	excl Base -Rate
Rat Class	-	-	-	Five-bin	Binary	Five-bin	Five-bin
Nr. of Banks	107	99	67	96	102	92	65

Notes: Table A.4 estimates the effect on the pricing behavior. Columns 1-3 study the average effect on margins irrespective of borrower risk. In column 1, we add up margins with base rates and use the logarithm of the sum as dependent variable. Column 2 includes only banks with total assets larger than USD 100 bn, while column 3 considers only banks that are included in the Basel Committee on Banking Supervision's G-SIB assessment sample. Columns 4-7 analyze the pricing sensitivity with respect to borrower risk. Column 4 includes the sum of margins and base rates as dependent variable (similar to column 1) and column 5 uses a binary rating classification (IG vs non-IG). In columns 6 and 7, we apply similar restrictions to the control group as in columns 2 and 3. ***, **, and * indicate statistical significance at the 1%-, 5%- and 10%-level.

Appendix B

Appendix to Chapter 2

B1 Empirical Appendix

B1.1 Variable Descriptions

Table B.1: Variable Descriptions and Data Sources

Variable	**Description**	**Source**
Investment Variables		
$\text{advertising}_{i,t}$	*advertising* represents the cost of advertising media (i.e., radio, television, and periodicals) and promotional expenses in millions USD; Compustat variable name: XAD	Compustat
$\text{R\&D}_{i,t}$	*research & development expenses* (period t) represent all direct and indirect costs related to the creation and development of new processes, techniques, applications and products with commercial possibilities in millions USD; Compustat variable name: XRD	Compustat
$\text{buildings}_{i,t}$	*buildings* (period t) - 0.97 $\times$ *buildings* (period $t-1$); *buildings* (gross property plant and equipment) represent the architectural structure used in a business such as a factory, office complex or warehouse in millions USD	FactSet
$\text{computer}_{i,t}$	*computer software & equipment* (period t) - 0.70 $\times$ *computer software & equipment* (period $t-1$); *computer software & equipment* (gross property plant and equipment) represents computer equipment and the information a computer uses to perform tasks in millions USD	FactSet
$\text{land}_{i,t}$	*land* (period t) - $\times$ *land* (period $t-1$); *land* (gross property plant and equipment) represents the real estate without buildings held for productive use, is recorded at its purchase price plus any costs related to its purchase such as lawyer's fees, escrow fees, title and recording fees in millions USD	FactSet
$\text{machines}_{i,t}$	*machinery & equipment* (period t) - 0.88 $\times$ *machinery & equipment* (period $t-1$); *machinery & equipment* (gross property plant and equipment) represent the machines and machine parts needed by the company to produce its products in millions USD	FactSet
$\text{transportation equipment}_{i,t}$	*transportation equipment* (period t) - 0.84 $\times$ *transportation equipment* (period $t-1$); *transportation equipment* (gross property plant and equipment) represents the cars, ships, planes or any other type of transportation equipment in millions USD	FactSet
Manager Variables		
$\text{option awards}_{2004}$	the aggregate value of stock options (expressed in thousands USD) granted to the executive during the year as valued using Standard & Poor's Black-Scholes methodology; ExecuComp variable name: *OPTION-AWARDS-BLK-VALUE*	ExecuComp
TDC_{2004}	total compensation (expressed in thousands USD) comprised of the following: Salary, Bonus, Other Annual, Total Value of Restricted Stock Granted, Total Value of Stock Options Granted (using Black-Scholes), Long-Term Incentive Payouts, and All Other Total; ExecuComp variable name: *TDC1*	ExecuComp
bonus share_{t}	this is the ratio between *Bonus* (i.e., an annual payment made in addition to salary) and *Total Compensation*, which is the sum of *Total Direct Compensation* and *Total Equity Linked Compensation*; *Total Direct Compensation* consists of *Salary* and *Bonus*, and *Total Equity Linked Compensation* is the sum of *Value of Shares Awarded*, *Value of LTIP Awarded* and *Estimated Value of Options Awarded*; *Value of LTIP Awarded* is the sum of all cash, equity, equity matched and Option plans received over time where the receipt of these awards is contingent on the company's performance	BoardEx
equity share_{t}	this is the ratio between *Total Equity Linked Compensation* (= *Value of Shares Awarded* + *Value of LTIP Awarded* + *Estimated Value of Options Awarded*) and *Total Compensation*, which is the sum of *Total Direct Compensation* and *Total Equity Linked Compensation*	BoardEx
pay duration $d_{i,t}$	duration d of firm i at time t is calculated as $d_{it} = \frac{(bonus_{it}+salary_{it})\cdot 0+\sum_{j=1}^{N}(Restr.stock_{ijt}+options_{ijt})\cdot \tau_j}{(salary_{it}+bonus_{it})+\sum_{j=1}^{N}(Restr.stock_{ijt}+options_{ijt})}$ where τ is the *vesting period* of equity-based component j; *vesting period* is obtained by taking the difference between the *vesting date*, which is the date from which options can be exercised, and the annual report date	BoardEx and Gopalan *et al.* (2014)
$\text{firm-related wealth}_{t}$	firm-specific wealth is the sum of the value of the stock and option portfolio held by the executive; the value of the option portfolio is computed as of the fiscal year end using the Black-Scholes formula; for pre-2006, the values of the three option portfolios are summed up: current year grants, previously-granted unvested options, and vested options; for post-2006, the values of all the tranches of options outstanding are summed up; the value of the share portfolio is computed by multiplying the number of shares (Execucomp: *SHROWN-EXCL-OPTS*) by the fiscal year end price (Execucomp: *PRCCF*); the sum of the two provides the value of the CEO's equity portfolio as of the end of the year	Coles *et al.* (2006) and Core & Guay (2002)
Firm Variables		
total assets_{t}	(log) total value of assets reported for 2004 in millions USD; Compustat variable name: AT	Compustat
employment_{t}	(log) number of company workers in 2004 (in thousands); Compustat variable name: EMP	Compustat
sales_{t}	gross sales in millions USD; Compustat variable name: SALE	Compustat
$\text{market capitalization}_{t}$	annual arithmetic mean of number of common shares (CSHOC) $\times$ daily closing price (PRCCD) in millions USD	Compustat

Notes: The Table contains descriptions of all empirical variables. Note that the variables firm-related wealth_t, sales_t and market capitalization_t are used in our quantitative analysis.

B1.2 Economic Significance: Calculating the Increase in Refinancing Costs

Column 1 in Table 2.9 reveals that for option-paying firms the average depreciation rate increased by 1.58 percentage points compared to non-option-paying firms. Assuming that the durability of the capital stock of non-option-paying firms was not affected by FAS 123R, we map this relative change to an absolute number. We compute the average pre-FAS-123R depreciation rate for option-paying firms, which is 16.81% in 2004. This rate converts into a durability of $2,171$ days ($\frac{1}{0.1681} \times 365$ days) for the capital stock. The FAS-123R-induced depreciation rate for option-paying firms is equal to 18.39% (16.81%+1.58%), which implies a durability for the firms' capital stock of 1,985 days. Therefore, FAS 123R decreased the durability of the capital stock by 186 days. Assuming an annual refinancing interest rate of 3%, this lower durability would be associated with an additional amount of interest payments of USD 15.29 for each USD 1,000 invested ($0.03 \times \frac{186}{365} \times$ USD $1,000$).

B1.3 Robustness and Additional Results

This Appendix presents several robustness analyses and additional results.

CEO Turnover: Table B.2 replicates estimates focusing on a subsample that includes only firms with a unique CEO to show that results are not determined by CEO-turnover events. Results indicate that the effect is even more pronounced when we exclude firms where CEO turnover occurred.

Measurement of Investments: Tables B.3 and B.4 show robustness regarding the measurement of investments. Table B.3 replicates our findings based on either Box-Cox transformation or logarithmized investments. Table B.4 replicates results when negative investments are either treated as disinvestments or as 0 expenditures.

Firm Size: Table B.5 includes additional interactions with firm size, using either assets or employment as a proxy for the size of firms.

Structural Parameters: Table B.6 exploits time variation in the model-derived parameter β to study its effect on investment and firm-specific depreciation rates.

Table B.2: Robustness: Incentives and the Durability of Investments – CEO Turnover

	Investments					
	(1)	(2)	(3)	(4)	(5)	(6)
Measure of Depreciation:	*Ordering*		*Depreciation Rate*			
FAS123 × Option-Dummy × Depr	0.0970***	0.0964***	1.010***	1.009***	1.244***	0.973***
	(0.0300)	(0.0301)	(0.288)	(0.289)	(0.367)	(0.303)
Option-Dummy × Depr	-0.0384	-0.0388	-0.775	-0.780	-0.772	-0.942*
	(0.0512)	(0.0513)	(0.478)	(0.479)	(0.483)	(0.482)
FAS123 × Depr	-0.0847***		-0.908***			
	(0.0238)		(0.216)			
Investment FE	×		×			
Investment-Year FE		×		×	×	×
Firm-Year FE	×	×	×	×	×	×
Observations	5,939	5,939	5,939	5,939	14,886	6,319
No. Firms	286	286	286	286	292	310
Sample Period	2002 - 2007	2002 - 2007	2002 - 2007	2002 - 2007	2000 - 2014	2002 - 2007
Sample	same CEO	same CEO	same CEO	same CEO	same CEO	same CEO incl. fin. & util.

Notes: The Table reports the results on the relationship between managerial incentives and investment decisions. There are only firms included which have been run by the same CEO between 2002 and 2007. *Option-Dummy* is a dummy that indicates if any options are awarded in 2004. *FAS123* takes value 0 for each year until 2005 and value 1 afterwards. *Depr* is the measure of depreciation, following an ordinal scale in columns 1 and 2, and expressed in absolute depreciation rates in columns 3 to 6. Standard errors (reported in parentheses) are clustered at the firm-level. ***, **, and * indicate statistical significance at the 1%-, 5%- and 10%-level.

Table B.3: Robustness: Incentives and the Durability of Investments – Alternative Transformation of the Investment Variable

	Investments							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Investment Measure:	*Box-Cox Transformation*				*Logarithms*			
FAS123 × Option-Dummy × Depr	0.924**	0.924**	0.934**	0.881**	0.490*	0.490*	0.862***	0.431
	(0.376)	(0.377)	(0.402)	(0.380)	(0.282)	(0.283)	(0.291)	(0.284)
Option-Dummy × Depr	-0.799	-0.800	-0.702	-1.167**	-0.430	-0.431	-0.428	-0.533
	(0.524)	(0.524)	(0.539)	(0.533)	(0.374)	(0.373)	(0.367)	(0.368)
FAS123 × Depr	-0.709**				-0.627**			
	(0.314)				(0.250)			
Investment FE	×				×			
Investment-Year FE		×	×	×		×	×	×
Firm-Year FE	×	×	×	×	×	×	×	×
Observations	13,422	13,422	33,737	14,200	12,400	12,400	31,080	13,106
No. Firms	667	667	684	721	664	664	682	711
Sample Period	2002 - 2007	2002 - 2007	2000 - 2014	2002 - 2007	2002 - 2007	2002 - 2007	2000 - 2014	2002 - 2007
Sample				incl. fin. & util.				incl. fin. & util.

Notes: This Table reports the results on the relationship between managerial incentives and investment decisions. The following transformation applies to the dependent variable y: $y = ln(x + 0.001)$ for columns $1 - 4$ and $y = ln(x)$ for columns $5 - 8$. *Option-Dummy* is a dummy that indicates if any options are awarded in 2004. *FAS123* takes value 0 for each year until 2005 and value 1 afterwards. *Depr* is the measure of depreciation expressed in absolute depreciation rates. Standard errors (reported in parentheses) are clustered at the firm-level. ***, **, and * indicate statistical significance at the 1%-, 5%- and 10%-level.

Table B.4: Robustness: Incentives and the Durability of Investments – Allowing for Negative Investments

	Investments							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Investment Sample:	*Include Negative Investments*				*Treat Negative Investments as 0s*			
FAS123 × Option-Dummy × Depr	1.024***	1.039***	1.132***	0.892**	0.707***	0.720***	0.832***	0.603**
	(0.389)	(0.390)	(0.336)	(0.391)	(0.262)	(0.262)	(0.260)	(0.260)
Option-Dummy × Depr	0.0448	0.0393	0.226	-0.156	-0.0289	-0.0346	0.0816	-0.198
	(0.414)	(0.415)	(0.404)	(0.413)	(0.356)	(0.356)	(0.355)	(0.352)
FAS123 * Depr	-1.084***				-0.770***			
	(0.330)				(0.224)			
Investment FE	×				×			
Investment-Year FE		×	×	×		×	×	×
Firm-Year FE	×	×	×	×	×	×	×	×
Observations	15,281	15,281	38,607	16,223	15,281	15,281	38,607	16,223
No. Firms	668	668	686	722	668	668	686	722
Sample Period	2002 - 2007	2002 - 2007	2000 - 2014	2002 - 2007	2002 - 2007	2002 - 2007	2000 - 2014	2002 - 2007
Sample				incl. fin. & util.				incl. fin. & util.

Notes: This Table reports the results on the relationship between managerial incentives and investment decisions. Columns 1 – 4 treat negative investment as true negatives, whereas in columns 5 – 8 negative values are set to zero. *Option-Dummy* is a dummy that indicates if any options are awarded in 2004. *FAS123* takes value 0 for each year until 2005 and value 1 afterwards. *Depr* is the measure of depreciation expressed in absolute depreciation rates. Standard errors (reported in parentheses) are clustered at the firm-level. ***, **, and * indicate statistical significance at the 1%-, 5%- and 10%-level.

Table B.5: Robustness: Incentives and the Durability of Investments – Controlling for Firm Size

	Investments							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Firm Size Measure:	*Employment*				*Assets*			
Measure of Depreciation:	*Ordering*		*Depreciation Rate*		*Ordering*		*Depreciation Rate*	
FAS123 × Option-Dummy × Depr	0.0439*	0.0441*	0.563**	0.564**	0.0493**	0.0498**	0.584**	0.586**
	(0.0243)	(0.0242)	(0.236)	(0.235)	(0.0245)	(0.0244)	(0.243)	(0.243)
Option-Dummy × Depr	0.0238	0.0233	-0.415	-0.418	0.00896	0.00847	-0.446	-0.450
	(0.0364)	(0.0363)	(0.353)	(0.352)	(0.0363)	(0.0363)	(0.357)	(0.357)
FAS123 × Depr	-0.0568**		-0.637***		-0.0283		-0.578	
	(0.0244)		(0.236)		(0.0487)		(0.471)	
FAS123 × Firm Size × Depr	0.00773	0.00775	0.0578	0.0554	-0.00172	-0.00214	0.00655	0.00288
	(0.00652)	(0.00670)	(0.0632)	(0.0638)	(0.00638)	(0.00646)	(0.0620)	(0.0623)
Firm Size × Depr	-0.0225*	-0.0224*	0.262***	0.264***	0.00720	0.00745	0.201**	0.203**
	(0.0119)	(0.0120)	(0.0955)	(0.0956)	(0.0117)	(0.0117)	(0.0917)	(0.0920)
Investment FE	×		×		×		×	
Investment-Year FE		×		×		×		×
Firm-Year FE	×	×	×	×	×	×	×	×
Observations	13,348	13,348	13,348	13,348	13,414	13,414	13,414	13,414
No. Firms	662	662	662	662	666	666	666	666
Sample Period	2002 - 2007	2002 - 2007	2002 - 2007	2002 - 2007	2002 - 2007	2002 - 2007	2002 - 2007	2002 - 2007

Notes: This Table reports the results on the relationship between managerial incentives and investment decisions. Value of total assets and number of employees are logarithmized. *Option-Dummy* is a dummy that indicates if any options are awarded in 2004. *FAS123* takes value 0 for each year until 2005 and value 1 afterwards. *Depr* is the measure of depreciation, following an ordinal scale in columns 1, 2, 5 and 6, and expressed in absolute depreciation rates in columns 3, 4, 7 and 8. Standard errors (reported in parentheses) are clustered at the firm-level. ***, **, and * indicate statistical significance at the 1%-, 5%-, and 10%-level.

Table B.6: Beta and the Durability of Investments/Capital Stock Depreciation

	Investments				Depr Rate
	(1)	(2)	(3)	(4)	(5)
Model	OLS		IV		OLS
			1st Stage	*2nd Stage*	
$(1-\beta)\times$ Depr	0.428***	0.416***			
	(0.108)	(0.117)			
FAS123 $\times$ Option-Dummy $\times$ Depr			0.028***		
			0.004		
$\widehat{(1-\beta)\times}$ Depr				1.849***	
				(0.648)	
$(1-\beta)$					0.027***
					(0.009)
Investment FE	$\times$		$\times$	$\times$	
Investment-Year FE		$\times$			
Firm-Year FE	$\times$	$\times$	$\times$	$\times$	
Firm FE					$\times$
Year FE					$\times$
Observations	29,940	29,940	29,940	29,940	9,015
No. Firms	656	656	656	656	676
Sample Time	2000 - 2014	2000 - 2014	2000 - 2014	2000 - 2014	2000 - 2014
Kleibergen-Paap F-Statistic			60.55		

Notes: The Table reports the results on the relationship between the model-specific incentive measure β and the durability of investments/capital stock depreciation. The calculation of β follows Equation (2.12), details on the computation can be found in Appendix B3.1. *Depr* is the measure of depreciation, following an ordinal scale (1=lowest, 7=category with highest depreciation rate). *Option-Dummy* is a dummy that indicates if any options are awarded in 2004. *FAS123* takes value 0 for each year until 2005 and value 1 afterwards. In column 1 and 2, we investigate the relationship between the firm-specific β and the durability of investments. In column 4, we address endogeneity concerns related to β by instrumenting $(1-\beta)\times$ *Depr* with *FAS123* $\times$ *Option-Dummy* $\times$ *Depr*. First Stage results are given in column 3. Column 5 estimates the effect of β on the capital stock depreciation by taking a firm-specific capital-stock-weighted depreciation rate as dependent variable. Standard errors (reported in parentheses) are clustered at the firm-level. ***, **, and * indicate statistical significance at the 1%-, 5%- and 10%-level.

B2 Theoretical Appendix

B2.1 Derivation of Managers' Optimal Behavior

To derive a manager's decision problem, we express the manager's optimization problem in recursive form. Formally, manager t chooses an action $a_t = (\mathbf{K}_{t+1}, N_t) \in \mathbb{R}^3_+$ depending on the history of previous managers' decisions $\mathcal{H}_t = (a_s | s < t)$. Denote by s_τ a strategy of manager τ. Manager t's problem in general follows as

$$\begin{aligned} &\max_{a_t} \Gamma_t \\ s.t.\, &(2.4), (2.5), (2.6), (2.14), \\ &\text{given } \mathcal{H}_t \\ &\text{given beliefs regarding } s_\tau, \tau > t. \end{aligned} \tag{B.1}$$

Generally, this type of problem has an extremely large strategy space and a multitude of equilibria can occur, which can be enforced through, e.g., trigger strategies. This, potentially, makes non-monotonic or discontinuous policy functions sustainable. Although a thorough examination of the strategy space of such a game seems interesting, it is beyond the scope of this paper. In line with most macroeconomic models, we focus on symmetric, smooth Markov-perfect equilibria, where the state of the game is entirely described by a_{t-1}. More specifically, we assume that the variable factor labor is always set optimally within each period such that strategies only effectively map from $\mathbf{K}_t$ into $\mathbf{K}_{t+1}$ and N_t.

Since we are interested in a symmetric equilibrium, we denote the policy function for capital as $\mathcal{K}(\mathbf{K}, \xi)$, i.e., if manager t follows this strategy profile, they will set $\mathbf{K}_{t+1} = \mathcal{K}(\mathbf{K}_t, \xi)$ when faced with a predetermined capital stock K_t. Here, ξ is a simple vector collecting the parameters of the model: $\xi = (a, b, Z, \nu, \gamma, \delta_l, \delta_s, \varphi, \beta, \theta, w)$. Likewise, $\mathcal{N}(\mathbf{K}, \xi)$ denotes the policy function for N_t. Note that $\mathcal{K}(\cdot)$ is a vector-valued function with two outputs (one for each capital good), which in turn we denote by $\mathcal{K}_j(\mathbf{K}, \xi)$, $j = l, s$. In particular, we denote

$$\mathbf{K}_{t+1} = \mathcal{K}(\mathbf{K}_t, \xi) := \begin{bmatrix} \mathcal{K}_l(\mathbf{K}_t, \xi) \\ \mathcal{K}_s(\mathbf{K}_t, \xi) \end{bmatrix}.$$

Under this restriction, we can represent manager t's maximization problem in a recursive way. Here, to save on notation, we drop time indices and follow a common convention in the literature: E.g., we denote by K_j the value of $K_{j,t}$ at some arbitrary point in time and by K'_j the value of $K_{j,t+1}$ for $j = l, s$. One can then use a similar approach for all other variables, in particular the current capital mix as $\mathbf{K} = [K_l \ K_s]$ and the capital mix one period later as $\mathbf{K}'$. First, we can combine equations (2.6),(2.4) and (2.5) to obtain a function for the period-profits, $\Pi = \pi(\mathbf{K}, \mathbf{K}', N, \xi)$:

$$\pi(\mathbf{K}, \mathbf{K}', N, \xi) = Z^{1-a-b}\left(K_l^{\nu} K_s^{1-\nu}\right)^a N^b - \sum_{j\in\{l,s\}}\left[\frac{\gamma}{2}\left(\frac{K_j'}{K_j} - 1\right)^2 K_j + K_j' - (1-\delta_j)K_j\right] - wN \tag{B.2}$$

Next, the value of equity $E(\cdot)$ can be decomposed into current profits and a continuation value, denoted by the function $V(\mathbf{K}', \xi)$:

$$E(\mathbf{K}, \mathbf{K}', N, \xi) = \pi(\mathbf{K}, \mathbf{K}', N, \xi) + \theta V(\mathbf{K}', \xi),$$

where this continuation value is given by

$$\begin{aligned} V(\mathbf{K}, \xi) &= E(\mathbf{K}, \mathcal{K}(\mathbf{K}, \xi), \mathcal{N}(\mathbf{K}, \xi), \xi) \\ &= \pi(\mathbf{K}, \mathcal{K}(\mathbf{K}, \xi), \mathcal{N}(\mathbf{K}, \xi), \xi) + \theta V(\mathcal{K}(\mathbf{K}, \xi), \xi) \end{aligned}$$

As a result, the value of the manager's remuneration is also a function of their decision according to:

$$\Gamma(\mathbf{K}, \mathbf{K}', N, \xi) = \varphi\left(\pi(\mathbf{K}, \mathbf{K}', N, \xi) + \beta\theta V(\mathbf{K}', \xi)\right)$$

Using these functional definitions, we can express a particular manager's optimized payoff from (B.1) as

$$\Gamma^*(\mathbf{K}, \xi) := \max_{(\mathbf{K}', N)}\{\Gamma(\mathbf{K}, \mathbf{K}', N, \xi)\}. \tag{B.3}$$

And similarly, the policy functions for the capital mix and labor are given by

$$(\mathcal{K}(\mathbf{K}, \xi), \mathcal{N}(\mathbf{K}, \xi)) := \arg\max_{(\mathbf{K}', N)}\{\Gamma(\mathbf{K}, \mathbf{K}', N, \xi)\}$$

These policy function thus need to satisfy a set of optimality conditions. In particular, the policy function for labor can be derived analytically as

$$\mathcal{N}(\mathbf{K}, \xi) = \left(\frac{bZ^{1-a-b}\left(K_l^{\nu} K_s^{1-\nu}\right)^a}{w}\right)^{\frac{1}{1-b}}. \tag{B.4}$$

This directly follows from the first-order condition

$$\frac{\partial}{\partial N}\Gamma(\cdot) \stackrel{!}{=} 0 \quad \Leftrightarrow \quad \varphi\frac{\partial}{\partial N}\pi(\cdot) \stackrel{!}{=} 0 \Leftrightarrow \quad \frac{\partial}{\partial N}\pi(\cdot) \stackrel{!}{=} 0,$$

whereas it is generally impossible to solve for analytical policy functions for the capital goods. At most, the following self-referencing characterization is possible:

$$\begin{aligned}\mathcal{K}_j(\mathbf{K},\xi) = \Bigg\{ K'_j \Bigg| \quad & 0 = \frac{\partial}{\partial K'_j}\pi(\mathbf{K},\mathbf{K'},N,\xi) + \beta\theta\frac{\partial}{\partial K_j}\pi(\mathbf{K'},\mathcal{K}(\mathbf{K'},\xi),\mathcal{N}(\mathbf{K'},\xi),\xi) \\ & + \theta(1-\beta)\sum_{k=l,s}\frac{\partial}{\partial K_j}\mathcal{K}_k(\mathbf{K'},\xi)\frac{\partial}{\partial K_k}V(\mathcal{K}(\mathbf{K'}),\xi) \Bigg\}\end{aligned} \tag{B.5}$$

To derive this condition, first note that the first-order condition can be stated as

$$\begin{aligned} & \frac{\partial}{\partial K'_j}\Gamma(\cdot) \stackrel{!}{=} 0 \\ \Leftrightarrow \varphi & \left(\frac{\partial}{\partial K_j}\pi(\cdot) + \beta\theta\frac{\partial}{\partial K_j}V(\cdot)\right) \stackrel{!}{=} 0 \end{aligned} \tag{B.6}$$

The envelope condition defining $\frac{\partial}{\partial K_j}V(\cdot)$ is given by

$$\begin{aligned}\frac{\partial}{\partial K_j}V(\cdot) &= \frac{\partial}{\partial K_j}E(\mathbf{K},\mathcal{K}(\mathbf{K},\xi),\mathcal{N}(\mathbf{K},\xi),\xi) + \sum_{k=l,s}\frac{\partial}{\partial K_j}\mathcal{K}_k(\mathbf{K},\xi)\frac{\partial}{\partial K'_k}E(\mathbf{K},\mathcal{K}(\mathbf{K},\xi),\mathcal{N}(\mathbf{K},\xi),\xi) \\ &\quad + \frac{\partial}{\partial K_j}\mathcal{N}(\mathbf{K},\xi)\frac{\partial}{\partial N}E(\mathbf{K},\mathcal{K}(\mathbf{K},\xi),\mathcal{N}(\mathbf{K},\xi),\xi) \\ &= \frac{\partial}{\partial K_j}\pi(\mathbf{K},\mathcal{K}(\mathbf{K},\xi),\mathcal{N}(\mathbf{K},\xi),\xi) \\ &\quad + \sum_{k=l,s}\frac{\partial}{\partial K_j}\mathcal{K}_k(\mathbf{K},\xi)\left[\frac{\partial}{\partial K'_k}\pi(\mathbf{K},\mathcal{K}(\mathbf{K},\xi),\mathcal{N}(\mathbf{K},\xi),\xi) + \theta\frac{\partial}{\partial K'_k}V(\mathcal{K}(\mathbf{K},\xi)\right] \\ &\quad + \frac{\partial}{\partial K_j}\mathcal{N}(\mathbf{K},\xi)\frac{\partial}{\partial N}\pi(\mathbf{K},\mathcal{K}(\mathbf{K},\xi),\mathcal{N}(\mathbf{K},\xi),\xi).\end{aligned}$$

From optimal labor demand, it follows that $\frac{\partial}{\partial N}\pi(\cdot) = 0$ such that this simplifies to

$$\begin{aligned}\frac{\partial}{\partial K_j}V(\cdot) &= \frac{\partial}{\partial K_j}\pi(\mathbf{K},\mathcal{K}(\mathbf{K},\xi),\mathcal{N}(\mathbf{K},\xi),\xi) \\ &\quad + \sum_{k=l,s}\frac{\partial}{\partial K_j}\mathcal{K}_k(\mathbf{K},\xi)\left[\frac{\partial}{\partial K'_k}\pi(\mathbf{K},\mathcal{K}(\mathbf{K},\xi),\mathcal{N}(\mathbf{K},\xi),\xi) + \theta\frac{\partial}{\partial K'_k}V(\mathcal{K}(\mathbf{K},\xi)\right].\end{aligned} \tag{B.7}$$

Inserting equation (B.6) on the left-hand side and –iterated by one period– on the right-hand side of (B.7) gives equation (B.5).

Finally, by re-inserting time indices and suppressing functional dependencies, we can reformulate equations (B.4) and (B.5) to obtain equations (2.15) and (2.16) in the main text.

B2.2 Pseudo-General-Equilibrium Effects

To test the mechanism for robustness to general-equilibrium effects, we reuse the firm sample from our quantitative exercise (including the relevant parameters and β-transitions) and assume that the $\mathcal{N}_f = 1,000$ firms inhabit one single economy, divided into the $S = 13$ sectors from Table 2.10. Each sector is denoted by $s = 1, \dots, S$, each firm by $f = 1, \dots, \mathcal{N}_f$. For future reference, we define two mappings that link firms and their industries: Firm f's sector is given by $s_f = 1, \dots, S$. And the sector s is composed of a set of firms $F_s = \{f = 1, \dots, \mathcal{N}_f | s_f = s\}$.

Demand

As before, we abstract from aggregate dynamics and we are only interested in the change of steady-state variables.[1] Also, as in the previous section, we use the notation x to represent a variable x's value in the current period and x' (x'') for the value of x one period (two periods) ahead.

A competitive final goods firm produces a final consumption good $\mathcal{Q}$ from the sectoral inputs Q_s according to the Cobb-Douglas production function

$$\mathcal{Q} = \prod_{s=1}^{S} \mathcal{Q}_s^{\psi_s}.$$

Here, the ψ_s are calculated from Table 2.10 as the respective shares of value added that sector s contributes to total value added such that they satisfy $\psi_s \in (0,1)$ and $\sum_{s=1}^{S} \psi_s = 1$.

The corresponding aggregate price-level is thus given by

$$\mathcal{P} = \prod_{s=1}^{S} \left(\frac{\mathcal{P}_s}{\psi_s} \right)^{\psi_s}, \tag{B.8}$$

where $\mathcal{P}_s$ denote sectoral price levels. Following standard logic, each sector thus faces a

[1] Solving the model with aggregate dynamics would, of course, be feasible, but it would be rather complicated (e.g., Krusell & Smith, 1998) and it is not clear what this would add to the analysis at hand.

demand curve

$$\mathcal{Q}_s = \frac{\psi_s \mathcal{P} \mathcal{Q}}{\mathcal{P}_s}. \tag{B.9}$$

The sectoral goods are a CES-aggregate of the individual firms' outputs Q_f according to

$$\mathcal{Q}_s = \left(\sum_{f \in F_s} Q_f^{\frac{\varepsilon_s - 1}{\varepsilon_s}} \right)^{\frac{\varepsilon_s}{\varepsilon_s - 1}}. \tag{B.10}$$

Here, the ε_s directly follow from our calibration exercise above. We assume that firms engage in monopolistic competition. The corresponding sectoral price level based on firms' prices P_f is thus

$$\mathcal{P}_s = \left(\sum_{f \in F_s} P_f^{1-\varepsilon_s} \right)^{\frac{1}{1-\varepsilon_s}}. \tag{B.11}$$

Consequently, each firm f in sector s faces the following demand:

$$Q_f = P_f^{-\varepsilon_s} \mathcal{P}_s^{\varepsilon_s} \mathcal{Q}_s. \tag{B.12}$$

Note how this equation compares to (2.3): we can now deduce that in each sector the demand shifter is given by

$$B_s = \mathcal{P}_s^{\varepsilon_s} \mathcal{Q}_s.$$

This links firms on product markets while we also need to link firms' input usage K_{lf}, K_{sf} and N_f to factor markets.

Firm Behavior

The problem of the firm is still the same as in the partial-equilibrium setup. We only need to add the respective firm and industry subscripts to the various variables in equations (2.2)–(2.16).

For concreteness, we restate these here, dropping time indices and adding subscripts f

and s. At a sectoral level, we have the following parameters:

$$a_s = \alpha_s \frac{\varepsilon_s - 1}{\varepsilon_s} \tag{B.13}$$

$$b_s = (1-\alpha_s)\frac{\varepsilon_s - 1}{\varepsilon_s} \tag{B.14}$$

In addition, the following relations characterize each firm's behavior:

$$Q_f = \widetilde{Z}_f \left(K_{l,f}^{\nu_s} K_{s,f}^{1-\nu_s}\right)^{\alpha_s} N_f^{1-\alpha_s} \tag{B.15}$$

$$Q_f = B_s P_f^{-\varepsilon_s} \tag{B.16}$$

$$R_f = P_f Q_f \tag{B.17}$$

$$= Z_f^{1-a_s-b_s} \left(K_{l,f}^{\nu_s} K_{s,f}^{1-\nu_s}\right)^{a_s} N_f^{b_s} \tag{B.18}$$

$$C_f^K = \sum_{j \in l,s} \left[\gamma \left(\frac{K'_{j,f}}{K_{j,f}} - 1\right)^2 K_{j,f} + \left(K'_{j,f} - (1-\delta_{j,s})K_{j,f}\right)\right] \tag{B.19}$$

$$\Pi_f = R_f - C_f^K - w_s N_f \tag{B.20}$$

$$E_f = (1-\eta_{b,f})\Pi_f + \frac{1}{1+r}\mathbb{E}\left\{(1-\eta_{e,f})E'_f\right\} \tag{B.21}$$

$$\Gamma_f = \eta_{b,f}\Pi_f + \eta_{e,f}E_f \tag{B.22}$$

$$\varphi_f := \eta_{b,f} + \eta_{e,f}(1-\eta_{b,f}), \tag{B.23}$$

$$\beta_f := \frac{\eta_{e,f}(1-\eta_{b,f})}{\eta_{b,f} + \eta_{e,f}(1-\eta_{b,f})}, \tag{B.24}$$

$$\theta_f := \frac{1-\eta_{e,f}}{1+r} \tag{B.25}$$

$$N_f = \left(\frac{b_s Z_f^{1-a_s-b_s}\left(K_{l,f}^{\nu_s} K_{s,f}^{1-\nu_s}\right)^{a_s}}{w_s}\right)^{\frac{1}{1-b_s}} \tag{B.26}$$

$$0 = \frac{\partial \Pi_f}{\partial K'_{j,f}} + \beta_f \theta_f \frac{\partial \Pi'_f}{\partial K'_{j,f}} + \theta_f(1-\beta_f)\sum_{k=l,s} \frac{\partial K''_{k,f}}{\partial K'_{j,f}} \frac{\partial}{\partial K''_{k,f}} V_f(\mathbf{K}''_f, \xi'_s) \tag{B.27}$$

Note that now, the continuation value $V_f(\cdot)$ also depends on ξ_s, which is a vector containing the sector-wide and aggregate variables, i.e., $\xi_s = (B_s, w_s, r)$. $V_f(\cdot)$ is now given by

$$V_f(\mathbf{K}_f, \xi_s) := \Pi_f + \theta_f V_f(\mathbf{K}'_f, \xi'_s).$$

Factor Markets

Regarding the labor market, we deviate from the partial-equilibrium calibration before and assume a fixed homogeneous labor supply per household $\bar{N}$, which we treat as numéraire.

This means the nominal wage across industries is fixed at $w_s = w = 1$ and the real wage is given by

$$w_{real} = \frac{w}{\mathcal{P}} = \frac{1}{\mathcal{P}}.$$

Since we assume that capital is owned by the firm and there are capital adjustment costs, we need an assumption how this investment is produced. For simplicity, we assume that capital goods are produced using only labor as an input and that the adjustment of capital goods also only requires labor as an input.[2]

I.e., the overall labor demand of firm f is given by

$$\bar{N}_f = N_f + \sum_{j \in \{l,s\}} I_{j,f} + \gamma \left(\frac{K'_{j,f}}{K_{j,f}} - 1 \right)^2 K_{j,f}, \tag{B.28}$$

where $I_{j,f} = K'_{j,f} - (1 - \delta_{j,s})K_{j,f}$ is the firm's gross investment in capital goods of type j.

Equilibrium

The economy is inhabited by a continuum of ex-ante homogeneous households (of measure 1). In every period, each household is endowed with $\bar{N} = 1$ units of labor that is inelastically offered on a competitive labor market in order to generate income w. Households are assumed to hold equity only indirectly via a competitive mutual fund. In each period, a single household ('manager') is randomly chosen to manage any given firm f for which they receive the corresponding compensation Γ_f. We assume that managers neglect the effects that their individual decisions have on the mutual fund and – as before – we assume they do not anticipate to manage the firm in the future. We further assume time-separable, homothetic preferences with respect to consumption of a final good as well as complete markets. This means we do not need to track the distribution of wealth and income to infer aggregate demand dynamics. On a related note, we do not impose any restrictions on how households distribute the Γ_f. In particular, it could be that managers just amass more wealth or that they use an insurance mechanism to distribute managers' income across all households.

For aggregate consumption C in any steady state, we thus end up with a simple relationship: all labor income $w \cdot 1$, managers' remuneration Γ_f and the remaining dividends of firms

[2] One could, of course, also assume that investment goods are produced using the final good, which would allow for input-output relationships to become important. For the sake of simplicity and comparability to the partial-equilibrium setup, we abstract from that. A side benefit is that this way, since both q_l, q_s and w are fixed, the firm is only linked to the aggregate economy via the demand shifter B_s. This simplifies calculations a lot because the firm's operations scale one-for-one with the the demand shifter. Hence, when solving the model, each firm's problem has to be solved exactly once and then its chosen quantities only need to be rescaled in order to guarantee market clearing in the aggregate.

$\Pi_f - \Gamma_f$ (where Π_f is the operating profit of firm f) are used to fund final consumption. Hence, we have

$$C = \sum_{f=1}^{\mathcal{N}_f} [\Gamma_f + (\Pi_f - \Gamma_f)] + w = \sum_{f=1}^{\mathcal{N}_f} \Pi_f + w.$$

Since we treat labor as numéraire, this becomes

$$C = \sum_{f=1}^{\mathcal{N}_f} \Pi_f + 1. \tag{B.29}$$

To close the model, we impose market clearing on both, goods and labor markets, which implies

$$C = \mathcal{Q} \tag{B.30}$$

$$1 = \sum_{f=1}^{\mathcal{N}_f} \bar{N}_f. \tag{B.31}$$

Limitations: Before moving on, it is important to note a few caveats in our general-equilibrium analysis. We abstract here from firm entry or exit, endogenous technological change and input-output relationships, which could all certainly alter some aspects of the quantification. We also still treat the remuneration packages as exogenous. However, since we are interested in the effects of changes in remuneration packages per se, we thus consider this to be a reasonable assumption

Experiment

The experiment we conduct in this general-equilibrium setting is very much akin to the one reported for the partial-equilibrium case in the main text. The firms have the same parameterization as before. The only differences are that $w = 1$ for all firms and that the sectoral demand shifter is endogenous and adapts to ensure that the labor-market-clearing condition holds. Since we abstract from aggregate dynamics here (otherwise the solution algorithm would be a lot more involved), we focus on a steady-state comparison taking the observed changes due to FAS 123R as a permanent 'shock'.

B3 Parameterization and Solution Method

B3.1 Remuneration Package

As we have derived in Subsection 2.3.1, for the purpose of our analysis we treat β as a structural parameter, which is determined solely by the bonus share η_b and the equity share η_e (see Equation (2.12)). Both parameters can be directly inferred from the data relying on different sources, which have been widely used in the literature. For η_b, we directly obtain the amount of bonus from Execucomp. Furthermore, due to a change in the reporting requirements for executive compensation after December 2006, we add the amount of non-equity incentive compensation to the bonus, which can be found in the *Plan-Based Awards (PBA)* file. This reclassification of bonuses is stressed by Hayes *et al.* (2012) and we follow their approach. In a next step, we scale the amount of bonus with the sales of the firm (obtained from Compustat), i.e., $\eta_b = \frac{\text{Bonus+Non-eq-Targ}}{\text{Sales}}$. For the equity share η_e, we rely on data on the manager's firm-related wealth provided by Coles *et al.* (2006) and Core & Guay (2002), which we divide by the total market capitalization of the respective firm (obtained from Compustat), i.e., $\eta_e = \frac{\text{Firm-related Wealth}}{\text{Market Capitalization}}$. We winsorize each parameter $\eta_{b/e}$ at the top and bottom 1%. In a final step, we calculate β by applying Equation (2.12). In Table B.7, we provide summary statistics on the key parameters η_b, η_e and β for our sample.

Table B.7: Summary Statistics

Variable	Mean	Std. Dev.	Min	p25	p50	p75	Max	Obs	Sample
η_b	0.0004028	0.001502	0	0.00004668	0.0001468	0.0003854	0.1242	16,320	2005 & 2007
η_e	0.007922	0.02142	0.00001916	0.0007241	0.001946	0.005445	0.1898	16,320	2005 & 2007
β	0.9033	0.0840	0.7500	0.8393	0.9281	0.9758	1	16,320	2005 & 2007

Notes: The Table reports summary statistics on the bonus share η_b, the equity share η_e and β, which is calculated by applying Equation (2.12).

B3.2 Other Parameters

Discount Factor: Given the parameters derived above, it would be straightforward to obtain $\theta = \frac{1-\eta_e}{1+r}$. Since we draw individual η_e values for each firm, θ would vary across firms and thus the entire calibration would differ. To avoid this, for the calibration of parameters, we assume $\theta = \frac{1}{1+r}$, i.e., we here neglect the dilution factor. In the exercise reported in the main text, we, however, include η_e.

For r, we use the real interest rate for the United States from the year 2005, which was 2.981% according to World Bank (2020). While the definition of the proper discount factor is an important ongoing discussion, in our model it seems justifiable to take the (safe, apart from inflation risk) real interest rate as a benchmark since we abstract from both, growth and risk.[3]

Production Function: We take δ_s, δ_l, R, $\frac{K_l}{K_l+K_s}$, $\frac{K_l}{R}$, $\frac{wN}{R}$ and w directly from the sectoral data.

Then, for $\beta = 1$, the steady-state conditions given in the main text can be re-arranged so as to yield direct expressions for the remaining parameters. Combining the two FOCs of individual capital goods, we obtain

$$\nu = \frac{1-\theta(1-\delta_l)}{1-\theta\left[1-\delta_s-\frac{K_l}{K_l+K_s}\left(\delta_l-\delta_s\right)\right]}\frac{K_l}{K_l+K_s}.$$

Given ν, we can solve the first-order condition of the long-term capital good for a as

$$a = \frac{\frac{1}{\theta}-(1-\delta_l)}{\nu}\frac{K_l}{R}.$$

Likewise, b directly follows from optimal labor demand as

$$b = \frac{wN}{R}.$$

This allows us to recover ε and α from

$$\varepsilon = \frac{1}{1-a-b}, \quad \alpha = \frac{a}{a+b}.$$

Finally the scaling parameter B^{ind} can be fixed using the labor demand as well as the

[3]The choice of r merits some discussion: In the US, around the time of the reform, the real interest rate fluctuated between a high of 6.845% in 2000 and a low of 1.137% in 2011. This happened against the background of an overall downward trend since the 1980s, which was overlaid between 2005 and 2007 by contractionary monetary policy. Over the years 2000-2009, the (geometric) average real interest rate in the US was about 3.677%, but for the years 2010–2019 it has fallen to 1.996%; between 2003 and 2008 the figure was 3.309%. It is thus not entirely clear which value one should choose as a steady-state value. However, our results would not change much if we used a different value for r. For private businesses, the discount factor should take into account risk premiums (related to, inter alia, idiosyncratic uncertainty and the financing structure of the firm) and thus be smaller. On the other hand, due to technological progress and the growth of the overall economy, a firm should expect the demand shifter as well as its TFP to change over time, changing the size of the firm. I.e., if we reinterpret our model's steady state as a balanced growth path with growth rate g and with the variables of the model properly detrended, the firm's discount factor would effectively be $\theta = \frac{(1-\eta_e)(1+g)}{(1+r)}$, which effectively increases the discount factor. Thus, our measure of the discount factor will most likely be either too high or too low. In fact, changing θ (thus, also changing r) has a somewhat similar effect as changing β, per se.

production function, which then yields

$$B^{ind} = \left(\frac{w^{\frac{b}{1-b}} R}{b^{\frac{b}{1-b}} \left(K_l^{\nu} K_s^{1-\nu}\right)^{\frac{a}{1-b}}} \right)^{\frac{1-b}{1-a-b}}.$$

Note that our assumptions so far imply that firms within an industry have the same parameters, apart from TFP, θ, and the remuneration package.

B3.3 Numerical Solution Method

To illustrate the solution method, we continue with the notation introduced in the previous section. Since the labor decision in the problem above is simply determined by the first-order condition (B.4), we can write per-period operating profits as a function of $\mathbf{K}, \mathbf{K}'$ only by defining:

$$\pi^*(\mathbf{K}, \mathbf{K}', \xi) = \max_N \{\pi(\mathbf{K}, \mathbf{K}', N, \xi)\}. \tag{B.32}$$

Importantly, this function satisfies

$$\frac{\partial}{\partial K_j'} \pi^*(\mathbf{K}, \mathbf{K}', \xi) = \frac{\partial}{\partial K_j'} \pi(\mathbf{K}, \mathbf{K}', N, \xi), \quad j = l, s.$$

The optimization problem of the manager can be re-stated in recursive form as

$$\Gamma(\mathbf{K}, \xi) = \max_{\mathbf{K}'} \{\pi^*(\mathbf{K}, \mathbf{K}', \xi) + \beta\theta V(\mathbf{K}', \xi) \tag{B.33}$$

$$\text{s.t. } V(\mathbf{K}', \xi) = \pi^*(\mathbf{K}', \mathcal{K}(\mathbf{K}', \xi), \xi) + \theta V(\mathcal{K}(\mathbf{K}', \xi), \xi)\}. \tag{B.34}$$

Here, the future policy function $\mathcal{K}(\cdot)$ is defined as

$$\mathcal{K}(\mathbf{K}, \xi) = \arg\max_{\mathbf{K}'} \{\pi^*(\mathbf{K}, \mathbf{K}', \xi) + \beta\theta V(\mathbf{K}', \xi)\}. \tag{B.35}$$

Note that we assume that this policy function is time-invariant, which results from our focus on symmetric strategies.

Next, to keep the notation concise, we define the gradient of a function $f(\mathcal{K}, \xi)$ in terms of elements of $\mathcal{K}$ to be given by

$$\nabla_{\mathbf{K}} f(\mathbf{K}, \xi) = \left[\frac{\partial f(\mathbf{K}, \xi)}{\partial K_l} \ \frac{\partial f(\mathbf{K}, \xi)}{\partial K_s} \right]'.$$

We use similar notation for functions with multiple inputs, and the index of ∇ gives the input the gradient applies to. Then, the first-order conditions (B.6) can be stated as

$$\nabla_{\mathbf{K}'}\pi^*(\mathbf{K},\mathbf{K}',\xi) = -\beta\theta\nabla_{\mathbf{K}'}V(\mathbf{K}',\xi). \tag{B.36}$$

From (B.32), we can derive

$$\begin{aligned}\nabla_{\mathbf{K}'}\pi^*(\mathbf{K},\mathbf{K}',\xi) &= -\nabla_{\mathbf{K}'}C^K(\mathbf{K},\mathbf{K}') \\ &= -\begin{bmatrix} \gamma\left(\frac{K_l'}{K_l}-1\right)+1 \\ \gamma\left(\frac{K_s'}{K_s}-1\right)+1 \end{bmatrix}.\end{aligned}$$

That is, in terms of any capital good, we obtain a first-order condition

$$\gamma\left(\frac{K_j'}{K_j}-1\right)+1 = \beta\theta\frac{\partial V}{\partial K_j'}(\mathbf{K}',\xi).$$

Note that this can be readily solved for K_j:

$$K_j = \frac{K_j'}{1+\frac{\frac{\partial V}{\partial K_j'}(\mathbf{K}',\xi)-1}{\gamma}}. \tag{B.37}$$

Equation (B.37) is the central ingredient in the endogenous grid method we apply. This method is best described by Algorithm 1 below.

Essentially, we start with a set of G gridpoints $\tilde{\mathcal{K}}' = (\tilde{\mathbf{K}}_h')_{h=1,\ldots,G}$, which represent different outcomes of $\mathbf{K}'$, and an initial (differentiable) guess $\hat{V}_0(\cdot)$ for $V(\cdot)$. By differentiating $V(\cdot)$, we get the gradient at each point in $\tilde{\mathcal{K}}'$. Then applying the backward induction step in (B.37), we can solve for the optimal solution of the previous manager. Next, we update our guess for the continuation value function $V(\cdot)$ according to the profit function and our current guess. One then iterates on this until convergence is achieved.

We implement this algorithm as MATLAB code (tested against MATLAB R2018b and R2020a), which can be found in the replication package.

The figures in this paper are based on a sample of 1,000 firms with idiosyncratic parameter draws 30-by-30 in the (K_l', K_s')-space. The coordinates of the gridpoints correspond to Chebyshev nodes in a range around the steady state with $\beta = 1$, (which can be computed analytically). To be precise, the grid ranges from 0.3 to 1.2 of the analytical steady state of that parameterization. As an interpolation scheme $\rho(\cdot)$, we opt for Chebyshev polynomials up to degree 10 in either dimension.[4] Since the endogenous grid method inherently involves interpolation with a changing set of interpolation bases, the domain of the chosen functions was expanded as needed to keep all points within the domain.

Finally, to specify an initial guess for the value function, we follow the following procedure: Initially, we consider with a model where β was set to 1, for this case a steady state can be derived analytically. As an initial guess of the value function, we simply assumed that the model would converge uniformly to that steady state within a certain period. Using the resulting net present value of profits gives a reasonably accurate initial guess for the case of $\beta = 1$. However, for lower $\beta < 1$, this does not necessarily lead to convergence. For this reason, we first solve the model for the $\beta = 1$ case. Then, we use the final value function computed and use this as an initial guess to solve the model with a slightly lower value of β. Repeating this process while slowly decreasing β yields satisfactory convergence. The entire process is then repeated for all 1,000 (differently parameterized) firms in the sample.

[4] We have chosen Chebyshev polynomials because they have preferable interpolation properties compared to other polynomials functions. Also Splines were considered, but computing the gradient of a spline is a computationally expensive exercise and experiments with cubic splines showed inferior convergence properties. We also experimented with Chebyshev polynomials with a total degree of 30. However, most coefficients with a higher degree are virtually identical to zero. In fact, higher order polynomials present a problem for the algorithm since for these higher order polynomials, the gradient quickly becomes very large in absolute terms, even if the corresponding coefficient is small; this generates additional sources of numeric error, which leads to far worse convergence properties. Given that this method ultimately generates an inverse of the policy function, we eventually have to back the real policy functions out. This final step is done using cubic splines.

Algorithm 1: Version of EGM used in the model solution

Set i_{max} as well as convergence thresholds $\bar{\epsilon}^v, \bar{\epsilon}^{invp} > 0$ for the continuation value and inverse policy, respectively. Pick a parameter vector ξ, a set of gridpoints $\tilde{\mathcal{K}}' = (\tilde{\mathbf{k}}'_g)_{g=1,\ldots,G}$, an initial guess for each of these points, i.e., $\hat{V}_{0,g}$ for $g = 1, \ldots, G$ and an interpolation scheme $\rho(x, X, Y)$ to be used. Find interpolated values $v_0(\mathbf{K}) = \rho(\mathbf{K}, (\mathbf{k}'_g)_{g=1,\ldots,G}, (\hat{V}_{0,g})_{g=1,\ldots,G})$.

Set *continue*=true. set i=1.

while *continue* **do**

  for *g=1,…,G* **do**

    Set $\hat{\mathbf{k}}_{j,i,g} = \frac{\gamma k'_{j,g}}{\gamma + \beta\theta \frac{\partial}{\partial \mathbf{K}'_j} v_{i-1}(\mathbf{k}'_g) - 1}$ for $j = l, s$.

    Set $\tilde{v}_g = \Pi(\mathbf{k}_{i,g}, \mathbf{k}_g, \xi) + \theta \hat{V}_{i-1,g}$.

  Find interpolant $v_i(\mathbf{K}) = \rho(\mathbf{K}, (\mathbf{k}_{i,g})_{g=1,\ldots,G}, (\tilde{v}_g)_{g=1,\ldots,G})$.

  for *g=1,…,G* **do**

    Set $\hat{V}_{i,g} = v_i(\mathbf{K}_g)$.

    Set $\epsilon^v_{i,g} = \left| \frac{\hat{V}_{i,g}}{\hat{V}_{i-1,g}} - 1 \right|$.

    Set $\epsilon^{invp}_{j,i,g} = \left| \frac{k_{j,i,g}}{k_{j,i-1,g}} - 1 \right|$.

  if $\max_{g\in(1,\ldots,G)}\{\epsilon^v_{i,g}\} < \bar{\epsilon}^v$ *and* $\max_{j\in(l,s),g\in(1,\ldots,G)}\{\epsilon^{invp}_{i,g}\} < \bar{\epsilon}^{invp}$ **then**

    Set *continue*=false.

  else

    Set i=i+1;

Obtain policy function as $\mathcal{K}(\mathbf{K}, \xi) \approx \tilde{\mathcal{K}}(\mathbf{K}, \xi) := \rho(\mathbf{K}, (k_{i,g})_{g\in\{1,\ldots,G\}}, (\mathbf{k}_g)_{g\in\{1,\ldots,G\}})$

Modification in the Pseudo-General-Equilibrium Exercise: If we want to use the previous algorithm in a general-equilibrium environment, we need to take into account that each firm now also takes aggregate state variables into account. These include in our framework the two aggregate capital stocks or more precisely, their distribution across all active firms. In the related literature with heterogeneous agents or firms (e.g., Krusell & Smith 1998, Khan & Thomas 2013), the distribution of capital across agents or firms becomes an important state variable, which is an infinitely-dimensional object with infinitely many firms or agents and thus needs to be approximated. In our simulated sample, we only use a finite number of firms (1,000) but accounting for this we would still have a 2,000-dimensional state variable for capital goods alone (1,000 firms × 2 capital goods). Since we are not interested in the dynamics per se, we can simplify matters a lot by only focusing on aggregate steady states.

When the economy at large is in a steady state, we can use our algorithm from before to solve for each single firm. Note that the only aggregate variable relevant for the firm's problem is the industry-level demand shifter B^{ind}. It is straightforward to show that this shifter proportionally scales the scale of the firm. To make this more precise, the policy function now depends on the demand shifter as well as on parameters ξ:

$$\mathbf{K}' = \mathcal{K}\left(\mathbf{K}, B^{ind}, \xi\right). \tag{B.38}$$

Notably, it can be shown that the policy functions scale with the demand shifter as follows:

$$\mathcal{K}(\mathbf{K}, B^{ind}, \xi) = B^{ind} \cdot \mathcal{K}\left(\frac{1}{B^{ind}}\mathbf{K}, 1, \xi\right). \tag{B.39}$$

From this, we can directly infer that the steady-state capital stock of the firm directly scales with B^{ind}.

The firm affects the general equilibrium through its factor choices, its output Q_f and its price level P_f. Notably, while a firm's steady-state output Q_f is directly proportional to B^{ind}, its price in steady state is fully determined by technology and the relative composition of its factor choices. We have just argued that the entire policy function is scaled up or down by B^{ind} and as a a result, B^{ind} does not affect the relative composition of its factor inputs in steady state. I.e., the steady-state price level of the firm is independent of macroeconomic outcomes. This allows us to solve for the pseudo-general-equilibrium solution in a simple way. For each firm, we can simply solve the firm's problem for an arbitrary B^{ind} and obtain the firm-level steady state. From now on, we only refer to steady-state values of all variables. We can do this exercise for our entire sample of firms, $f = 1, \ldots, 1,000$. As a result, we have a steady-state price level P_f for each firm. The resulting steady-state price level can be used to infer sectoral and aggregate price levels $\mathcal{P}_s$ and $\mathcal{P}$ using (B.11) and (B.8). From (B.9), it is possible to show that the demand shifter in any sector is then proportional to aggregate demand $\mathcal{Q}$ times a function purely dependent on the pricing choices of all firms. As a result, also the quantity produced by any firm and ultimately factor choices are simply proportional to aggregate demand.

Thus, to derive general equilibrium, we simply obtain all the relevant price levels.

Using (B.9) and (B.12), we can obtain

$$Q_f = \psi_s P_f^{-\varepsilon_s} \mathcal{P}_s^{\varepsilon_s - 1} \mathcal{P} \mathcal{Q}, \tag{B.40}$$

i.e., the output of any firm and hence its factor demand is proportional to aggregate demand.

Here, since prices are fully determined by parameters and firms' incentive structure, we get

$$Q_f = p_f \mathcal{Q}, \tag{B.41}$$

where $p_f = \psi_s P_f^{-\varepsilon_s} \mathcal{P}_s^{\varepsilon_s - 1} \mathcal{P}$ does not depend on $\mathcal{Q}$. From the firm's individual problem, we can derive a steady-state ratio of total labor used to output produced as $n_f = \frac{\bar{N}_f}{Q_f}$, which again is independent of $\mathcal{Q}$. Total labor demand is then given by

$$\bar{N} = \sum_{f=1} \bar{N}_f = \sum_{f=1}^{\mathcal{N}_f} (n_f p_f) \mathcal{Q}.$$

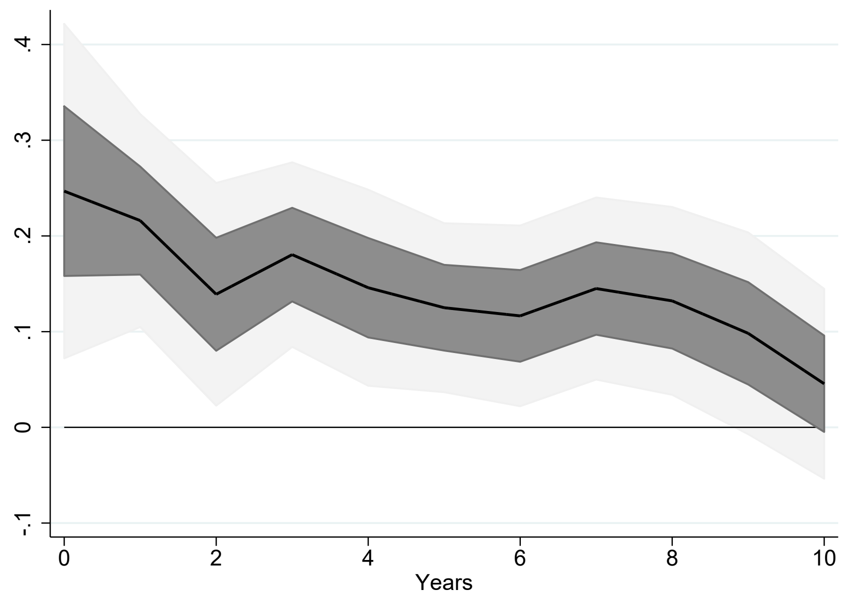
$\mathcal{Q}$ directly follows by imposing market clearing on the labor market. We then scale each firm accordingly, taking into account p_f and n_f.

Appendix C

Appendix to Chapter 3

C1 Estimating Local Projections

Figure C.1: Dynamic Effect of Uncertainty on Investments with Different Durabilities



Notes: Figure C.1 shows the dynamic response of uncertainty on investments with different durabilities when the specification from Table 3.3, column 3 is estimated in the spirit of Jordà (2005). This is, I estimate for each horizon h $invest_{i,c,t+h} = \beta_1^h \times \delta_c \times \Delta\sigma_{i,t-1} + \lambda_{i,t} + \lambda_{c,t} + \lambda_{i,c} + \varepsilon_{i,c,t+h}$ with $h = 0, ..., 10$. Dark and light gray-shaded areas are corresponding 1-standard error and 2-standard error confidence bands, where the construction is based on Newey & West (1987) standard errors.

C2 Derivation of the Revenue Function

A representative firm combines two types of capital, K_s and K_l, and labor L to produce in each period t output Q with the following Cobb-Douglas production function

$$Q_t(Z_t, K_{s,t}, K_{l,t}, L_t) = Z_t(K_{s,t}^{\nu} K_{l,t}^{1-\nu})^a L_t^{1-a}, \tag{B.1}$$

where Z measures firm productivity. The firm faces isoelastic demand for its product with elasticity ϵ

$$Q_t = BP_t^{-\epsilon}, \tag{B.2}$$

where B is a demand shifter. Combining the production function with the demand curve yields the following revenue production function:

$$R_t = P_t Q_t = (Z_t B^{\frac{1}{\epsilon-1}})^c (K_{s,t}^{\nu} K_{l,t}^{1-\nu})^{ac} L_t^{(1-a)c}, \tag{B.3}$$

with $c = 1 - \frac{1}{\epsilon}$. One-period profit Π_t can be expressed by

$$\Pi_t = R_t - wL_t - C_t^K = (Z_t B^{\frac{1}{\epsilon-1}})^c (K_{s,t}^{\nu} K_{l,t}^{1-\nu})^{ac} L_t^{(1-a)c} - wL_t - C_t^K. \tag{B.4}$$

Solving the FOC for labor, I obtain optimal labor input L^*:

$$\frac{\partial \Pi_t}{\partial L_t} = (1-a)c(Z_t B^{\frac{1}{\epsilon-1}})^c (K_{s,t}^{\nu} K_{l,t}^{1-\nu})^{ac} L_t^{(1-a)c-1} - w \overset{!}{=} 0 \tag{B.5}$$

$$L^* = \left(\frac{w}{(1-a)c}\right)^{\frac{1}{(1-a)c-1}} (Z_t B^{\frac{1}{\epsilon-1}})^{\frac{c}{1-(1-a)c}} (K_{s,t}^{\nu} K_{l,t}^{1-\nu})^{\frac{ac}{1-(1-a)c}} \tag{B.6}$$

Plugging L^* into the revenue function yields:

$$R_t = \left(\frac{w}{(1-a)c}\right)^{\frac{(1-a)c}{(1-a)c-1}} (Z_t B^{\frac{1}{\epsilon-1}})^c (Z_t B^{\frac{1}{\epsilon-1}})^{\frac{(1-a)c^2}{1-(1-a)c}} (K_{s,t}^{\nu} K_{l,t}^{1-\nu})^{ac} (K_{s,t}^{\nu} K_{l,t}^{1-\nu})^{\frac{a(1-a)c^2}{1-(1-a)c}} \tag{B.7}$$

$$= \left(\frac{w}{(1-a)c}\right)^{\frac{(1-a)c}{(1-a)c-1}} (Z_t B^{\frac{1}{\epsilon-1}})^{\frac{c}{1-(1-a)c}} (K_{s,t}^{\nu} K_{l,t}^{1-\nu})^{\frac{ac}{1-(1-a)c}} \tag{B.8}$$

$$= \left(\left(\frac{w}{(1-a)c}\right)^{-(1-a)} Z_t B^{\frac{1}{\epsilon-1}}\right)^{\frac{c}{1-(1-a)c}} (K_{s,t}^{\nu} K_{l,t}^{1-\nu})^{\frac{ac}{1-(1-a)c}} \tag{B.9}$$

I normalize $\left(\frac{w}{(1-a)c}\right)^{-(1-a)} B^{\frac{1}{\epsilon-1}}$ to one, assume a demand elasticity ϵ of 3 and set $a = 0.5$. Finally, this gives the revenue function stated in the main part (Equation 3.7), i.e.,

$$R_t = Z_t K_{s,t}^{\alpha_s} K_{l,t}^{\alpha_l} \tag{B.10}$$

with $\alpha_s = \frac{\nu ac}{1-(1-a)c}$ and $\alpha_l = \frac{(1-\nu)ac}{1-(1-a)c}$.
Furthermore, it holds that $\alpha_s + \alpha_l < 1$ since $\frac{ac}{1-(1-a)c} < 1$.[1]

[1]This is the case if $c < 1$, which is similar to assuming a positive demand elasticity ($\epsilon > 0$).

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