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For Yara and Anic

... may your worlds be full of love, friends, adventures, and moments of joy!

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Bern, July 2023 *Marc Brunner*

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Introduction

Since the Great Financial Crisis in 2008 and the subsequent European sovereign debt crisis, the question of economic stability has arisen in many Western countries. One threat to this stability are zombie firms. These firms cannot pay their debts and have only a small chance of survival but are kept alive by banks and other financiers (see Caballero et al. (2008)). These lenders provide the companies with additional capital at favorable conditions to avoid realizing any losses from bankruptcy (see Acharya et al. (2019)). From a economic policy perspective, zombie firms increase the entry barriers for more productive firms, therefore changing the competitive environment, and slow down economic growth. In the wake of the Corona pandemic and the associated handsome support for firms, zombies are also known to the general public (e.g. "Why covid-19 will make killing zombie firms off harder" (2020)). Therefore, I dedicate the first two chapters of my thesis to said firms.

Chapter 1: Zombie Firms in the US

The first chapter is single-authored. I investigate the zombie phenomena in the US across multiple dimensions, before focusing on how those firms raise capital in the US. In the first half, I start by looking at simple firm characteristics and replicate findings by Hoshi (2006). My results show that, on average, 10% of all firm-year observations across the sample period from 1975 to 2018 are classified as zombies. Interestingly, the number of zombie firms is higher at the beginning of the sample resulting in a negative time trend. I then report detailed industry and region trend of the zombie share. While some industries generally suffer from a higher zombie share, a similar observation does not emerge regarding the regional distribution. In the second half, I focus on the capital structure of zombies and use three additional data sets to describe how zombie firms raise capital. As expected, zombie firms are more levered, however, they raise more equity than debt capital, suggesting that they are in the process of deleveraging. Using DealScan Loan data, I find that zombie firms raise smaller loans that are more often secured but they do not need to pay higher interest rates. This is also true for the second investigated source of debt capital: bonds. Last, I also cover zombie firms' Seasoned Equity Offerings (SEO) characteristics using SDC Platinum SEO data.

Again, my results do not suggest that zombie firms need to pay a premium, but their SEOs are significantly smaller.
By investigating the zombie phenomena in the US, my paper contributes to the increasing literature which describes the prevalence of zombie firms on the country level (e.g. McGowan et al. (2017b, 2017a), Banerjee and Hofmann (2018), and Acharya et al. (2019)). Additionally, it extends the knowledge about the behavior of said firms by describing how and under which terms they raise capital. Therefore, the paper is also linked to the vast literature about firms' capital structure and financial policies (e.g. Lemmon and Roberts (2008), Leary and Roberts (2014), and Grennan (2019)).

Chapter 2: How does Competition affect Zombie Firms?
The second chapter is joint work with Angela De Martiis and Philip Valta. We investigate the effect of competition on zombie firms' existence and financial policy choices in the US. In order to mitigate the endogeneity issue arising from the simultaneous effect between zombies and competition, we use the Instrumental Variable framework suggested by Autor et al. (2013). The main idea of this approach is to use the import penetration from China into eight developed countries as an instrument for the import penetration from China into the US. By establishing causality, we show that the asset-weighted zombie share is negatively affected after an increase in competition. We call this the *cleansing* effect, and we find, that it is stronger for industries with an already high level of competition, i.e. with low concentration and low margins. In order to identify the channel which drives down the asset-weighted zombie share, we extend our analysis to the default and recovery likelihood of zombie firms. Both variables are not affected by changes in competition. Therefore, we run firm-level regressions and find that zombies scaled down their assets more than healthy firms as a reaction to an increase in competition. This then drives the negative effect on the zombie share. Additionally, zombies also hold less cash, issue less equity, and obtain smaller loans as a reaction to more competition compared to healthy firms.
The main contribution of the paper is on the literature about zombie firms (e.g. Caballero et al. (2008), Banerjee and Hofmann (2018, 2022), Acharya et al. (2019), Acharya et al. (2020), Acharya et al. (2021), and Acharya et al. (2022)). We are the first to document the effect of competition on zombie firms, providing new insights into what drives the zombie share. We also contribute to the literature about (product market) competition and risk of default (e.g. Valta (2012a) and Xu (2012)) and firms' financing policy choices (e.g. Leary and Roberts (2014) and Begenau and Salomao (2019)).

Finally, the last chapter of my thesis is situated on the overlap between macroeconomics and household finance. While not linked to the main focus of my thesis, it aligns with my interests in macroeconomics, gave me the opportunity to pursue an interdisciplinary project with two fellow doctoral students, and allowed me to work on a topic of great importance for today's society: wealth inequality.

Chapter 3: Heterogeneity in Returns to Wealth - Evidence from Swiss Administrative Data
The third and last chapter is written by Jonas Meier, Armando Näf, and myself. While many different models exist to explain the heterogeneity in returns to wealth (e.g. Benhabib et al. (2011) and Gabaix et al. (2016)), empirical evidence is scarce. Two notable exceptions are Fagereng et al. (2020) and Bach et al. (2020), which both show that returns are *type* and *scale* dependent on average. We build on those results and extend them by modeling the whole distribution of returns to wealth using distributional regressions techniques introduced by Chernozhukov et al. (2013). This allows us to unveil the heterogenous effect of wealth on the return to wealth unconditional on all other observables, i.e. the pure effect of wealth on the heterogeneity of returns to wealth. Our results are based on an extensive data set with administrative tax records of individual households, which covers all taxpayers in the canton of Bern, Switzerland, from 2002 to 2017. They show that the two drivers of returns are not additively separable and that *scale* dependence becomes more influential for high-type investors. We also find that the effect of *scale* dependence increases with the asset class's volatility.
By applying a more sophisticated estimation approach in order to explain the heterogeneity in returns to wealth, our paper contributes to the intensively discussed topic of wealth inequality (e.g. Piketty and Saez (2003), Piketty (2014), or Saez and Zucman (2016)). In a narrower perspective, we add additional insights on the stream of literature which tries to explain this inequality with heterogeneous returns to wealth, such as Benhabib et al. (2011) and Gabaix et al. (2016) as well as to the literature which empirically investigates the wealth inequality in Switzerland (e.g. Martínez (2020a, 2020b)).

Altogether, my thesis provides new empirical insights in financial economics. The first paper shows that zombie firms are also present in the US and that they access the financial market similarly to healthy firms, but raise less capital and more equity in order to reduce their leverage, therefore adding descriptive empirical evidence to the literature about zombie firms. The contribution of the second paper is to provide an identification method based on which one can conclude that an increase in competition has a negative effect on the zombie share. Finally, the third paper adds to the empirical literature about the heterogeneity in returns to wealth by estimating the unconditional effect of wealth on the whole distribution of returns to wealth using distributional regressions.

Without data, you're just another person with an opinion.

– W. Edwards Deming

Chapter 1

Zombie Firms in the US

Abstract

Firms that are supposed to go bankrupt, but are kept alive by creditors, raise concerns about the economy's health. This paper provides an in-depth empirical description of the so-called zombie firms phenomena in the US. Zombies account on average for 10% of all firms in the US between 1975 and 2018. Their occurrence is not limited to certain industries, even though some sectors are more affected. Geographically their occurrence is unstable over time. US zombies are highly levered but raise more equity than debt. There are no differences compared to their healthy peers in loans, bonds, or SEO pricing; the only differences emerge in the amount and the securitization.

1.1 Introduction

For some years now, a new specter has emerged which may cause a potential threat to an economy: zombie firms.[1] The term describes a company that can not cover its debt obligations and has only a small chance of recovery but is kept alive by banks using partial debt allowance and interest concessions (see Hoshi (2006) and Caballero et al. (2008)). Under normal circumstances, such unprofitable firms would go bankrupt and leave the market, clearing the way for new, more profitable and productive firms. However, certain market frictions may help those firms to survive, therefore lowering the productivity of the whole economy.

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1. See, for example, Wigglesworth (2022) and "Why covid-19 will make killing zombie firms off harder" (2020).

First described in connection with Japan's Lost Decade in the 90s by Hoshi (2006) and Caballero et al. (2008), zombie firms have become an increasingly debated policy topic in many economies around the world (e.g., Banerjee and Hofmann (2018, 2022), Acharya et al. (2019), Acharya et al. (2020), and De Martiis et al. (2022)). Apart from cross-country analysis, many investigations on the zombification take place on the country level, e.g., Japan (Hoshi (2006) and Caballero et al. (2008)), Italy (Schivardi et al. (2017)), Portugal (Bonfim et al. (2021) and Carreira et al. (2022)), Canada (Grider and Ortega (2020)), and others. Table 1.18 in appendix 1.A provides a detailed overview. What stands out from this table is that, as of now, the largest economy in the world, the US, is only part of two studies by Banerjee and Hofmann (2018) and De Martiis et al. (2022) but was so far not the scope of a detailed analysis regarding zombie firms.[2]
Most existing papers focus on the economy-wide consequences of zombie firms without investigating the firms themselves. Two exceptions are Banerjee and Hofmann (2022) and De Martiis et al. (2022). While the first paper focuses on the life cycles of zombie firms, the second uses firm-level variables to predict the likelihood of a firm turning into a zombie. However, both do not specifically look at zombie firms from a capital structure and financing policy perspective.

Hence, the goal of this paper is twofold. First, I provide an in-depth study of zombie firms in the US by investigating the existence of said firms across industries and geographical locations and comparing their characteristics to healthy peers. To see if there are any major differences between zombies in the US to zombies in other countries, I replicate results by Hoshi (2006), Caballero et al. (2008), and Banerjee and Hofmann (2022) using my US data sample. Second, I use US firm-level data and provide detailed descriptive statistics and conditional correlations on the capital structure, and show how zombie firms finance themselves with loans, bonds, and equity.

To describe the current state of zombie firms in the US, I take data from Compustat from 1975 until 2018 and follow Acharya et al. (2020) to identify the zombie firms. All results in chapter 1.4 are based on this core data set. In chapter 1.5, I merge this core sample with loan data from DealScan, bond issue data from Mergent FISD, and SEO data from SDC Platinum. Since the linkage table or general data coverage is limited before 1994, I only use the period from 1994 to 2018 when merging. I track the zombie status of 17,249 unique firms in the core sample as well as over 29,853 loans, 8,311 bond issues, and 3,433 Seasoned Equity Offerings (SEOs) in the other samples.

2. In the process of writing this paper, the FED released a note on this issue. See Favara et al. (2021). Additionally, Brunner et al. (2022) investigate the effect of competition on zombie firms in the US.

According to my results, the average asset-weighted zombie share in the US over the sample period is 9.6%. However, the share shows a negative time trend ranging from 20% at the beginning to 6% at the end. Comparing the simple average of some key firm characteristics shows that the zombie identification method provides plausible results. While there are some differences, most of the variables which, according to Hoshi (2006), help predict the zombie status and exits, i.e. default or recovery, do the same for zombies in the US. Similarly, the results concerning the zombie life cycle are broadly in line with Banerjee and Hofmann (2022). The industry cross-section shows that while the negative time trend is present across all industries, there are also some differences in volatility and size of the asset-weighted zombie share. The industry most affected by zombies is the Agriculture, Forestry, and Fishing industry, followed by Construction and Wholesale trade. Investigating the geographical cross-sections does not reveal a clear pattern. Across the whole sample period, zombie firms seem to be more often located on the northeast coast and around the great lakes; however, this pattern vanishes when clustering zombie firms based on their location without considering state borders. My results with respect to the economic impact of zombie firms differ significantly from the ones provided in Caballero et al. (2008) for Japan. Zombie firms have a higher investment share and stronger employment growth than non-zombies while suffering from lower productivity. Importantly, my results do not support negative spillovers to healthy firms in the US.
Comparing the capital structure between the two groups of firms shows that zombie firms are more levered. They also raise less outside capital, however, if they do, they raise equity and reduce the outstanding debt. While this might seem puzzling initially, it is in line with the high recovery rate of zombies and the results by Banerjee and Hofmann (2022). Next, I focus solely on loans and find that the fraction of loans given to zombies follows the zombie share, however, it increases more during crisis periods. This highlights the dependency of zombie firms on external capital providers. Nevertheless, they receive smaller loans, often junior and provided by only one manager. The last result aligns with the finding by Hoshi (2006). Interestingly, once I control for some key characteristics of zombie firms, there is no significant difference in loan pricing. Comparing bond characteristics reveals similar results; the zombie dummy negatively affects the likelihood of a bond being secured and the offering yield. Finally, I investigate the differences in terms of SEO characteristics of the two firm groups. While the time trend of SEOs conducted by zombie firms seems to show that those are larger than the average SEO, conditional correlations do not support this result. Overall, there seem to be no major differences regarding SEO characteristics.

My paper contributes to the literature about zombie companies in two ways. First, I provide an in-depth analysis of zombie firms in the US. While Favara et al. (2021) also provides an analysis on this issue in the US, I provided additional results in terms of industry and geographical cross-section as well as by replicating some mature findings from other papers (e.g., Hoshi (2006), Caballero et al. (2008), and Banerjee and Hofmann (2022)). Second, I extend the general knowledge about zombie firms with respect to corporate financing decisions. While papers such as the one by Acharya et al. (2019) already investigate loans to zombie firms, they are only interested in identifying the channel which produces zombie firms and not in the capital structure and financial policies of said firms. I, however, provide an extensive overview of the capital structure and financial policies regarding loans, bonds, and equity issuances. By doing so, the paper is also linked to the vast literature about firms' capital structure and financial policies (e.g., Lemmon and Roberts (2008), Leary and Roberts (2014), and Grennan (2019)).

The rest of this paper is structured as follows: In the next chapter, I present the current state of the literature with respect to zombie firms. I focus on the reasons for the existence of zombie firms, their characteristics, and the economic implications of their existence. Since this paper's primary focus is to investigate zombie firms empirically, I start the third chapter by presenting my initial data set before discussing how I identify zombie firms. In chapter four, I provide summary statistics on the zombie phenomena in the US before focusing on the financing channels and capital structure in chapter five. Finally, I conclude in the last chapter.

1.2 Literature

1.2.1 Why do zombie firms exist?

Kane (2000) uses the term *zombie banks* to characterize banks that suffer from losses and low profitability during a banking crisis but are kept alive by government support. He states that those zombie banks are vulnerable to bank runs and may increase their risk-taking due to adverse incentives. While he focuses on bad banks and does not consider zombie firms, he sees bad loans as the key driver for banks to become zombies. In contrast, Hoshi (2006) sees bad or zombie banks as a necessary criterion for the emergence of zombie firms. His paper points out that during the land price collapse in Japan, the loan system was flooded with non-performing loans backed by properties. Whereas a healthy bank, i.e. a bank with sufficient equity, can write off those loans, a bad bank may violate capital requirements if it realizes the losses. Hence, the bad bank has the incentive to restructure the loan and grant more favorable terms to the borrower to be able to classify the loan as collectible (see also Kashyap and Hoshi (2005) and Hosono and Sakuragawa (2003)). The author therefore identifies zombie firms based on the negative difference between the effective interest payments and a hypothetical lower bound on those payments, which should only be offered to the highest quality borrowers. Empirical evidence is provided by Rosengren and Peek (2005), who use a bank-borrower panel data set from 1993 to 1999 to show that weaker firms are more likely to receive a new loan during the 1990s. They can also identify the main drivers: low capital ratios, long-lasting banking relationships, and government pressure. The last driver, government pressure, is also acknowledged by Caballero et al. (2008). In the following years, the topic of zombie firms disappears from the scientific agenda.

However, the issue becomes topical in the course of the GFC. Bruche and Llobet (2014) discuss the role of banks' limited liability in zombie lending and propose a theoretical scheme for regulators to mitigate this problem. In their scheme, banks have the incentive to share private information about the loan quality with the regulators to be able to sell a fraction of those loans to the government. Empirical evidence about the emergence of zombie firms during and after the GFC, especially in Southern Europe, is provided by McGowan et al. (2017b), Storz et al. (2017), Banerjee and Hofmann (2018), and Acharya et al. (2019). Using cross-country data on insolvency regimes of 14 OECD countries[3], McGowan et al. (2017a) show that the number of zombie firms and the capital sunk in those firms is lower in countries with more restructuring-friendly regimes. Conversely, they identify insolvency regimes as an important structural factor for the emergence and existence of zombie firms. Using firm-level data and the difference-in-difference method, they estimate that barriers to restructuring and personal costs to failed entrepreneurs increase the capital-weighted zombie share in an industry with a high firm turnover by 1.4 percentage points compared to industries with lower firm turnover. Similar results are found by Andrews et al. (2017), however, they also find evidence for a link between zombie firms and weak banks. Using bank-firm relationship data from Europe, Acharya et al. (2019) use the Outright Monetary Transactions (OMT) program launched in 2012 by the European Central Bank (ECB) as an exogenous shock to bank capitalization to show that post-OMT, weakly capitalized banks used the windfall gains to grant loans to zombie firms. For the Japanese banking crisis, a similar finding is made by Giannetti and Simonov (2013). Based on a sample of listed firms, their results suggest that banks, which are well capitalized after the capital injection, reduced their zombie lending. In contrast, undercapitalized banks use the liquidity to expand zombie lending to defer writing off their loans to those firms. Additionally, the study finds evidence that strong firm-bank relationships lower firm valuation, as measured by cumulative abnormal returns after the announcement of a recapitalization, if the relationship is with a bank that remains

3. Austria, Belgium, Finland, France, Germany, Greece, Italy, Japan, Korea, Portugal, Slovenia, Spain, Sweden, and the United Kingdom.

undercapitalized. Banerjee and Hofmann (2018) identify another trigger for the recent rise of zombie firms: low-interest rates regimes since the GFC. Due to the low-interest rate environment, zombie firms can refinance themself at low rates and are, therefore, less exposed to financial pressure. At the same time, banks face lower opportunity costs of bad loans since new loans would not generate significantly higher returns. Therefore, zombie firms tend to stay alive longer (or recover later) during low-interest rate periods. The authors test their hypotheses by conducting difference-in-difference regressions between industries with a high dependence on external finance and those without. Their findings, which are based on a sample of publicly traded firms in 14 developed countries[4] from 1987 until 2016, suggest that the capital weighted zombie share in industries, who heavily depend on external finance, increases by 3.5 percentage points if the interest rates decline by one percentage point compared to industries with less reliance on external financing. At the same time, they do not find statistically significant effects for the interaction between dependence on external finance and bank health.

To summarise, the current state of the literature identifies four reasons for the existence of zombies: *i*) low-capitalized banks have the incentive to support their (weak) borrowers to postpone or, in the best case, mitigate the realization of losses on their loans, *ii*) government support, either directly or indirectly by forcing banks to grant loan forbearance, *iii*) policy weaknesses in the insolvency regimes, and *iv*) low-interest rates during crises periods.

1.2.2 How do zombie firms differ from other firms?

Apart from the effect of economic and institutional settings which affect the existence of zombie firms, the difference in the characteristics of said is also of large interest. However, inevitably the endogeneity problem arises because it is unclear whether a company becomes a zombie because of its characteristics or the characteristics change due to the zombie status of the firm. Nevertheless, Hoshi (2006) finds that high leverage, low profitability, and high dependence on the main bank increase the likelihood of becoming a zombie firm. The same holds for firms operating in non-manufacturing industries and outside of metropolitan areas. Regarding exit probabilities between zombies and non-zombies, he finds only a small difference, largely explained by the lower profitability of zombie firms. McGowan et al. (2017b) note that the likelihood of being identified as a zombie increases with firm age and size within their sample. Using data on Japanese firms from 1995 to 2004 Fukuda and Nakamura (2011) find that most zombie firms recover without outside help during economic upturns. To recover,

4. Australia, Belgium, Canada, Denmark, France, Germany, Italy, Japan, the Netherlands, Spain, Sweden, Switzerland, the United Kingdom, and the United States.

zombie firms in their sample reduce the number of employees, sell a large portion of their fixed assets, and reduce their leverage. However, the strongest effect on the probability of recovering has a debt cut. If debt holders decide to forgive a part of the firm's debt, the recovering probability increases by 1.9%. Whereas the previously named studies only consider public firms in Japan, Imai (2016) focuses on Japanese small and medium-sized enterprises (SMEs) between 1998 to 2008. According to the author, including SMEs in the research agenda is important since they rely heavily on bank loans and make up a large part of the economy[5]. The typical zombie SME is small and mainly operates in the real estate or the transportation industry. Estimating borrowing functions, Imai (2016) finds that the lagged property value to borrowing ratio has no statistical explanatory power on the borrowing decisions of zombie firms, however, it does so for all firms in the sample. This observation can be seen as evidence of evergreening since banks may be incentivized to keep the firms alive due to the lower collateral value.

1.2.3 Economic consequences of zombie firms

Based on a Schumpeterian type model, Caballero et al. (2008) show how zombie firms suppress the entry and investment of non-zombie firms. The model implies that the existence of zombie firms hinders the creative destruction process, which should occur after a negative shock to firms' productivity or operating costs. Zombie firms do not exit the economy[6] because their creditors support them. Retaining their position makes it harder for new entrants to enter the economy. Since the lower creation rate does not offset the reduced destruction process, economies with a large zombie share suffer from congestion. This has implications for the job creation rate and the productivity gap between incumbents and entrants. The former is suppressed by zombie firms since, after a negative shock, the labor market requires fewer people, however, the destruction process is lower, and hence the job creation rate needs to adjust. The widening of the productivity gap[7] occurs because the less productive zombie firms remain in the economy. At the same time, only entrants with high productivity, higher than without zombies, enter the economy. To empirically test the implications of their model, Caballero et al. (2008) use Japanese firm-level data from 1980 until 2002. The results underline the predictions made by their model. For example, the median non-zombie firm in the service industry invested 11.8% less and hired 3.6 percentage points fewer people than it would have without the existence of zombie firms in the period from 1993 to 2002. The industry that suffered

5. Less than 1% of all firms in Japan are not SME, and they employ almost two-thirds of the labor force in 2012 according to Imai (2016).

6. Caballero et al. (2008) call this feature *sclerosis*.

7. The authors refer to this effect as *scrambling*.

most from the zombie firms was the wholesale industry, where the median firm invested 17% less and the employment growth rate was 4 percentage points lower.

Using their sample of over 700'000 private and public firms from 9 OECD countries[8] from 2003 to 2013, McGowan et al. (2017b) find that a 3.5% increase in the capital-weighted zombie share depresses the industry labor productivity by 1.2%. Looking at the effect of the zombie share on non-zombie firms, they find similar results as Caballero et al. (2008) concerning investment, employment growth, and multi-factor productivity. However, they also focus on firms younger than five years and note that those firms are even more affected by zombies than older incumbents. Finally, the authors also find evidence that the main channel over which zombies affect non-zombies is a reduction in the efficiency of capital allocation. Using a larger sample of 14 OECD countries or over 32'000 public firms Banerjee and Hofmann (2018) also find empirical evidence for a crowding-out effect on employment and investment. According to their results, the capital expenditure of a non-zombie firm reacts one-to-one with the zombie share in the same industry. In contrast, employment growth seems less affected and only decreases by 0.26 percentage points if the zombie share increases by one percentage point. According to the authors, zombie firms also slow down productivity growth by almost 0.3% for each additional percentage point increase of the zombie share in a given country.

Combining the DealScan loan data set from 2009 to 2014 with firm and bank-level data from Europe, Acharya et al. (2019) can also quantify the effect of zombie congestion. According to the authors, southern European countries are most affected and suffer lower employment growth and investment losses corresponding to 1.5 years of investment expenditures.[9] Tracking the borrowers over time, they note that zombie firms, which by definition suffer from low performance, can not use the additional debt capital to increase their performance. On top of that, zombie firms have a twice as high default rate as non-zombies by 2016, whereas the default rates are similar after the OMT announcement suggesting that zombies are kept alive by the use of the windfall gains. So far, all papers find evidence for negative spillovers from zombies to non-zombies. However, those findings are challenged by Schivardi et al. (2017) using a detailed sample of bank-firm relationships in Italy from 2004 to 2013. Whereas they also identify weakly capitalized banks as the main driver of the zombie share and credit misallocation, their results suggest that zombie lending has a negligible impact on the growth rate of healthy firms and the multi-factor productivity gap. They attribute their controversial findings to a different identification strategy and criticize the previously

8. Belgium, Finland, France, Italy, Korea, Slovenia, Spain, Sweden, and the United Kingdom.

9. Using a slightly different sample and especially focusing on SME, Storz et al. (2017) come to the same conclusion.

used strategy based on regressing the variable of interest on the (non-)zombie share and including industry-year fixed effects to absorb adverse industry shocks. As Schivardi et al. (2017) state, the inclusion of these fixed effects makes it impossible to estimate the absolute effect of zombies on healthy firms. It implicitly assumes that both groups of firms are affected similarly by the shock. To mitigate this issue, they use the average bank capitalization in a given province sector as a proxy for the zombie share and find only a negligible absolute effect of this variable on economic indicators. The authors explain this finding with the fact that weak banks, which engage in zombie lending, have two effects on the economy. On the one hand, they hurt the economy by reducing credit availability for healthy firms and subsidizing unhealthy competitors. On the other hand, they reduced default rates and, therefore, negative demand shocks due to high levels of employment as well as costly disruption to input-output relationships. Finally, a recent paper by Acharya et al. (2020) looks at the effect of zombie lending on disinflation in 11 European countries. In cross-sectional tests across industries and countries, the authors find that more zombies increase sales and costs while decreasing average markups, product prices, productivity, and investment. Those findings again support the theoretical prediction by Caballero et al. (2008).

1.3 Data and zombie identification

1.3.1 Data

Throughout this paper, my primary data source is the Compustat database.[10] To get a meaningful sample, I only use the years between 1975 and 2020 and drop all financial and utility firms (SIC 4900 - 4999, SIC 6000 - 6999) as well as all government-related entities (SIC 9000 - 9999). Since I am only interested in US firms, I exclude firms incorporated outside the US[11] and firms which are incorporated in Puerto Rico or the Virgin Islands. Finally, the sample does not consider firms with missing total assets or sales, or negative total assets or sales. This cleaning procedure yields my core sample of 177,253 observations from 17,249 different firms. Variables are constructed according to Table 1.19 in appendix 1.B. Using the US Bureau of Economic Analysis GDP Deflator[12] all nominal values are deflated to 2012 US-Dollars. To mitigate the influence of outliers, I winsorize all constructed continuous variables at the 1%- and 99%-level, except book- and market leverage, which are set to zero or one if the value is below or above. Based on this cleaned sample, I can identify the zombie firms (see section 1.3.2)

10. This database is widely used in empirical corporate finance research, see for example Valta (2012b) or Leary and Roberts (2014).

11. Firms which have *loc* or the country code from the HERE API unequal to USA.

12. Available on FRED: https://fred.stlouisfed.org/series/GDPDEF

and merge the zombie dummies with other data sets as described at the beginning of each respective section. Table 1.1 gives an overview.

Table 1.1: Data sources, time range, and sample sizes

Source	Data range	Observations	Sample structure	Merge variable
Compustat	1975-2018	141,597	panel (firm-year)	-
DealScan	1994-2016	29,853	cross-section (loan)	gvkey
Mergent FISD	1994-2018	8,311	cross-section (bond)	6-digit CUSIP
SDC Platinum	1994-2018	3,433	cross-section (deal)	6-digit CUSIP

Displayed are the number of observations reported after the data cleaning process and for all the sources, except Compustat, after the merge with the core sample. Details on the merge and the cleaning process of the different data sets are provided at the beginning of each respective section.

Table 1.20 in appendix 1.C shows the summary statistics of the core sample. The statistics are similar to others reported in previous empirical studies, such as Lemmon and Roberts (2008), Leary and Roberts (2014), and Grennan (2019), and I will therefore refrain from them in detail.

1.3.2 Identifying zombie firms

Within the literature, two main approaches co-exist to identify zombie firms. First, an identification based on the difference between the effective and hypothetical interest expenses in relation to total debt. The hypothetical interest expenditure is calculated based on a very advantageous interest rate. If the difference is negative, a firm pays significantly less interest than expected and may likely benefit from favorable terms (e.g. Hoshi (2006), Caballero et al. (2008), and Acharya et al. (2019)). Second, identification is also possible via the interest coverage ratio (IRC). If this ratio is less than one over a longer period, the respective firm may have difficulties covering its interest expenses with its operating income (e.g. McGowan et al. (2017b) and Banerjee and Hofmann (2018)). This paper identifies zombies similarly to the identification method employed by Acharya et al. (2020), which is based on picking up firms that pay less interest than expected. I will outline the exact procedure in the following.

The main advantage of the chosen identification method, first used in Acharya et al. (2019) and subsequently improved in Acharya et al. (2020), is that it solely relies on widely available accounting data. More specifically, one first calculates the average interest rate r_{ijt} of a firm i in industry j in year t by dividing the total interest expenses R_{ijt} by the outstanding amount of debt B_{ijt}, i.e.

$$r_{ijt} = \frac{R_{ijt}}{B_{ijt}} = \frac{xint_{ijt}}{dlc_{ijt} + dltt_{ijt}}.$$

Next, a benchmark interest rate is needed. Acharya et al. (2020) suggest using the median rate of all high credit-worthy firms in a given industry j and year t with similar reliance on short- and long-term debt as the benchmark rate $r*^{g}_{jt}$ where $g \in \{s, l\}$ with s if the firm has more short- then long-term debt and l for the opposite case. A firm is considered highly creditworthy if its rating is AAA.[13] The difference between the actual interest expenses and the benchmark, x_{ijt}, is called the interest gap. According to Acharya et al. (2020), a firm is classified as a zombie in any given year, i.e., has the value of one for the zombie dummy Z_{ijt}, if i) the interest gap is negative, ii) its book leverage is above the industry-year median, and iii) its ICR is below the industry-year median. Whenever the information on one of those three criteria is missing, Z_{ijt} is set to missing.

In many cases, it is more useful to aggregate the number of zombie firms on the industry level. A simple approach divides the number of zombie firms by the overall number of firms in a given industry-year. Formally,

$$ZS_{jt} = \frac{\sum_N Z_{ijt}}{\sum_N 1}$$

where N corresponds to the number of firms in the respective industry and year. However, existent research by, e.g., Caballero et al. (2008) and Banerjee and Hofmann (2018, 2022), shows that zombies differ considerably from healthy firms in terms of their size. Therefore, the additionally calculated asset-weighted zombie share is more insightful. Formally, it is defined as:

$$aZS_{jt} = \frac{\sum_N Z_{ijt} \times at_{ijt}}{\sum_N at_{ijt}}$$

where at_{ijt} is the total book value of assets according to Compustat. Using the presented zombie identification method, I will describe the occurrence and behavior of zombie firms in the US in the next chapter.

13. Since not all firms in the sample have an S&P credit rating, I only calculate synthetic ratings based on the 3-year median ICR and market capitalization following the data provided by Damodaran (2019).

1.4 Zombies in the US

The US is the largest economy in the world, with a GDP of USD 20.89 trillion, according to the Bureau of Economic Analysis (2019). Studying the phenomena of zombie firms in the US is therefore of great importance to the world economy, as many shocks to its economy translate throughout the world. At the same time, the US institutional system is one of the most efficient in terms of handling bankruptcies[14] and the culture is characterized by an entrepreneurial spirit, which also includes social acceptance of corporate bankruptcy. Overall, the issue of zombies within the US economy is expected to be not as large as in other countries, such as Italy, Spain, or Japan.

1.4.1 Zombie share

Figure 1.1 plots the absolute and the asset-weighted zombie share over time. Both decrease significantly over time while fluctuating considerably. Some spikes are related to recessions, e.g. the 1980 recession, the dot-com bubble, and the GFC, but not all of them. In the first half of the sample period, zombies tend to be larger than the average firm, however, in the second half, the opposite is the case. Overall, the absolute share decreases from 17% in 1975 to 6% in 2018. In comparison, the asset-weighted share is 20% in the beginning and identical to the absolute share at the end of the sample. Comparing the US zombie share to other countries shows that the US suffered from an especially large zombification until the beginning of the 2000s. Afterward, the share declined below the reported averages for many other countries, e.g. Banerjee and Hofmann (2018), Acharya et al. (2019), or De Martiis et al. (2022). Comparing the results in Figure 1.1 to the existing literature on US zombie firms indicates that my results are similar to the one of De Martiis et al. (2022) but lower than the ones reported by Favara et al. (2021).

1.4.2 Difference between zombies and non-zombies

Zombies are described as smaller, less profitable, more in debt, obtaining lower cash flows, and less liquid than their healthy competitors (e.g. Hoshi (2006), Banerjee and Hofmann (2022), Favara et al. (2021)). The results in Table 1.2 align with those findings. Within the sample period, zombie firms are significantly smaller in terms of total assets, employees, sales, and market capitalization. As expected, zombie firms are more levered and suffer from lower profitability. Interestingly, their growth perspectives are not statistically different from healthy firms. Regarding financial policies, they spend more on SG&A but less on R&D

14. According to the report by DoingBusiness (2019), the US is ranked 2 in the bankruptcy category.

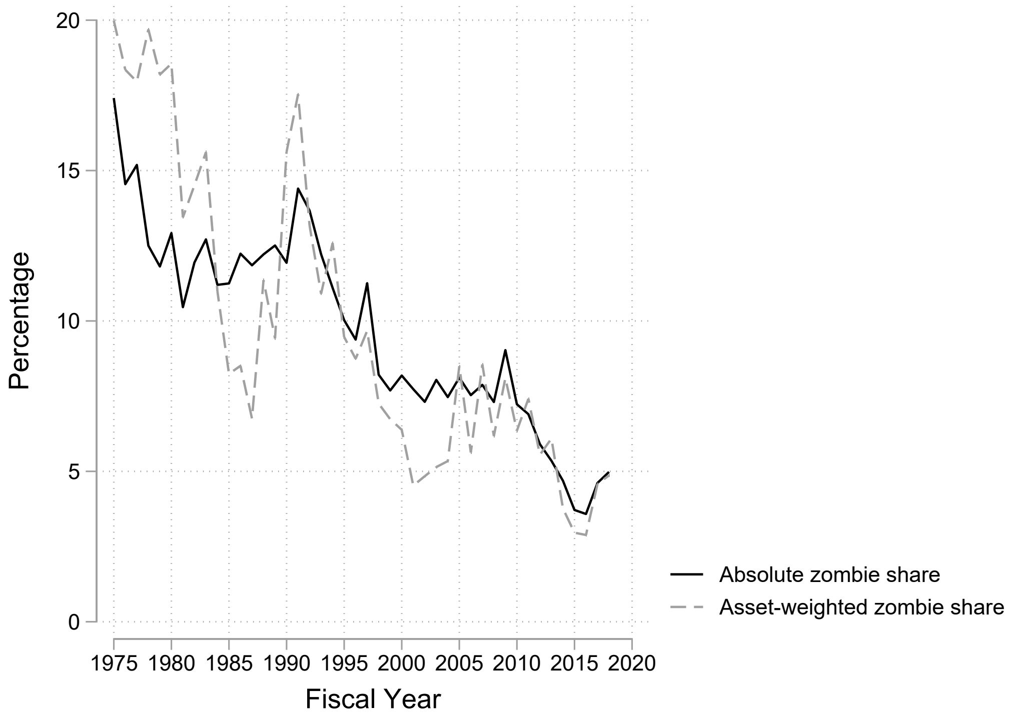

Figure 1.1: Evolution of the zombie share between 1975 and 2018

This figure displays the time trend of the absolute and asset-weighted zombie share over time. The sample consists of all firm-year observations between 1975 and 2018 for non-financial, non-utility, and non-governmental US firms from the Compustat universe. Zombies are identified as described in section 1.3.2.

and tangible assets on average and are less likely to pay dividends to shareholders. One would expect that zombie firms, because of their low profitability, should suffer from a higher default rate than healthy firms.[15] The Altman (1968) z-score for zombie firms is significantly lower than for non-zombies, supporting this hypothesis. Even though highly negative observations drive the mean, the median is smaller and lies exactly at the threshold for being classified as likely heading towards bankruptcy. Of the 17,249 firms, 1,008 defaulted within the sample period, corresponding to a default rate of 5.8%. The default rate of firms classified as a zombie at least once during the sample period but not necessarily when defaulting is 7.6% or almost two percentage points higher than the average default rate. The percentage of zombie firms that defaulted when classified as a zombie relative to all defaulted firms, i.e. the zombie observation default rate, is 19.0%.

15. This would not be true if one specifically looks at distressed firms. In this setting, zombie firms should have a lower default rate since they receive favorable interest rates and/or are protected by the government.

Even though this seems significant, it implies that almost 80% of the firms do not default but recover from their zombie status or are part of an acquisition or merger. Overall, zombie firms' default rates align with the expectation that zombies should have a higher default rate than the average firm.

Next, I tabulate synthetic debt ratings for each firm-year based on the ICR and data from Damodaran (2019).[16] Again, one would expect that zombie firms have a lower rating, especially since having an ICR ratio below the industry median is an identification criterion by Acharya et al. (2020). Table 1.3 shows the absolute and relative frequency of each rating for zombies on the left and for healthy firms on the right. Roughly 49% of the healthy firm-years are classified as investment grade, i.e. BBB or higher, compared to only 11% of all zombie-years. Ideally, zombie firms would never have a rating within the investment grade category, and there are indeed some identification methods that require a low rating as a classification criterion, e.g. McGowan et al. (2017a), Banerjee and Hofmann (2018), or Acharya et al. (2019). Since, in some industries, the median ICR might be high, firms can be classified as zombies with the chosen identification method even if they have a reasonable ICR. Nevertheless, the statistics on credit rating show that the identification method picks up the right firms.

16. I thank Aswath Damodaran for making this data publicly available

Table 1.2: Summary statistics zombies vs. non-zombies

	N	Mean	Median	SD	Difference	t
			Zombies			
Ln(assets)	16,939	4.55	4.49	2.42	0.29***	(14.63)
Employees	16,145	5.25	0.54	15.55	0.73***	(5.67)
Size	16,553	4.47	4.53	2.58	0.38***	(18.09)
Market Capitalization	16,939	721.82	44.33	2808.45	717.68***	(29.07)
Tobin's q	16,939	3.02	1.23	7.36	0.08	(1.32)
Negative profit	16,939	0.54	1.00	0.50	-0.17***	(-43.29)
Profitability	16,889	-0.16	0.05	0.81	0.08***	(12.13)
Tangibility	16,911	0.31	0.25	0.23	-0.03***	(-13.94)
Book Leverage	16,939	0.46	0.41	0.22	-0.21***	(-116.92)
Market Leverage	16,939	0.46	0.45	0.27	-0.20***	(-91.55)
Dividend Dummy	16,939	0.25	0.00	0.43	0.08***	(22.15)
Sales, General, and Administrative Expenses	16,553	0.51	0.23	1.28	-0.03**	(-2.63)
Research and Development Expenses	16,553	0.22	0.00	1.12	0.02*	(2.50)
CAPEX to total assets	16,192	0.09	0.04	0.15	-0.01***	(-11.52)
Altmans (1968) Z-Score	15,977	-1.94	1.81	20.40	3.40***	(19.92)
Default Dummy	16,939	0.07	0.00	0.25	-0.03***	(-13.68)
			Non-zombies			
Ln(assets)	156,928	4.84	4.83	2.39		
Employees	151,811	5.99	0.69	16.34		
Size	152,212	4.85	5.02	2.57		
Market Capitalization	156,928	1439.51	107.30	4751.68		
Tobin's q	156,928	3.10	1.46	6.91		
Negative profit	156,927	0.37	0.00	0.48		
Profitability	156,603	-0.08	0.11	0.78		
Tangibility	156,729	0.28	0.22	0.23		
Book Leverage	156,928	0.25	0.19	0.25		
Market Leverage	156,928	0.26	0.17	0.28		
Dividend Dummy	156,928	0.33	0.00	0.47		
Sales, General, and Administrative Expenses	152,212	0.49	0.22	1.24		
Research and Development Expenses	152,212	0.24	0.00	1.20		
CAPEX to total assets	151,975	0.08	0.04	0.12		
Altmans (1968) Z-Score	152,038	1.45	3.20	21.37		
Default Dummy	156,928	0.04	0.00	0.20		

The table shows some key variables' summary statistics for zombies and non-zombies. The sample consists of all firm-year observations between 1975 and 2018 for non-financial, non-utility, and non-governmental US firms from the Compustat universe. Variables are constructed as described in Table 1.19 in the appendix and then, apart from book and market leverage, winsorized at the 1%- and 99%-level. If book or market leverage is below 0 (above 1), the respective observation is replaced with the 0 (1) value. Zombies are identified as described in section 1.3.2, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 1.3: Synthetic debt ratings

	Zombies		Healthy firms	
Rating	Frequency	Percent	Frequency	Percent
AAA	115	0.68	43,243	27.61
AA	78	0.46	6,672	4.26
A+	134	0.79	6,543	4.18
A	365	2.15	6,811	4.35
A-	795	4.69	9,218	5.89
BBB	406	2.39	3,722	2.38
BB+	548	3.23	4,246	2.71
BB	715	4.22	4,643	2.96
B+	1,023	6.03	5,320	3.40
B	1,243	7.33	5,527	3.53
B-	1,299	7.66	5,970	3.81
CCC	741	4.37	3,157	2.02
CC	1,082	6.38	5,326	3.40
C	608	3.59	2,903	1.85
D	7,805	46.03	43,318	27.66

The table shows the absolute and relative frequency of each synthetic rating for the two groups of firms. The rating is derived from ICR. The sample consists of all firm-year observations between 1975 and 2018 for non-financial, non-utility, and non-governmental US firms from the Compustat universe. Variables are constructed as described in Table 1.19 in the appendix and then, apart from book and market leverage, winsorized at the 1%- and 99%-level. If book or market leverage is below 0 (above 1), the respective observation is replaced with the 0 (1) value. Zombies are identified as described in section 1.3.2.

1.4.3 How to become a zombie and how to recover

As Table 1.2 indicates, zombie firms differ greatly from their healthy competitors. An interesting question is whether those differences help predict the probability of a healthy firm turning into a zombie. To analyze the effect of the characteristics on the probability of turning into a zombie firm, I partly follow Hoshi (2006) and run OLS regressions of the zombie dummy on one-year lagged accounting figures, industry dummies, and year-fixed effects. The results are displayed in Table 1.4 and are, for the accounting figures, in line with the finding by Hoshi (2006). A negative income in the previous year increases the likelihood of becoming a zombie by more than 4 percentage points. In comparison, increasing the leverage by 10 percentage points yields a 2.1 percentage points higher chance of turning into a zombie. In line with Banerjee and Hofmann (2022) and De Martiis et al. (2022), size affects the zombie dummy significantly negatively. The result for the rate of profit is puzzling, as more profitable firms are more likely to become zombies. However, as already mentioned by Hoshi (2006), this positive correlation might arise because firms are classified based on having low interest expenses, which help to improve the rate of profit. According to the results, the industry[17], in which a firm operates, also plays an important role in affecting the likelihood of becoming a zombie. Compared to the reference industry of Agriculture, Forestry, and Fishing, firms in all other industries, apart from Retail Trade, have a lower likelihood of turning into a zombie, with the lowest probability in the Mining and Transportation industries. Comparing the point estimates of the firm characteristics with the ones from the industry dummies highlights the importance of industry dynamics. This finding aligns with Caballero et al. (2008), who show that a higher zombie share negatively affects non-zombies within the same industry, making them more prone to becoming zombies.

Existing research shows that once a firm is classified as a zombie, it will most likely recover. However, it is unclear whether such a firm is more likely to be classified as a zombie later on, which would raise the question if it indeed recovered or if the identification method is not sufficiently sticky. In Table 1.5 panel A, I count the number of times a firm is classified as a zombie and for how long. For example, if a firm is classified as a zombie for three consecutive years, recovers, and then is once again classified as a zombie for two years, it would count as one observation for three and one observation for two years. Over 70% of the classified firms remain in the zombie status for just one year, while 18% remain zombies for two years, and less than 1% are classified for five or more consecutive years. The average duration of a firm being a zombie is 2.06 years. Concerning the number of times a firm is classified as a zombie with gaps in between, panel B reveals that 62% of the firms classified as a zombie are so for only one time with an average duration of 2.1 years, while the rest are classified more than once. However, only 1% percent of the firms are classified more than five times. Interestingly, the average duration first increases with the number of zombie incidences per firm before a decrease for firms classified between four and six years. After that, the average duration increases again, suggesting that those firms are classified repeatedly and for more than the average duration. Considering that the classification by Acharya et al. (2020) is based on contemporary items only, it is unsurprising that a large fraction of zombies is only classified for one year. At the same time, many zombies are not repeatedly classified, suggesting that the classification method does not necessarily declassify zombies too early.

17. Industry definitions are based on SIC and according to https://mckimmoncenter.ncsu.edu/2digitsiccodes-2/.

Table 1.4: Probability of being a zombie according to Hoshi (2006), Table 3

	Zombie Dummy
Rate of profit_{t-1}	0.016***
	(0.003)
Negative profit_{t-1}	0.046***
	(0.007)
Book leverage_{t-1}	0.210***
	(0.027)
$\text{Ln(employment)}_{t-1}$	-0.004**
	(0.001)
Mining	-0.096***
	(0.011)
Construction	-0.040***
	(0.008)
Manufacturing	-0.031**
	(0.010)
Transportation	-0.079***
	(0.015)
Wholesale Trade	-0.046***
	(0.008)
Retail Trade	-0.028
	(0.019)
Services	-0.043*
	(0.017)
Year FE	Yes
N	147,613
Zombie Obs.	13,994
adj. R^2	0.046

Displayed are coefficient estimations of regressing the zombie dummy, as described in section 1.3.2, on explanatory variables and year and industry fixed effects as in Hoshi (2006). The sample consists of all firm-year observations between 1975 and 2018 for non-financial, non-utility, and non-governmental US firms from the Compustat universe. Variables are constructed as described in Table 1.19 in the appendix and then, apart from book and market leverage, trimmed at the 1%- and 99%-level. If book or market leverage is below 0 (above 1), the respective observation is replaced with the 0 (1) value. Standard errors clustered at the year and industry level in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 1.5: Duration and frequency of being a zombie

Panel A: Duration			
Years	Freq.	Percent	% cum.
1	8,409	72.17	72.17
2	2,105	18.07	90.24
3	663	5.69	95.93
4	278	2.39	98.32
5	95	0.82	99.13
6	49	0.42	99.55
7	25	0.21	99.77
8	7	0.06	99.83
9	5	0.04	99.87
10	4	0.03	99.91
>10	11	0.09	100
Mean		2.06	

Panel B: Occurrence of classifications			
Times	Freq.	%	∅-Duration
1	4,467	62.44	2.11
2	1,620	22.64	2.16
3	637	8.90	2.24
4	233	3.26	2.05
5	125	1.75	1.97
6	45	0.63	1.73
7	14	0.20	2.44
8	10	0.14	2.56
9	2	0.03	2.33
10	1	0.01	1.00

This table shows the absolute and relative frequency of the duration of the zombie status in panel A. In panel B, the absolute and relative frequency of the number of times a firm is classified as a zombie and the respective average duration in years are displayed. The sample consists of all firm-year observations between 1975 and 2018 for non-financial, non-utility, and non-governmental US firms from the Compustat universe. Variables are constructed as described in Table 1.19 in the appendix and then, apart from book and market leverage, winsorized at the 1%- and 99%-level. If book or market leverage is below 0 (above 1), the respective observation is replaced with the 0 (1) value. Zombies are identified as described in section 1.3.2.

Zombie firms may either exit the economy, i.e. they default or are bought up by other firms, or they may recover. I first focus on the reclassification back to healthy and plot the median percentage changes in some key variables around the reclassification event of a former zombie firm back to a healthy firm as also done in Banerjee and Hofmann (2022). The x-axis in Figure 1.2 represents the recovery timeline, whereas the y-axis represents the percentage change of the respective variable. At $t = 0$, the change is displayed when the firm is reclassified as healthy. All negative (positive) t's represent the first difference before (after) the healing, e.g. $t = -2$ is the first difference between the third and the second last zombie year, and $t = 2$ is the first difference between the second and the third year after the healing. In terms of employees and sales, zombie firms grow more than when they leave the zombie status, even though there is a slightly negative trend around $t = -1$. Recall that the model by Caballero et al. (2008) predicts that zombie firms crowd out employment growth and sales of their competitors, however, the zombies themselves do not cut jobs, and they also do not suffer from lower sales growth. To leave the zombie status, Banerjee and Hofmann (2022) find that zombies reduce their assets. The figures for tangibility and investments show that US zombie firms also sell parts of their fixed assets and reduce investments to recover. The same holds for R&D and SG&A expenses and working capital investments. Finally, they also reduce the debt burden. Overall, a clear pattern emerges in which zombie firms reduce their investments to recover but do not reduce sales or employment growth.

In the second step, I investigate to which extent zombies have a different probability of exiting. To do so, I again follow Hoshi (2006) and regress an exit dummy on the zombie dummy and other covariates. The exit dummy in columns one and two is equal to one if a firm stops being listed in Compustat, whereas, in columns three and four, the reason for exit needs to be a default. Table 1.6 shows the results of those regressions. Across all specifications, the zombie dummy has a statistically significant positive effect, suggesting that zombie firms are more likely to exit. Additionally, the results reveal that controlling for the rate of profit increases the adjusted R^2 and reduces the effect of the zombie dummy but does not alter its statistical significance. This result is at odds with Hoshi (2006), who finds that the zombie dummy loses its significance once controlling for this rate. When only considering defaults, i.e. columns three and four, the result of the zombie dummy becomes even more pronounced. Interestingly, adding the rate of profit does not explain more of the variance of the dependent variable, and it also has no statistically significant effect. Regarding industry fixed effects, Table 1.6 implies that firms operating in the Construction and Manufacturing industries have a lower probability of exit than the baseline industry. When only considering defaults, the Wholesale Trade and Services industry also profits from lower default probabilities.

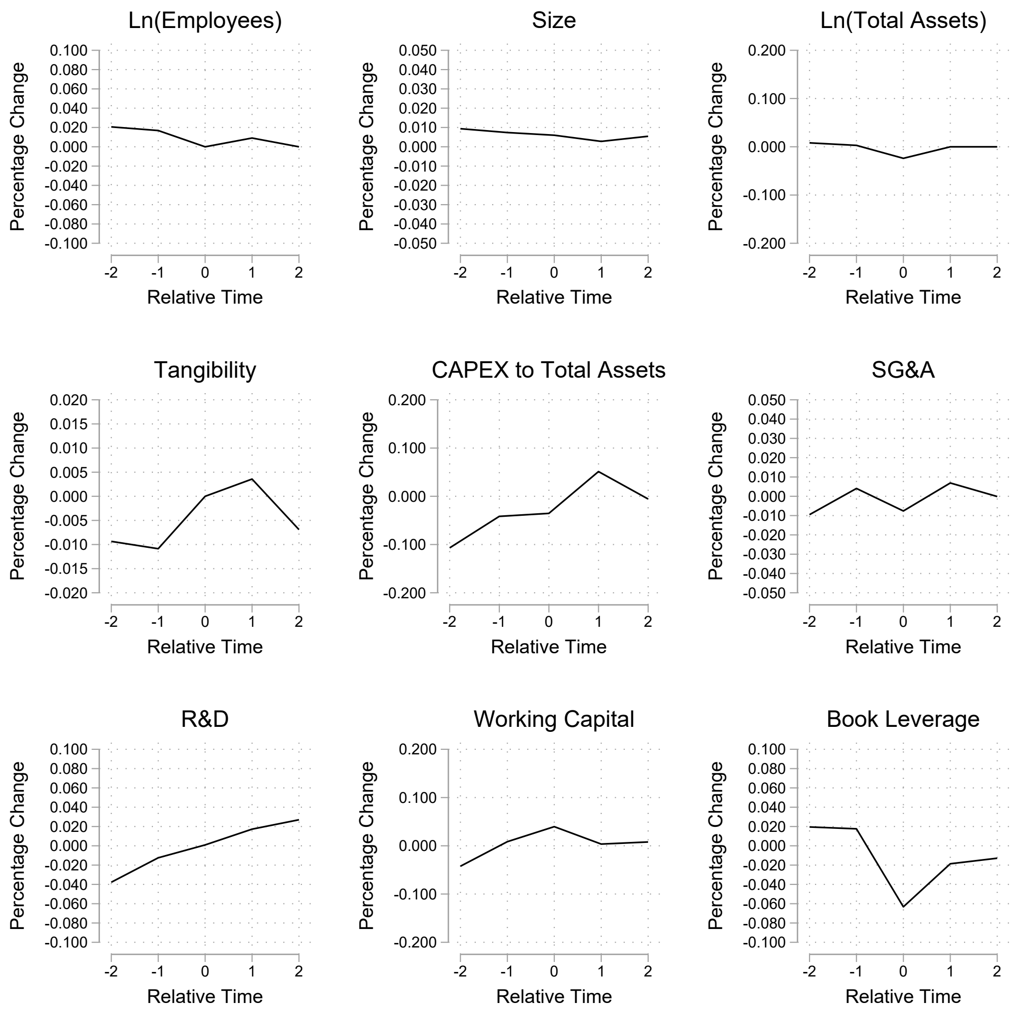

Figure 1.2: Change of key variables relative to zombie status

The figure plots the median percentage changes of the indicated variables. The relative time is zero when the firm status changes from zombie to recovered. The sample consists of all firm-year observations between 1975 and 2018 for non-financial, non-utility, and non-governmental US firms from the Compustat universe. Only firms that are a zombie for the first time and longer than three years and heal afterward are considered. Only first-time zombie firms classified for at least three years are considered. In total, 577 firms (and observations) satisfy this criterion. Variables are constructed as described in Table 1.19 in the appendix and then, apart from book and market leverage, winsorized at the 1%- and 99%-level. If book or market leverage is below 0 (above 1), the respective observation is replaced with the 0 (1) value. Zombies are identified as described in section 1.3.2.

Table 1.6: Probability of exit according to Hoshi (2006), Table 4

	Exit		Default	
Zombie Dummy	0.0186***	0.018***	0.042***	0.037***
	(0.003)	(0.003)	(0.009)	(0.008)
Mining	-0.010	-0.018	-0.049***	-0.056***
	(0.013)	(0.014)	(0.013)	(0.012)
Construction	-0.027*	-0.034*	-0.028**	-0.035***
	(0.013)	(0.013)	(0.010)	(0.009)
Manufacturing	-0.031*	-0.041**	-0.052***	-0.063***
	(0.013)	(0.014)	(0.012)	(0.011)
Transportation	-0.018	-0.026	-0.036	-0.050*
	(0.014)	(0.015)	(0.026)	(0.022)
Wholesale Trade	-0.020	-0.028*	-0.051***	-0.068***
	(0.013)	(0.013)	(0.010)	(0.009)
Retail Trade	-0.019	-0.027	-0.012	-0.023*
	(0.013)	(0.014)	(0.012)	(0.011)
Services	-0.004	-0.015	-0.063***	-0.075***
	(0.013)	(0.014)	(0.012)	(0.011)
Rate of profit$_{t-1}$		-0.017***		-0.001
		(0.002)		(0.001)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
N	171,036	151,219	14,041	12,589
Zombie Obs.	16,798	14,591	1,592	1,424
adj. R^2	0.007	0.010	0.038	0.037

The dependent variable in columns 1 and 2 is a dummy equal to one if a company is no longer part of the sample. In columns 3 and 4 it is a dummy equal to one if a company's reason for exit is default. Displayed are the coefficient estimates of the OLS regression. The sample consists of all firm-year observations between 1975 and 2018 for non-financial, non-utility, and non-governmental US firms from the Compustat universe. Zombies are identified as described in section 1.3.2. Variables are constructed as described in Table 1.19 in the appendix and then, apart from book and market leverage, trimmed at the 1%- and 99%-level. If book or market leverage is below 0 (above 1), the respective observation is replaced with the 0 (1) value. Standard errors clustered at the year and industry level in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

To summarise, the likelihood of a firm becoming a zombie is mainly driven by the positive effect of having negative profits and high leverage. Once a firm is classified as a zombie according to the definition of Acharya et al. (2020), it remains in this condition for two years on average. Even though more than 50% of the zombie firms are classified only once as such, there are almost 3% of zombie firms that are classified five or more times as a zombie throughout the sample period. To recover, an analysis in the spirit of Banerjee and Hofmann (2022), suggest that zombie firms reduce their investments but do not shrink in terms of assets or employees. Finally, zombie firms are more likely to default than their healthy peers.

1.4.4 Prevalence across industries

As noted by Hoshi (2006) and Caballero et al. (2008), the zombie share is not constant across industries. According to the two sources, the zombie share in Japan is the lowest in the manufacturing industry since this industry is exposed to global competition and hence relatively "fit". Since the lost decade has its starting point in a decline in property prices, the real estate and the construction sector are more exposed to negative shocks and suffer from higher zombie shares. Using a broader sample of public and private European firms, Acharya et al. (2019) find similar results.

To investigate the zombie shares across industries in the US, Figure 1.3 plots the absolute and asset-weighted zombie share over time for eight different industries.[18] As expected, the cross-industry heterogeneity in terms of the size of the zombie share is significant. However, many industries show the same negative time trend as prevalent in Figure 1.1. Additionally, zombie firms seem to be similar in size to the average firm in almost all industries, as the difference between the two shares is only minor. Agriculture, Forestry, and Fishing shows the highest within-industry volatility. The small number of firms in this industry is the main driver of said result. Another industry consisting of only a small number of firms is the Mining industry. The time trend for it is negative, with a major bump around 2005. According to Canart et al. (2020), the mining industry suffered from a decrease in productivity starting in 2004 and lasting up to 2009, which may explain this bump. Since then, the industry has increased its productivity, which makes it hard to explain the step increase in the last year of the sample period. The Construction industry suffers from the highest zombie shares across all industries. This share is also highly volatile over time and follows, with a time lag of between two and three years, roughly the business cycles of the construction sector.[19] The Manufacturing, Transportation and Public utilities, and Services industries are similarly affected by zombie firms and show a similar time trend. Finally, the zombie shares of the Wholesale Trade and the Retail Trade industry

18. Industries are classified based on SIC and https://mckimmoncenter.ncsu.edu/2digitsiccodes/.

19. In unreported results I find a correlation of 0.4 between the three-year lagged weighted zombie share and the GDP of the construction industry.

also evolve in parallel. Those two also show the strongest increase in zombie firms after the GFC, together with the Construction industry. While Transportation and Service mainly drive the overall zombie share in the first half of the sample period, the main drivers of the second half are the two trade industries, with the construction sector always being an important contributor.

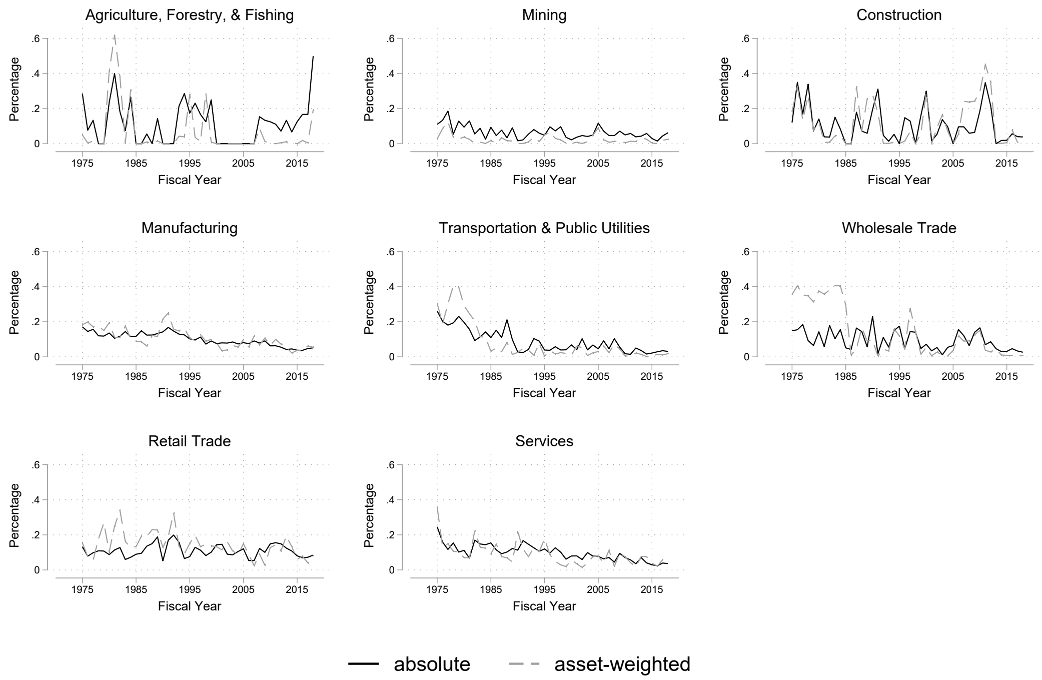

Figure 1.3: Evolution of the zombie share between 1975 and 2018 across industries
This figure displays the time trend of the absolute and asset-weighted zombie share over time for each indicated industry. The sample consists of all firm-year observations between 1975 and 2018 for non-financial, non-utility, non-governmental US firms from the Compustat universe. Zombies are identified as described in section 1.3.2.

1.4.5 Geographical prevalence

Apart from differences across industries, one might also expect to find differences across geographic locations, e.g. states or metropolitan areas. Hoshi (2006), for example, finds a negative effect of a headquarter in an urban area on the probability of turning into a zombie firm. Figure 1.4 plots a map of the US where each state is colored based on its average asset-weighted zombie share. Most states are moderately affected by zombies, and no clear pattern emerges apart from the East suffering slightly more. The most affected state is Michigan (20%), followed by Utah (16.7%), Delaware (16.4%), and Connecticut (15.3%).

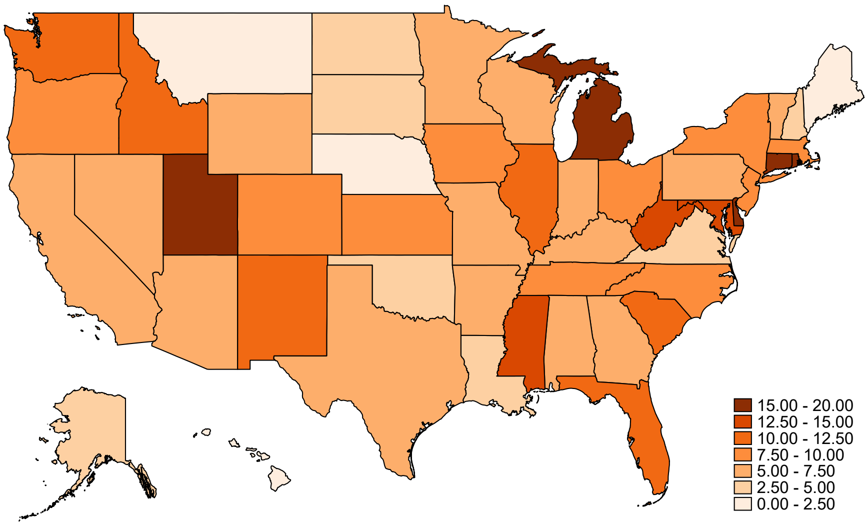

Figure 1.4: State level zombie share

This figure displays the average prevalence of zombies weighted by their assets in each state. The shares are grouped into seven groups as indicated in the legend. The sample consists of all firm-year observations between 1975 and 2018 for non-financial, non-utility, and non-governmental US firms from the Compustat universe. Zombies are identified as described in section 1.3.2.

To track the changes in the zombie share across states over time, Figure 1.5 shows the zombie map for six different years. As expected from Figure 1.1, some time trend is visible across the US. However, there is also considerable heterogeneity across states over time. In the sample's first year, mainly the east coast and the South are affected by zombies. Florida and Mississippi show the highest numbers. Ten years later and in line with Figure 1.1, more states show low zombie shares, and the main area of zombification is now the midwest. In 1995, Washington is the most affected state, however, apart from Nevada, it is the only largely affected state in the west, whereas many states in the east are moderately affected. Three years before the GFC, the focus lies again on the east and south, with some outliers in the northern parts of the US. In 2015 the share of zombie firms drops again, and the distribution is even across all states except New Mexico. Finally, in the last year of the sample, the overall trend is similar to 2015, however, the numbers are now mainly driven by states around the great lakes. For the most part, there is no clear time trend visible, e.g. a shift from one coast to the other, however, Figure 1.5 shows that the zombie phenomena is geographically unstable and is likely driven by state-level characteristics at each time snapshot.

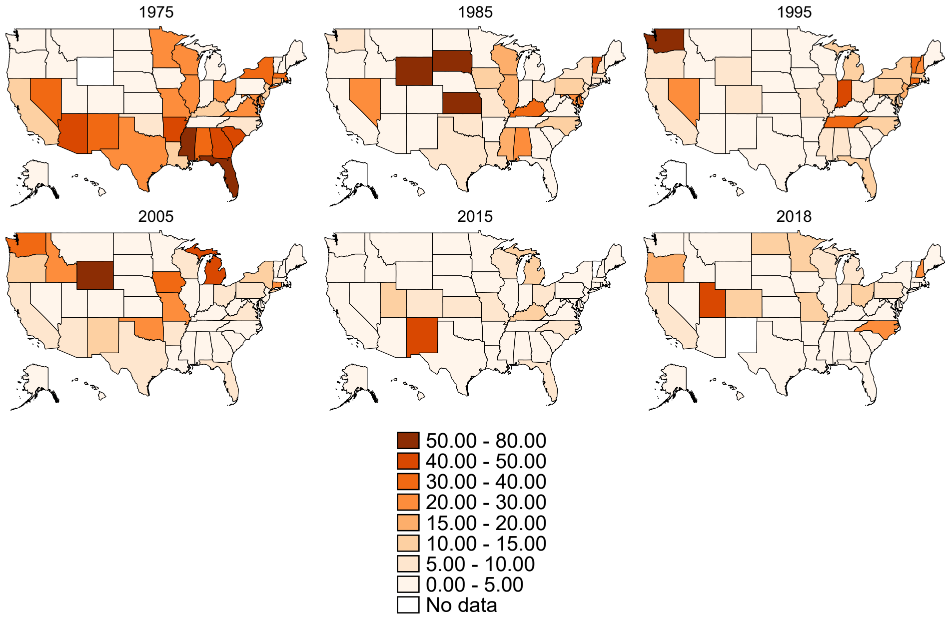

Figure 1.5: State level zombie share over time
This figure displays the prevalence of zombies weighted by their assets in each state for selected years. The shares are binned into seven bins as indicated in the legend. The sample consists of all firm-year observations between 1975 and 2018 for non-financial, non-utility, and non-governmental US firms from the Compustat universe. Zombies are identified as described in section 1.3.2.

The zombie share calculated within state boundaries comes with two issues. First, states with a low number of firms may have high zombie shares even though the issue is less severe than states with more firms and lower shares. Second, firms may cluster in metropolitan areas, reaching across borders.[20] Hence, the state prevalence is an inaccurate measure of the zombie share in a given region. To mitigate this issue, I cluster all firms in specific years based on the coordinates of their headquarters using the k-means algorithm.[21] I then calculate the zombie share for each cluster and display the clusters in Figure 1.6. Note that the size of each cluster is relative to its zombie share, therefore, the larger the cluster is, the higher is the fraction of assets sunk in zombie firms within this cluster. In general, the results for the clusters are in line with the results at the state level. However, some geographical trends are now better visible than in Figure 1.5. For example, the northeast coast suffers from zombification for almost 30 years. An

20. One example is the Logan metropolitan statistical area which includes counties from Utah and Idaho.

21. The coordinates are downloaded from the HERE API using the `geocodehere` command written by Hess (2015) in Stata. 97.8 percent of all firms in the sample have a matching accuracy on at least the county level, and only those firms are included.

observation that could not be made when the zombie shares are calculated on the state level. New clusters emerge, such as the one in Michigan in 2015. Another advantage of clustering is that it allows for identifying the concourses of zombies within states. In 1975 it was not Seattle that was mainly affected by zombies as the cluster is more to the east. Similarly, it was not only Oregon that was affected by a large zombie share in 2018 but also the northern part of California.

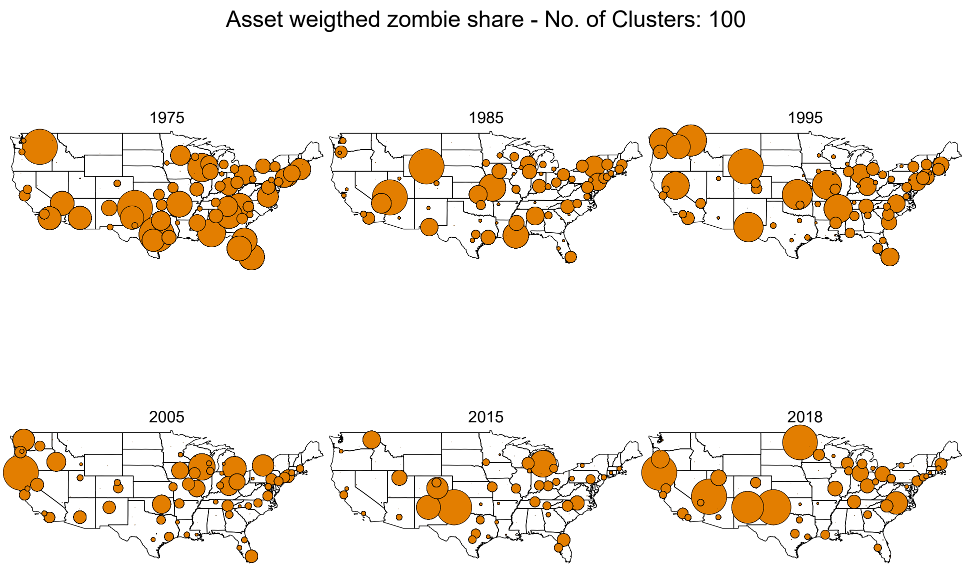

Figure 1.6: Zombie clusters over time

The figures shows the prevalence of zombie firms clustered based on their geographical location for selected years. The size of the clusters is relative to the asset-weighted zombie share in the cluster. The sample consists of all firm-year observations between 1975 and 2018 for non-financial, non-utility, and non-governmental US firms from the Compustat universe. Zombies are identified as described in section 1.3.2.

The geographical analysis of US zombie firms suggests that some states seem more affected by zombies than others. Especially the ones in the East. Additionally, it shows that clustering firms across state boundaries provides a clearer picture of the geographical distribution of zombies. More importantly, however, the state-level analysis shows that the level of zombies is linked to how many firms are incorporated in a given year and to the dominant industry in this state or area. This suggests that looking at the overall US-level zombie share might be misleading if one is interested in linking the occurrence of such firms to economic forces.

1.4.6 Economic Impact

One of the main goals in the existing literature about zombie firms is to infer whether they hurt the economy as a whole. The Schumpetrian model proposed by Caballero et al. (2008) predicts that less productive firms, i.e. the zombie firms, will stay within the economy and hinder new, more productive firms from entering. Therefore, the overall productivity of an economy or an industry will be lower than the benchmark level of productivity without zombies. Additionally, zombie firms are expected to reduce employment growth and investments of healthy firms. Empirical evidence which supports the predictions of the model is presented in Caballero et al. (2008), McGowan et al. (2017b), and Banerjee and Hofmann (2018). Acharya et al. (2019) shows that zombie firms also receive loans that would otherwise have been granted to healthy firms, therefore zombies also lower the available capital of non-zombies.
To test whether the same effects are empirically detectable in the US, I follow Caballero et al. (2008)[22] and run the following fixed effect regression:

$$y_{ijt} = \beta \text{non}z_{ijt} + \xi Z_{jt} + \omega \text{non}z_{ijt} \times Z_{jt} + \delta_1' D_t + \delta_2' D_j + \epsilon_{ijt} \qquad (1.1)$$

where y_{ijt} stands for the dependent variable, i.e. the investment ratio, employment growth, or productivity of firm i operating in industry j in year t. β captures the effect of the non-zombie dummy and therefore shows the difference between a healthy and a zombie firm, whereas ξ stands for the effect of the asset-weighted industry zombie share. By including the interaction term non$z_{ijt} \times Z_{jt}$, the model also accounts for the effect of zombies on healthy firms. Finally, D_t and D_j are time- and industry-fixed effects. The results are displayed in Table 1.7 and the main interest lies in the estimation of ω, since this parameter represents the harm of zombies on non-zombies. Non-zombies have a statistically significant lower investment ratio and employment growth, i.e., compared to zombie firms, non-zombies invest less and hire fewer people over time. This seems implausible given that zombie firms have lower profitability and low growth opportunities, and the finding is also contradicted by Caballero et al. (2008). Concerning the effect of the non-zombie dummy on productivity, the result is in line with the literature. All the effects are amplified in industries with a higher asset-weighted zombie share. Most interestingly, the sign of ω shows positive spillover effects of zombies on the investment ratio and the employment growth of non-zombies. Both effects have opposite signs compared to the literature. While I do not have a reasonable explanation for the positive effect on investments, the effect on employment growth might be explained by the size of the US. According to Caballero et al. (2008) zombies retain their workforce and even increase the competition in

22. In a footnote, Caballero et al. (2008) state that they also use US data between 1995 and 2004 to estimate the economic impact of zombie firms, but they are not able to identify a statistically significant effect.

the labor market due to their access to cheap funding, suggesting that the labor market should dry up. However, Since the US is large and section 1.4.4 has shown that most of the time, only certain regions are affected, it might be the case that employees from other states and regions are recruited to compete with the zombie firms.

Table 1.7: Economic impact of zombie firms according to Caballero et al. (2008)

	I/K	Δ ln(E)	Productivity
Non-zombie Dummy	-0.021**	-0.035**	0.210***
	(0.007)	(0.011)	(0.038)
Industry zombie share (asset weighted)	-0.044*	-0.098*	0.310*
	(0.019)	(0.040)	(0.148)
Non-zombie Dummy × Industry zombie share	0.047*	0.094*	-0.220
	(0.022)	(0.044)	(0.128)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
N	168,167	145,851	161,068
adj. R^2	0.135	0.013	0.177

The dependent variables are indicated in each column. I/K is the ratio of investments to total assets, Δ *ln(E)* is the change in the natural logarithm of employees, and *Productivity* is defined as *ln(sales)* - $\frac{2}{3}$ *ln(E)* - $\frac{1}{3}$ *ln(K)*. Displayed are the estimation coefficients from the OLS regression. The sample consists of all firm-year observations between 1975 and 2018 for non-financial, non-utility, and non-governmental US firms from the Compustat universe. Zombies are identified as described in section 1.3.2. Variables are constructed as described in Table 1.19 in the appendix and then, apart from book and market leverage, trimmed at the 1%- and 99%-level. If book or market leverage is below 0 (above 1), the respective observation is replaced with the 0 (1) value. Standard errors clustered at the year and industry level in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

This chapter shows that the prevalence of zombie firms is decreasing over time in the US and that there is a large heterogeneity across industries and geographic locations. However, a state-level analysis might be misleading as the clustering approach provides more details on the location of the clusters over time. Most firms are classified only once and for a short period as a zombie. Key drivers of becoming a zombie are negative profits and high leverage, an observation in line with the results emerging from a simple comparison of means between healthy and zombie firms. Almost 80% of the zombies recover, mostly by reducing investments and debt levels. Finally, zombie firms do not significantly impact non-zombies, but they affect industry-level outcomes such as investment rates and employment growth.

1.5 How zombies raise capital

After describing the characteristics of the zombie phenomena in the US in dept in the previous chapter, this chapter focuses on how zombie firms raise capital and whether they do it differently than non-zombies. To answer this question, I first investigate the passive side of the balance sheet before I concentrate on the different capital sources, i.e. loans, bonds, and SEOs.

According to the existing literature, zombie firms are more levered than non-zombies, e.g. Banerjee and Hofmann (2018) and De Martiis et al. (2022). Table 1.8 confirms this also for my US sample. This is true for total leverage and if leverage is split separately into short- and long-term based on debt maturity. In terms of equity capital, zombie firms have significantly lower stockholders' equity. This is not due to higher levels of treasury stock but less common equity, where the latter is mainly driven by lower retained earnings and not by the common equity stock.

The results in terms of capital structure discussed so far are simple averages without considering the different characteristics of zombies, which may also affect the difference between zombies and non-zombies of the variables of interest. Table 1.9 shows conditional correlations derived by regressing the dependent variable on the zombie dummy and controls. Formally the model is defined as follows:

$$y_{ijt} = \alpha + \beta Z_{ijt} + \gamma' X_{ijt-1} + \delta_1' \rho_t + \delta_2' \mu_j + \epsilon_{ijt}, \tag{1.2}$$

where y_{ijt} is the dependent variable of interest, Z_{ijt} is the zombie dummy of firm i in industry j at time t, X_{ijt-1} is a vector of firm-level controls and ρ_t and μ_j are time and industry fixed effects. Concerning the debt structure, the results are similar to the ones in Table 1.8. The zombie dummy increases the book leverage by almost half its standard deviation, while the short-term and long-term debt leverages are between 20% and 30% higher. Since zombie firms are unprofitable and carry a higher risk of default than healthy firms, their access to long-term debt is limited, and they need to rely more on short-term funding. This hypothesis is supported by the strong positive effect of the zombie dummy on the ratio between short- and long-term debt. Regarding equity and its decomposition, some results change compared to Table 1.8. While stockholders equity and common equity is still significantly lower for zombie (8% and 4%), the difference in treasury stock is now positive and statistically significant, amounting to 2% of its standard deviation. Additionally, the large difference in retained earnings has vanished, and the point estimation is even positive, although not statistically significant.

Table 1.8: Capital structure: zombies vs. non-zombies

	N	Mean	Median	SD	Difference	t
			Zombies			
Book Leverage	16,939	0.46	0.41	0.22	-0.21***	(-116.92)
Short-term debt	16,939	0.21	0.09	0.38	-0.11***	(-37.84)
Long-term debt	16,939	0.30	0.27	0.23	-0.12***	(-63.56)
ST to LT debt	15,728	3.59	0.27	12.98	-1.23***	(-11.41)
Equity (ceq)	16,939	0.05	0.31	1.29	0.24***	(22.83)
Equity (teq)	3,389	-0.63	0.32	4.53	0.44***	(5.58)
Equity stock	16,786	0.13	0.01	0.50	-0.01**	(-2.78)
Retained earnings	16,778	-2.40	-0.03	10.74	0.18*	(2.08)
Treasury stock	15,445	0.02	0.00	0.08	0.01***	(-21.93)
			Non-zombies			
Book Leverage	156,928	0.25	0.19	0.25		
Short-term debt	156,928	0.09	0.02	0.29		
Long-term debt	156,928	0.18	0.12	0.21		
ST to LT debt	123,813	2.36	0.16	10.20		
Equity (ceq)	156,928	0.29	0.49	1.20		
Equity (teq)	48,091	-0.19	0.49	3.85		
Equity stock	155,396	0.12	0.01	0.47		
Retained earnings	155,294	-2.22	0.09	10.65		
Treasury stock	146,006	0.04	0.00	0.11		

The table shows some key variables' summary statistics for the capital structure of zombies and non-zombies. The sample consists of all firm-year observations between 1975 and 2018 for non-financial, non-utility, and non-governmental US firms from the Compustat universe. Variables are constructed as described in Table 1.19 in the appendix and then, apart from book and market leverage, winsorized at the 1%- and 99%-level. If book or market leverage is below 0 (above 1), the respective observation is replaced with the 0 (1) value. Zombies are identified as described in section 1.3.2. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 1.9: Capital structure regressions

	Book leverage	ST debt	LT debt	ST to LT debt	
Zombie Dummy	0.118***	0.059***	0.066***	0.734***	
	(0.004)	(0.004)	(0.004)	(0.205)	
Ln(assets)_{t-1}	0.010**	-0.025***	0.018***	-0.265***	
	(0.004)	(0.004)	(0.003)	(0.070)	
MtB ratio_{t-1}	-0.001**	0.001	-0.000	-0.096***	
	(0.000)	(0.001)	(0.000)	(0.029)	
$\text{Profitability}_{t-1}$	-0.061***	-0.101***	-0.029***	-0.819***	
	(0.006)	(0.010)	(0.004)	(0.133)	
Tangibility_{t-1}	0.164***	0.040**	0.125***	-0.972**	
	(0.014)	(0.018)	(0.012)	(0.371)	
Year FE	Yes	Yes	Yes	Yes	
Firm FE	Yes	Yes	Yes	Yes	
N	147,144	147,144	147,144	118,434	
No. of Zombies	14,060	14,060	14,060	12,991	
adj. R^2	0.585	0.533	0.512	0.219	
	Common E	Stockholder E	Shareholders E	RE	TS
Zombie Dummy	-0.099***	-0.135**	-0.005	0.032	0.002***
	(0.011)	(0.062)	(0.003)	(0.079)	(0.001)
Ln(assets)_{t-1}	0.134***	0.339***	-0.056***	1.908***	-0.007***
	(0.020)	(0.066)	(0.005)	(0.281)	(0.001)
MtB ratio_{t-1}	0.000	-0.025***	0.001*	0.014	-0.000*
	(0.002)	(0.008)	(0.001)	(0.032)	(0.000)
$\text{Profitability}_{t-1}$	0.543***	1.093***	-0.079***	4.705***	0.000
	(0.040)	(0.139)	(0.016)	(0.221)	(0.001)
Tangibility_{t-1}	-0.109**	0.188	-0.044*	1.1962**	-0.006
	(0.054)	(0.264)	(0.022)	(0.486)	(0.006)
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
N	147,144	44,501	145,765	145,690	137,307
No. of Zombies	14,060	2,871	13,939	13,932	12,941
adj. R^2		0.645	0.700	0.670	0.536

The table shows coefficient estimates of regressions of the dependent variables on the indicated regressors. The dependent variables are indicated in each column and scaled by total assets. RE stands for retained earnings and TS for Treasury stocks. The sample consists of all firm-year observations between 1975 and 2018 for non-financial, non-utility, and non-governmental US firms from the Compustat universe. Variables are constructed as described in Table 1.19 in the appendix and then, apart from book and market leverage, winsorized at the 1%- and 99%-level. If book or market leverage is below 0 (above 1), the respective observation is replaced with the 0 (1) value. Zombies are identified as described in section 1.3.2. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Tables 1.8 and 1.9 show the difference in terms of levels. While this information highlights the difference between zombies and non-zombies, it only shows a time snapshot. It does not reveal any information about the change in the variables of interest. Therefore, Table 1.10 focuses on debt and equity issuances, which drive the changes in the capital structure. The average total financing cash flow is significantly higher for zombie firms. Since zombie firms are, by definition, kept alive by the support of capital providers, the higher dependence on financing cash flows is not surprising. Zombie firms do not only issue more debt but also do it more often, as indicated by the debt issue dummies, which are equal to one whenever the short- or long-term debt increase is larger than 5% of the total outstanding assets. Zombie firms still issue equity with almost the same frequency as non-zombies. However, they raise less equity, both in terms of gross and net values.[23] Finally, zombie firms' average ratio between debt and equity financing is twice as large. This underscores the strong dependency of zombie firms on debt capital.

Similar to Table 1.9, I derive conditional correlations between the zombie dummy and the flow variables by regressing the latter on the former and the control variables. Since the dependent variables are flow variables from $t-1$ to t, I use the zombie dummy at $t-1$ as the variable of interest. Controlling for the book value of assets, the market-to-book ratio, the profitability, and the tangibility dramatically change the results compared to Table 1.10. In unreported results, I find that profitability is the main driver of this change, as, without it, the signs of the point estimators of the zombie dummy are not statistically significant. Using the full set of controls, Table 1.11 suggests that zombie firms raise less outside capital since the zombie dummy is statistically significant and amounts to 2% of the standard deviation of the dependent variable. Zombies also repay more debt (19% of the standard deviation) but raise more equity (3.2% of the standard deviation). Even though the results contradict the findings in Table 1.10, they align with the results described in Banerjee and Hofmann (2022) and highlight the importance of controlling for key characteristics of zombie firms.

Overall, the results on the capital structure in terms of levels show that zombie firms are more levered than healthy firms. This aligns with existing research and the applied definition of zombie firms, e.g. Hoshi (2006), Banerjee and Hofmann (2022), and De Martiis et al. (2022). While the results concerning averages suggest that zombie firms raise outside capital in line with the pecking order theory, that is, they raise on average more short- than long-term debt and more debt than equity, this observation becomes invalid once I calculate conditional correlations. In this case, zombie firms rely less on outside financing and debt

23. The net values are equal to the gross values minus dividends and share repurchases.

but issue more equity than normal firms. This change is driven by controlling for profitability and aligns the results with Banerjee and Hofmann (2022).

Table 1.10: Financing: zombies vs. non-zombies

	N	Mean	Median	SD	Difference	t
			Zombies			
Total financing CF	10,631	0.43	0.06	1.35	-0.08***	(-6.16)
Debt change	16,393	0.18	0.05	0.42	-0.15***	(-45.82)
ST Debt issues (net)	7,025	0.06	0.00	0.29	-0.03***	(-9.56)
ST Debt issues dummy (net)	16,939	0.70	1.00	0.46	-0.09***	(-23.32)
LT Debt issues (net)	15,625	0.10	0.01	0.26	-0.07***	(-33.64)
LT Debt issues dummy (net)	16,939	0.42	0.00	0.49	-0.17***	(-42.42)
Equity issues (gross)	16,008	0.16	0.00	0.64	0.05***	(9.92)
Equity issues dummy (gross)	16,939	0.19	0.00	0.39	0.01***	(3.94)
Equity issues (net)	15,140	0.13	0.00	0.57	0.03***	(5.16)
Equity issues dummy (net)	16,939	0.16	0.00	0.37	0.00	(0.61)
DtoE change (gross)	4,550	103.28	3.05	334.62	-54.82***	(-10.81)
DtoE change (net)	4,944	8.64	0.10	79.10	-7.18***	(-6.26)
			Non-zombies			
Total financing CF	113,008	0.35	0.00	1.34		
Debt change	153,294	0.03	0.00	0.27		
ST Debt issues (net)	69,450	0.03	0.00	0.22		
ST Debt issues dummy (net)	156,928	0.61	1.00	0.49		
LT Debt issues (net)	145,691	0.03	0.00	0.18		
LT Debt issues dummy (net)	156,928	0.25	0.00	0.43		
Equity issues (gross)	150,495	0.21	0.00	0.77		
Equity issues dummy (gross)	156,928	0.20	0.00	0.40		
Equity issues (net)	141,673	0.15	0.00	0.67		
Equity issues dummy (net)	156,928	0.16	0.00	0.37		
DtoE change (gross)	49,328	48.47	0.00	234.84		
DtoE change (net)	53,322	1.46	0.00	50.37		

The table shows some key variables' summary statistics for financing policies for zombies and non-zombies. The sample consists of all firm-year observations between 1975 and 2018 for non-financial, non-utility, and non-governmental US firms from the Compustat universe. Variables are constructed as described in Table 1.19 in the appendix and then, apart from book and market leverage, winsorized at the 1%- and 99%-level. If book or market leverage is below 0 (above 1), the respective observation is replaced with the 0 (1) value. Zombies are identified as described in section 1.3.2. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 1.11: Financing regressions

	Fin CF	Δ D	Δ STD (n)	STD issue	Δ LTD (n)	LTD issue
Zombie Dummy$_{t-1}$	-0.023***	-0.054***	-0.011***	-0.017***	-0.015***	-0.018***
	(0.008)	(0.004)	(0.003)	(0.006)	(0.003)	(0.005)
Ln(assets)$_{t-1}$	-0.147***	-0.044***	-0.015***	0.008**	-0.021***	-0.016***
	(0.018)	(0.004)	(0.003)	(0.003)	(0.002)	(0.004)
MtB ratio$_{t-1}$	0.067***	0.006***	0.005***	0.001*	0.002***	0.001*
	(0.004)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)
Profitability$_{t-1}$	-0.532***	-0.032***	-0.067***	-0.029***	-0.019***	-0.004
	(0.024)	(0.005)	(0.008)	(0.004)	(0.006)	(0.009)
Tangibility$_{t-1}$	0.051	-0.062***	0.016	0.120***	0.011	0.108***
	(0.066)	(0.010)	(0.011)	(0.019)	(0.006)	(0.014)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
N	108,625	147,250	66,044	147,250	139,667	147,250
No. of Zombies	9,265	13,904	6,043	13,904	13,209	13,904
adj. R^2	0.618	0.141	0.394	0.392	0.135	0.123
	Δ E (g)	E issue (g)	Δ E (n)	E issue (n)	Δ D to E (g)	Δ D to E (n)
Zombie Dummy$_{t-1}$	0.008	0.025***	0.014***	0.022***	-0.092*	0.228***
	(0.005)	(0.005)	(0.005)	(0.004)	(0.051)	(0.067)
Ln(assets)$_{t-1}$	-0.075***	-0.058***	-0.063***	-0.052***	0.224***	0.105**
	(0.011)	(0.004)	(0.008)	(0.003)	(0.044)	(0.049)
MtB ratio$_{t-1}$	0.032***	0.007***	0.028***	0.006***	-0.014***	-0.025***
	(0.002)	(0.001)	(0.002)	(0.001)	(0.005)	(0.005)
Profitability$_{t-1}$	-0.198***	0.004	-0.149***	0.009*	-0.103*	-0.150***
	(0.021)	(0.007)	(0.014)	(0.005)	(0.051)	(0.039)
Tangibility$_{t-1}$	0.055*	0.090***	0.046*	0.068***	0.285	0.425*
	(0.031)	(0.021)	(0.026)	(0.018)	(0.222)	(0.242)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
N	144,249	147,250	135,941	147,250	21,452	16,220
No. of Zombies	13,536	13,904	12,793	13,904	2,551	1,784
adj. R^2	0.44	0.314	0.428	0.284	0.338	0.302

The table shows coefficient estimates of regressions of the dependent variables on the indicated regressors. The dependent variables are indicated in each column and scaled by total assets, n indicates net and g gross values. STD issue and LTD issue are dummy variables. The sample consists of all firm-year observations between 1975 and 2018 for non-financial, non-utility, and non-governmental US firms from the Compustat universe. Variables are constructed as described in Table 1.19 in the appendix and then, apart from book and market leverage, trimmed at the 1%- and 99%-level. If book or market leverage is below 0 (above 1), the respective observation is replaced with the 0 (1) value. Zombies are identified as described in section 1.3.2. Standard errors clustered at the industry level in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

1.5.1 Loans

According to the zombie definition of Caballero et al. (2008), zombies are firms that receive subsidized credit. Using an extract from the Loan Pricing Corporations (LPC) DealScan database, I can compare loan characteristics between zombie and non-zombie firms. I clean the DealScan data following Valta (2012a) and drop loan facility observations with missing facility amount, maturity, or loan pricing. I also drop loans for which I cannot find the respective information about their base rate. Using the link table provided by Chava and Roberts (2008), I then merge the data with the zombie information from Compustat.[24] Since this link table is based on the borrower ID in Compustat (gvkey), I lose all loans which miss this variable, i.e. for which no link between Compustat and DealScan exists. The final DealScan sample ranges from 1994 until 2016 and consists of 29,853 loans.[25] Of those loans, 2,282 (7.6%) were granted to firms classified as zombies in the previous year. Figure 1.7 displays the course of loans granted to zombies as an absolute and amount-weighted fraction. Additionally, to facilitate interpretation, the asset-weighted zombie share is also plotted. Even though both fractions show a similar time trend as the zombie share, they still fluctuate considerably around it. This fluctuation seems to be related to business cycles, as both fractions significantly increase during crises, suggesting that creditors expand their exposure toward zombie firms during such periods. During booms, only the amount-weighted zombie loan share drops below the asset-weighted zombie share while the absolute loan share remains above. These results imply that zombie firms rely more on creditors than healthy firms, as suggested by Caballero et al. (2008) and others. However, the lenders reduce their exposure during boom periods when zombies profit from a stimulating economic environment. In turn, they need to significantly increase the exposure in terms of the number of loans and their size during downturns.

24. I thank Michael R. Roberts for making this data publicly available.

25. The shorter period of this sample is due to the limited coverage of DealScan before 1994 and the fact that the linking table currently only covers loans until 2017. Since I can only match a few loans in 2017, I also abstract from this year.

Figure 1.7: Loans granted to zombie firms between 1994 and 2016
This figure displays the time trend of the fraction of zombie loans (absolute and amount-weighted) and the asset-weighted zombie share over time. The sample consists of all loans between 1994 and 2016 for which a match to the zombie sample is possible. Loans are classified as loans to zombies whenever granted to firms classified as zombies. Those firms are identified as described in section 1.3.2.

Comparing average loan characteristics over the whole sample period between the two groups of firms indicates that zombies receive smaller loans with shorter maturity and higher all-in-drawn, as displayed in Table 1.12. The latter represents the costs, interest, and fees, in basis points, which the firms must pay for the loans above the defined underlying rate, e.g. LIBOR or Prime rate. Those three differences suggest that creditors can identify zombies and reduce their financial and risk exposure due to the higher uncertainty of the future outlook of those firms. In line with this observation is the significantly higher fraction of secured loans granted to zombie firms. Zombie firms are often said to have a close relationship with their creditors, e.g. Kane (2000) and Hoshi (2006). My results support this hypothesis for zombie firms in the U.S. as the average number of banks involved in a loan is smaller for this group of firms, while the fraction of loans with only one manager is higher.

As in the previous subsection, I will extend the descriptive statistics from Table 1.12 with conditional correlations. The results are shown in Table 1.13 and relativize some of the previous observations. While there is still a negative and statistically significant effect of the zombie dummy on the loan size amounting to 12% of the standard deviation of said variable, there is no significant effect on the all-in-drawn, the maturity, or the number of managers. This might arise through the positive correlation between zombie and loan size and loan size with the other variables of interest, i.e. the loan size is the main driver of higher all-in-drawn and maturity and a lower number of managers. In unreported results, I find that, once I exclude loan characteristics, the zombie dummy has a significant negative effect on maturity and a positive effect on the number of managers. Interestingly, loans to zombie firms are less likely to be senior. At first, this might seem counteractive, as previous results suggest that banks access loans to zombies correctly and try to reduce the counterparty risk. However, since zombies suffer from a high debt burden, setting up new loans at a high seniority might be difficult due to seniority covenants of existing loans. Finally, the zombie dummy does not significantly affect the likelihood of the loan being secured. This result contrasts with Table 1.12 and the intuition, but since all controls have a significant effect, they most likely capture all the variation of the zombie dummy. Finally, loans to zombie firms are 4 percentage points more likely to be handled by only one bank.

To conclude, loans to zombie firms have different characteristics than those to non-zombies. The difference likely emerges from the poor financial state in which zombies are trapped. Importantly, I do not find evidence that banks would provide loans at terms that would be unreasonable and in favor of the zombie firms. However, whether those firms should receive additional loans in the first place remains an open question.

Table 1.12: Loan characteristics: zombies vs. non-zombies

	N	Mean	Median	SD	Difference	t
			Zombies			
Facility Amount	2,447	331.89	112.11	673.37	82.69***	(5.75)
Maturity	2,447	46.39	48.00	22.70	2.07***	(4.33)
Effective Rate	2,447	0.08	0.08	0.03	-0.01***	(-11.77)
All In Drawn	2,447	258.47	250.00	164.60	-30.10***	(-8.67)
Fixed Rate	2,447	0.04	0.00	0.19	-0.01**	(-3.02)
Seniority dummy	2,445	0.99	1.00	0.09	0.00*	(2.44)
Secured dummy	1,892	0.85	1.00	0.36	-0.09***	(-9.67)
No. of banks	2,447	7.01	4.00	8.45	0.66***	(3.69)
One Manager	2,447	0.30	0.00	0.46	-0.09***	(-9.41)
			Non-zombies			
Facility Amount	27,469	414.58	156.34	773.17		
Maturity	27,469	48.47	60.00	22.71		
Effective Rate	27,469	0.07	0.07	0.03		
All In Drawn	27,469	228.36	200.00	163.28		
Fixed Rate	27,469	0.03	0.00	0.16		
Seniority dummy	27,458	1.00	1.00	0.06		
Secured dummy	20,992	0.76	1.00	0.43		
No. of banks	27,469	7.67	5.00	8.31		
One Manager	27,469	0.21	0.00	0.41		

The table shows some key variables' summary statistics for loan characteristics for zombies and non-zombies. The sample consists of all loans between 1994 and 2017 for which a match to the zombie sample is possible. Loans are classified as loans to zombies whenever granted to firms classified as zombies. Those firms are identified as described in section 1.3.2. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 1.13: Loan characteristics regressions

	Amount	All in drawn	Fixed rate	Maturity
Zombie Dummy	-0.087**	-0.015	-0.007*	-0.028
	(0.039)	(0.657)	(0.084)	(0.167)
Log(Facility amount)		-0.171***	-0.015***	0.096***
		(0.000)	(0.000)	(0.000)
Log(All in drawn)	-0.424***			0.191***
	(0.000)			(0.000)
Log(loan maturity)	0.256***	0.206***	0.026***	
	(0.000)	(0.000)	(0.000)	
Ln(assets)	0.556***	-0.120***	0.004**	-0.031***
	(0.000)	(0.000)	(0.041)	(0.000)
Tobin's q	0.038***	-0.074***	0.000	0.002
	(0.000)	(0.000)	(0.815)	(0.661)
Book Leverage	0.328***	0.874***	0.030***	0.087*
	(0.000)	(0.000)	(0.000)	(0.082)
Tangibility	-0.021	-0.160**	0.040***	-0.011
	(0.852)	(0.019)	(0.000)	(0.731)
Profitability	0.001	-0.718***	-0.108***	0.382***
	(0.991)	(0.000)	(0.000)	(0.000)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
N	29,804	29,804	29,804	29,804
Zombie Obs.	2,433	2,433	2,433	2,433
adj. R^2	0.655	0.470	0.061	0.173
	Senior	Secured	No. managers	One manager
Zombie Dummy	-0.004**	0.014*	-0.035	0.037***
	(0.030)	(0.073)	(0.173)	(0.001)
Log(Facility amount)	-0.002***	-0.014*	0.323***	-0.087***
	(0.003)	(0.052)	(0.000)	(0.000)
Log(All in drawn)	-0.010***	0.261***	-0.114***	0.014***
	(0.000)	(0.000)	(0.000)	(0.008)
Log(loan maturity)	-0.002	0.076***	0.209***	-0.094***
	(0.114)	(0.000)	(0.000)	(0.000)
Ln(assets)	-0.001	-0.043***	0.104***	-0.041***
	(0.143)	(0.000)	(0.000)	(0.000)
Tobin's q	-0.001***	-0.012***	0.010**	-0.008***
	(0.000)	(0.000)	(0.012)	(0.006)
Book Leverage	0.006**	0.159***	0.155***	-0.081***
	(0.035)	(0.000)	(0.001)	(0.000)
Tangibility	-0.006	-0.070**	-0.109*	0.012
	(0.251)	(0.022)	(0.062)	(0.581)
Profitability	-0.010***	-0.023	0.070*	-0.121***
	(0.000)	(0.410)	(0.055)	(0.000)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
N	29,791	22,797	29,804	29,804
Zombie Obs.	2,431	1,879	2,433	2,433
adj. R^2	0.015	0.395	0.522	0.377

The table shows coefficient estimates of regressions of the dependent variables on the indicated regressors. The dependent variables are indicated in each column. The sample consists of all loans between 1994 and 2017 for which a match to the zombie sample is possible. Loans are classified as loans to zombies whenever granted to firms classified as zombies. Those firms are identified as described in section 1.3.2 * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

1.5.2 Bonds

Apart from loans, firms can also raise debt capital by issuing bonds. To conduct a similar analysis as in section 1.5.1, I merge the Compustat zombie sample with bond data from the Mergent Fixed Income Database (FISD) based on the 6-digit CUSIP. The resulting sample covers 8,311 bonds issued by 1,677 distinct firms from 1994 until 2018. The sample does not include bonds with missing offering dates or prices or without information about maturity, and I also drop perpetuity bonds. The number of bonds granted to zombies amounts to 551 or 6.6.% in total. According to Figure 1.8 the absolute fraction of bonds issued by zombies closely follows the evolution of the asset-weighted zombie share. Similarly to the evolution of the loans, significant spikes can be observed around crisis periods. Also, the nominal amount-weighted fraction of bonds issued by zombie firms is mostly below the asset-weighted zombie share, while the opposite is true for the absolute fraction of zombie loans. This suggests that zombies issue more but smaller bonds than non-zombies.

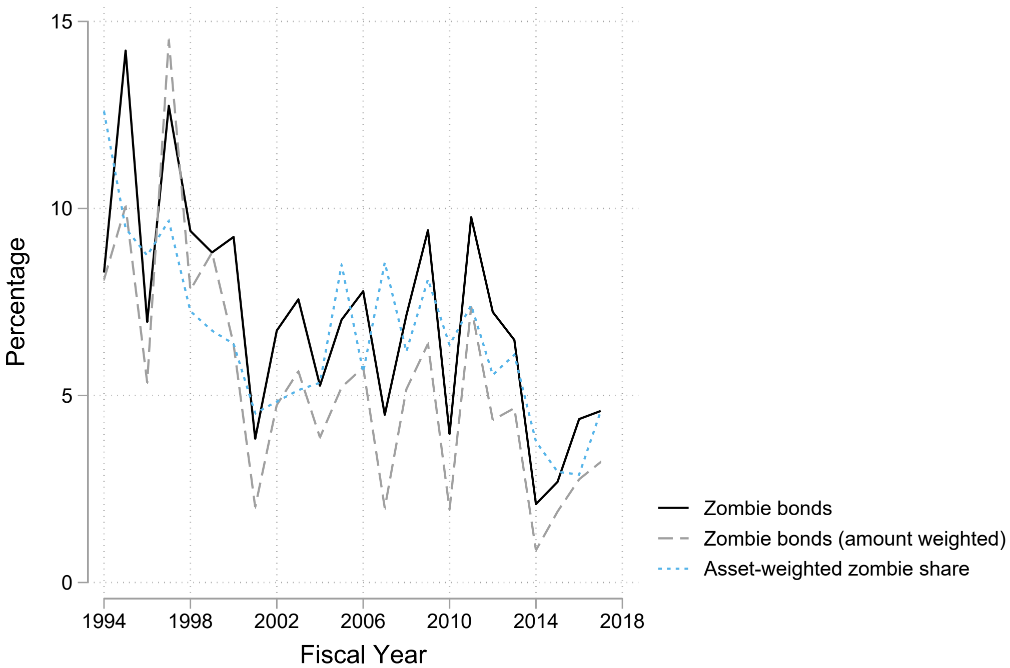

Figure 1.8: Bonds issued by zombie firms between 1994 and 2018

This figure displays the time trend of the fraction of zombie bonds (absolute and amount-weighted) and the asset-weighted zombie share over time. The sample consists of all bonds issued between 1994 and 2018 for which a match to the zombie sample is possible. Bonds are classified as bonds from zombies whenever they are issued by firms classified as zombies. Those firms are identified as described in section 1.3.2.

The observation that zombie firms issue smaller bonds, is confirmed in Table 1.14. While the average size of a bond issued by a non-zombie firm is USD 5.8 million, it is only USD 3.9 million for zombies. Concerning the issuing price, no statistically significant differences emerge, however, zombie firms pay a significantly higher yield to maturity with 6.13% compared to 5.36%. Incorporating the potentially higher risk of default of those firms, it is reasonable that they need to provide additional compensation to their bondholders. The same statement is true for the interest rate, which is 90 basis points higher on average. As for loans, the time-to-maturity of zombie bonds is more than one year, or 10%, shorter. Due to the possible higher asset volatility of zombies, the option to convert debt into equity is more valuable. Hence, zombie firms issue 22% more convertible bonds than non-zombies with only 15%. Finally, bonds issued by non-zombies are more often secured than the ones by zombies. The high debt burden and the associated covenants of zombie firms could again explain this difference.

When looking at conditional correlations for loans, many differences between non-zombies and zombies concerning loan characteristics vanish once I control for additional variables. A similar effect emerges in Table 1.15. The zombie dummy does not statistically affect the natural logarithm of the nominal amount, the offering price, or the time-to-maturity. The yield to maturity is significantly negatively affected by the zombie dummy, suggesting that zombie firms pay a yield that is 10% of its standard deviation lower. This result, together with the result for the coupon, contrasts with the result in Table 1.14. The main driver seems to be the large positive effect of book leverage. The higher book leverage of zombie firms might explain this. The simple averages overestimate the difference, but the results change once I only look at the isolated effect of being a zombie, i.e. controlling for book leverage. Since zombie firms have higher book leverage on average, they also pay more on average because of this characteristic. Once I control for the variable, the main effect of the zombie dummy then becomes negative. A possible explanation for this negative effect could again be their stakeholders' support. The results for the secured and convertible dummies align with the previous findings, even though only the secured dummy is statistically significantly affected by the zombie dummy.

Summarizing this section, I note that the differences between the two groups of firms are similar for loans and bonds. However, I do not find a statistically significant conditional correlation between the issuing amount, the offering price, or the bond duration and the zombie dummy. While the point estimator for the loan pricing is negative but insignificant, zombie firms issue bonds with a lower yield to maturity.

Table 1.14: Bond characteristics: zombies vs. non-zombies

	N	Mean	Median	SD	Difference	t
Zombies						
Amount issued	564	387,465.42	307,376.48	322,683.27	191,478.51***	(12.96)
Price in %	564	98.61	100.00	6.91	0.12	(0.38)
Time-to-maturity	564	10.69	10.13	8.35	1.20**	(3.23)
Yield to maturity	542	6.14	6.13	2.81	-0.77***	(-6.17)
Coupon in %	564	5.99	6.00	2.88	-0.90***	(-7.19)
Securization dummy	564	0.77	1.00	0.42	0.11***	(6.07)
Convertibility dummy	562	0.22	0.00	0.42	-0.07***	(-3.73)
Non-zombies						
Amount issued	7,670	578,943.93	419,203.72	509,433.23		
Price in %	7,670	98.73	99.89	6.23		
Time-to-maturity	7,670	11.88	10.14	10.20		
Yield to maturity	7,235	5.37	5.25	2.64		
Coupon in %	7,660	5.09	5.00	2.72		
Securization dummy	7,670	0.88	1.00	0.32		
Convertibility dummy	7,656	0.15	0.00	0.36		

The table shows some key variables' summary statistics for bond characteristics for zombies and non-zombies. The sample consists of all bonds issued between 1994 and 2018 for which a match to the zombie sample is possible. Bonds are classified as bonds from zombies whenever they are issued by firms classified as zombies. Financial, utilities, and governmental firms are excluded. Zombies are identified as described in section 1.3.2. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 1.15: Bond characteristics regressions

	Amount	Offer Price	Duration	Offering Yield
Zombie Dummy	-0.051*	0.002	-0.004	-0.289**
	(0.030)	(0.006)	(0.034)	(0.124)
Log(Amount issued)		-0.029***	0.035*	0.159*
		(0.005)	(0.018)	(0.092)
Log(Time-to-maturity)	0.026*	-0.017***		0.403***
	(0.014)	(0.002)		(0.075)
Yield to maturity	0.014		0.047***	
	(0.008)		(0.010)	
Ln(assets)	0.342***	0.013***	0.055***	-0.422***
	(0.010)	(0.002)	(0.012)	(0.094)
Tobin's q	0.055***	0.001	0.011*	-0.265***
	(0.016)	(0.001)	(0.006)	(0.074)
Book Leverage	-0.071	-0.021*	-0.293***	2.920***
	(0.084)	(0.011)	(0.067)	(0.349)
Tangibility	-0.097	0.021**	-0.016	0.585*
	(0.083)	(0.009)	(0.106)	(0.301)
Profitability	0.268**	0.022	0.384***	-1.364**
	(0.104)	(0.025)	(0.093)	(0.653)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
N	7,755	8,212	7,755	7,755
Zombie Obs.	538	560	538	538
adj. R^2	0.562	0.121	0.088	0.540

	Coupon	Secured	Convertible
Zombie Dummy	-0.11757	-0.05458*	0.01407
	(0.104)	(0.028)	(0.025)
Log(Amount issued)	-0.03503	0.00306	-0.00798
	(0.086)	(0.012)	(0.011)
Log(Time-to-maturity)	0.36599***	0.00041	0.06037***
	(0.084)	(0.008)	(0.006)
Yield to maturity		0.00767**	-0.09377***
		(0.004)	(0.004)
Ln(assets)	-0.36463***	0.06725***	-0.12566***
	(0.090)	(0.009)	(0.011)
Tobin's q	-0.26624***	0.00748	-0.01000*
	(0.079)	(0.008)	(0.005)
Book Leverage	2.59075***	-0.08853*	0.05194*
	(0.353)	(0.046)	(0.028)
Tangibility	0.71667**	0.03939	0.02085
	(0.288)	(0.073)	(0.067)
Profitability	-0.81155*	-0.04190	-0.60215***
	(0.478)	(0.035)	(0.126)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
N	8,202	7,755	7,739
Zombie Obs.	560	538	536
adj. R^2	0.452	0.221	0.548

The table shows coefficient estimates of regressions of the dependent variables on the indicated regressors. The dependent variables are indicated in each column. The sample consists of all bonds issued between 1994 and 2018 for which a match to the zombie sample is possible. Bonds are classified as bonds from zombies whenever they are issued by firms classified as zombies. Financial, utilities, and governmental firms are excluded. Zombies are identified as described in section 1.3.2. Standard errors clustered at the industry level in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

1.5.3 SEO

Apart from using debt, firms may also rely on raising new equity to fund their operations. They do so by conducting a Seasoned Equity Offering (SEO). I investigate the characteristics of SEOs using the SDC database. To clean the SEO data, I follow Lee and Masulis (2009) and exclude SEOs where the offering price is less than USD 5, Spin-Offs, and firms previously involved in a Leveraged Buyout. I also drop observation with *MasterDealType* unequal to C whenever there are firm-date duplicates. Finally, I merge the SEO data with the Compustat sample based on the issuing date and the 6-digit CUSIP. Similar to the loan and bond sample, I restrict the beginning of the resulting sample to 1994 and only use data up to 2018. In total, 3,433 SEOs remain from 1,757 distinct firms. The overall fraction of zombie SEOs, defined as SEO granted to firms classified as zombies in the previous year, is 8.8%. According to Figure 1.9, even though the general trend of both the absolute and amount-weighted SEO zombie share follows the trend of the asset-weighted zombie share, it is more volatile. Like loan and bond issuance, zombie firms raise more capital during crises. Most of the time, the absolute fraction of zombie SEOs is above the asset-weighted zombie share, suggesting that zombies issue more equity than healthy firms. However, the picture is less clear once I weigh the SEOs by their issuance amount.

Table 1.16 reveals that zombies raise, on average, less money in an SEO than healthy firms. This seems to be the only difference in important characteristics, as there are no differences in the likelihood and the amount of underpricing, as well as in the discount and the likelihood of offering a discount. The discount is the percentage difference between the offer price and the closing price of the day before the issuance. In line with expectations, zombie firms must pay a slightly higher gross spread and management fee on average. The difference is, however, not statistically significant. Finally, there is no notable difference in the likelihood of having a bank syndicate or doing a public SEO.

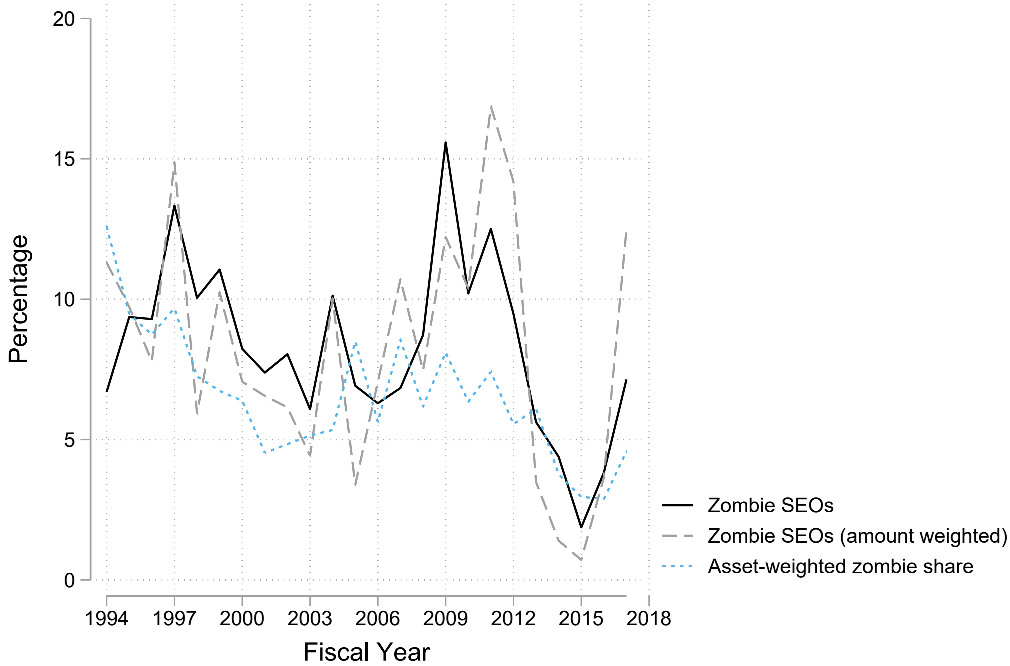

Figure 1.9: SEOs conducted by zombie firms between 1994 and 2018

This figure displays the time trend of the fraction of zombie SEOs (absolute and amount-weighted) and the asset-weighted zombie share over time. The sample consists of all SEOs conducted between 1994 and 2018 for which a match to the zombie sample is possible. SEOs are classified as zombie SEOs whenever they are conducted by firms classified as zombies. Those firms are identified as described in section 1.3.2.

As seen in the last two sections, comparing averages might be misleading, and I once again calculate conditional correlations according to equation 1.2. The results are displayed in Table 1.17 and reveal that the zombie dummy does not statistically significantly affect the issuing amount. Only the discount is significantly negatively affected. A negative effect is surprising since it suggests that zombie firms can offer a lower discount compared to non-zombies. Given the fragile state of zombies, it is remarkable that equity providers are willing to provide capital for less upside potential. However, it might well be the case that, similar to debt providers, shareholders of zombies might already hold a large stake in the firm and are, therefore, willing to invest additional funds close to market prices.

Table 1.16: SEO characteristics: zombies vs. non-zombies

	N	Mean	Median	SD	Difference	t
			Zombies			
Principal amount	371	0.35	0.18	0.56	0.14***	(4.56)
1st day underpricing	329	0.03	0.02	0.06	0.00	(-0.52)
Underpricing dummy	371	0.18	0.00	0.39	0.01	(0.60)
Discount	318	4.44	3.85	6.89	0.27	(0.68)
Discount dummy	318	0.83	1.00	0.38	0.01	(0.50)
Float offer dummy	308	0.25	0.18	0.22	-0.02	(-1.14)
Gross spread in %	313	4.53	5.00	1.56	0.06	(0.62)
Management fee in %	199	0.99	1.00	0.26	0.02	(0.85)
Syndicated dummy	371	0.72	1.00	0.45	0.00	(0.02)
Public dummy	371	0.93	1.00	0.26	-0.01	(-0.98)
			Non-zombies			
Principal amount	4,139	0.49	0.27	0.62		
1st day underpricing	3,687	0.03	0.02	0.05		
Underpricing dummy	4,139	0.20	0.00	0.40		
Discount	3,643	4.71	3.54	6.52		
Discount dummy	3,643	0.84	1.00	0.37		
Float offer dummy	3,404	0.23	0.17	0.21		
Gross spread in %	3,532	4.58	5.00	1.64		
Management fee in %	1,838	1.00	1.01	0.23		
Syndicated dummy	4,139	0.72	1.00	0.45		
Public dummy	4,139	0.91	1.00	0.28		

The table shows some key variables' summary statistics for SEO characteristics for zombies and non-zombies. The sample consists of all SEOs between 1994 and 2018 for which a match to the zombie sample is possible. SEOs are classified as zombie SEOs whenever they are conducted by firms classified as zombies. Financial, utilities, and governmental firms are excluded. Zombies are identified as described in section 1.3.2. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.17: SEO characteristics regressions

	Amount	Underpricing	Underpricing D	Discount	Discount D
Zombie Dummy	-0.018	0.004	-0.017	-0.149	-0.014
	(0.023)	(0.003)	(0.021)	(0.379)	(0.025)
Log(Principal Amount)		-0.001	0.027**	-0.591**	0.002
		(0.002)	(0.013)	(0.277)	(0.013)
Log(Market Cap)	0.253***	-0.002	0.005	-1.085***	-0.028**
	(0.043)	(0.001)	(0.007)	(0.242)	(0.012)
Volatility	0.007**	0.000	0.001	0.123***	0.002
	(0.003)	(0.000)	(0.001)	(0.037)	(0.001)
Volume	0.003***	0.000	0.000	0.006	-0.000
	(0.001)	(0.000)	(0.000)	(0.019)	(0.001)
Log(No. of managers)	0.090***	0.005***	-0.049***	-0.023	-0.019**
	(0.014)	(0.001)	(0.013)	(0.101)	(0.008)
Tobin's q	0.021***	-0.001*	-0.001	0.085	0.001
	(0.006)	(0.000)	(0.001)	(0.055)	(0.003)
Book Leverage	0.092***	-0.001	0.029	-1.146**	-0.019
	(0.033)	(0.006)	(0.028)	(0.463)	(0.025)
Profitability	-0.241***	0.002	-0.015	0.727	0.040**
	(0.039)	(0.003)	(0.013)	(0.670)	(0.015)
Ln(total assets)	-0.348***	-0.006***	0.003	0.343*	0.007
	(0.052)	(0.001)	(0.008)	(0.180)	(0.010)
Tangibility	-0.072*	0.004	0.005	0.484	0.020
	(0.042)	(0.004)	(0.029)	(0.698)	(0.047)
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
N	4,335	3,912	4,335	3,845	3,845
Zombie Obs.	359	321	359	310	310
adj. R^2	0.619	0.052	0.064	0.102	0.006

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	Float D	Gross spread	Mgmt fees	Syndicated	Public D
Zombie Dummy	-0.006	0.059	0.006	0.024	0.001
	(0.011)	(0.092)	(0.011)	(0.019)	(0.011)
Log(Principal Amount)	0.159***	-0.278***	-0.046***	0.086***	0.089***
	(0.012)	(0.049)	(0.006)	(0.013)	(0.014)
Log(Market Cap)	-0.202***	-0.479***	-0.075***	-0.057***	-0.016**
	(0.014)	(0.042)	(0.009)	(0.009)	(0.008)
Volatility	0.003**	0.007***	0.000	0.001	-0.001
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Volume	0.000	0.002	0.001	-0.000	-0.000
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
Log(No. of managers)	-0.012***	0.816***	0.048***	0.369***	0.055***
	(0.004)	(0.035)	(0.009)	(0.016)	(0.014)
Tobin's q	0.002*	0.004	0.001	-0.002	-0.003**
	(0.001)	(0.003)	(0.001)	(0.002)	(0.001)
Book Leverage	0.006	-0.192**	0.026*	-0.058	0.033**
	(0.015)	(0.088)	(0.015)	(0.038)	(0.015)
Profitability	-0.010	0.036	-0.017	0.051***	0.052
	(0.011)	(0.076)	(0.018)	(0.010)	(0.037)
Ln(total assets)	0.033***	-0.172***	-0.033***	-0.028***	-0.010**
	(0.006)	(0.032)	(0.006)	(0.007)	(0.004)
Tangibility	-0.036*	0.231	-0.003	0.007	0.002
	(0.021)	(0.165)	(0.021)	(0.038)	(0.024)
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
N	3,589	3,814	2,023	4,335	4,335
Zombie Obs.	300	310	196	359	359
adj. R^2	0.590	0.673	0.620	0.637	0.247

The table shows coefficient estimates of regressions of the dependent variables on the indicated regressors. The dependent variables are indicated in each column.The sample consists of all SEOs between 1994 and 2018 for which a match to the zombie sample is possible. SEOs are classified as zombie SEOs whenever they are conducted by firms classified as zombies. Financial, utilities, and governmental firms are excluded. Volume and volatility are calculated as in Huang and Zhang (2011). Zombies are identified as described in section 1.3.2. Standard errors clustered at the industry level in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

1.6 Conclusion

This paper investigates zombie firms in the US and how they raise capital. In order to identify zombies, I follow Acharya et al. (2020). First, I provide detailed descriptive statistics and a cross-sectional analysis of the zombie phenomena. While the average asset-weighted zombie share over the sample period from 1975 to 2018 is roughly 10%, the time trend is negative. In line with existing research, comparing summary statistics between zombies and healthy firms reveals that zombies are smaller, more levered, and suffer from lower profitability. The average zombie firm is classified as such for two years before recovering or exiting the sample. However, almost 40% relapse and become a zombie again later in the sample period. To recover, zombie firms reduce their investment and lower their debt burden. Investigating the heterogeneity across industries, I find that Wholesale, Retail Trade, and Construction mostly suffer from high zombie shares, especially later in the sample period. Geographically, there emerges no clear pattern apart from the observation that the zombie phenomena do not affect all states simultaneously and that different regions are affected differently over time.

Second, I describe how zombie firms in the US raise capital. Starting with an analysis of the capital structure, I document that zombie firms rely more on debt and less on equity, however, in terms of financing, the opposite is true. While the overall financing cash flow is smaller for zombie firms, they still raise equity, possibly to reduce their debt burden. Using DealScan data on loans, my results suggest that zombie firms receive smaller loans and do not rely on bank syndicates as often as their healthy peers. Meanwhile, many other loan characteristics do not differ between the two groups. Conducting the same analysis for bond characteristics, I only find a negative effect of being a zombie on the offering yield and the likelihood of the bond being secured. Finally, I investigate SEOs but do not find significant differences in SEO characteristics between zombies and healthy firms. Across all three sources of capital, I find that zombie firms raise more outside capital during crises.

By providing descriptive evidence on zombie firms in the US, my paper contributes to the literature that tries to describe those firms, e.g. Banerjee and Hofmann (2018, 2022) and De Martiis et al. (2022). I also extend the knowledge about zombie firms in the context of financial policies, therefore adding to the vast literature about said policies, e.g. Lemmon and Roberts (2008), Leary and Roberts (2014), and Grennan (2019).

Even though this paper can provide additional insights on zombie firms in the US similar to Favara et al. (2021), the results, especially the ones in section 1.5, need to be interpreted with caution as I only report conditional correlations. To provide causal results, one needs exogenous variation in either the zombie share or the options for outside financing. As mentioned in section 1.3.2, other zombie identification approaches exist. It remains an open question as to which is the correct one and if my results would be affected when using another identification method. Lastly, the capital structure and financing policies analysis might differ between European and Anglo-Saxon countries since those typically differ in the relative importance of private and public financing, e.g., Öztekin (2015). Therefore, my results can not necessarily be generalized for zombie firms outside the US.

1.A Zombie Shares across the literature

Table 1.18 summarises the estimated zombie shares in the literature over time. In Japan, they range between 2% (4%) and 16% (35%) if one considers the asset-weighted (absolute) fraction of zombie firms. In comparison, the average absolute zombie shares in the OECD countries fluctuate over time between 0.5% and 6%. The asset-weighted share in Europe ranges between 2% and 12%. Different studies find that especially the southern European countries are more affected by zombie firms, e.g. Acharya et al. (2019) and Schivardi et al. (2017). The numbers may seem small, but if one multiplies the percentage numbers by the respective country-level aggregates, the true extent of the zombie infestation is revealed. For example, the numbers provided by Caballero et al. (2008) translate to USD 150 billion of capital sunk in zombie firms in 2002.

The table also shows that comparing zombie shares across studies is challenging. First, the scope of the sample may vary with respect to the firm's legal status, i.e. are only public, private, or both firms considered, and the time range. Second and more important, different identification strategies exist to identify the zombie firms, which vary from study to study.[26] Those strategies may be broadly divided into two groups. On the one hand, the identification may be based on a negative interest rate gap. This gap is the difference between hypothetical and effective interest expenses in any given year. Different proxies for the hypothetical interest expenses are used, however, they all have in common that they rely on extremely favorable interest rates, which may be only granted to the most creditworthy firms in an economy under normal circumstances. The other group of criteria uses the interest coverage ratio (ICR), i.e. the relation of interest expenses to operating profit, to identify the zombies. Both criteria may be extended by additional criteria such as age, credit rating, and/or existing banking relationships.

26. Even the same authors may adjust their identification methods from paper to paper. See for example Banerjee and Hofmann (2018) and Banerjee and Hofmann (2022) or Acharya et al. (2019) and Acharya et al. (2020).

Table 1.18: Estimated zombie shares according to the current state of the literature

Paper	Country	Time range	Estimated zombie share
Hoshi (2006)	Japan	1981 - 2002	between 5% at the beginning and 35% at the end of all public firms (absolute)
Caballero et al. (2008)	Japan	1980 - 2002	between 2% at the beginning and 16% (in 1994) of all public firms (asset-weighted)
Fukuda and Nakamura (2011)	Japan	1995 - 2004	between 4% and 11% of all firms public (absolute)
Imai (2016)	Japan	1999 - 2008	between 4% and 13% of all SME (absolute)
McGowan et al. (2017b)	8 OECD countries	2003 - 2013	between 3% and 5% of all firms (absolute, cross-country average)
Schivardi et al. (2017)	Italy	2004 - 2013	between 14% and 18.5% of all firms (absolute)
Banerjee and Hofmann (2018)	14 OECD countries	1985 - 2017	between 0.5% and 6% of all public firms (absolute, cross-country average)
Acharya et al. (2019)	Europe	2009 - 2014	between 2% and 12% of all firms (asset-weighted, cross-country average)
Banerjee and Hofmann (2022)	14 ad. economies	1980 - 2017	between 4% and 16% of all public firms (absolute, cross-country average)
Acharya et al. (2020)	Europe	2009 - 2016	between 4.5% and 6.5% of all firms (asset-weighted, cross-country average)
De Martiis et al. (2022)	World	1996 - 2020	between 0% and 16% of listed firms (asset-weighted)
Favara et al. (2021)	US	2015 - 2019	10% of listed and 5% of private firms (absolute)

The table summarises the current estimates of zombie shares in the literature.

1.B Variable Definition

Table 1.19: Variable construction

Variable	Description	Calculation
	Compustat	
Size	Log of sales	ln(sale)
Tangibility	Net PPE/Book Assets	ppent/at
Profitability	EBITDA/Book Assets	oibdp/at
Profit Rate	Profit/Book Assets	ni/at
Neg. Profit Dummy	=1, if neg. profit	
Total Debt	Short-Term Debt + Long-Term Debt	dltt + dlc
Book Leverage	Total Debt/Book Assets	(dltt + dlc)/at
Market Capitalization	Share price (fiscal year ending) * Shares outstanding	prcc_f*csho
Market Leverage	Total Debt/Market Value of Assets	(dltt + dlc)/mv
Tobin's q	Market Value of Assets/Book Assets	(at-ceq+prcc_f*csho)/at
Altman (1968) Z-Score		(3.3 * pi + sale + 1.4 * re + 1.2*(act-lct))/at
Dividend Dummy	=1, if Dividend payments were made	
Sales, General, and Administrative Expenses	Sales, General, and Administrative Expenses/Sales	xsga/sale
Research and Development Expenses	Research and Development Expenses/Sales	xrd/sale
Working Capital	(Current assets - current liabilities)/total assets	(act-lct)/at
Capital Investments	Capital Expenditures/Total assets$_{t-1}$	capx/at$_{t-1}$
Interest Coverage Ratio	EBIT/Interest Expenses	oiadp/xint
Short-term debt	Short-term debt/total assets	dlc/at
Long-term debt	Long-term debt/total assets	dltt/at
Short- to long-term debt	Short-term debt/Long-term debt	dlc/dltt
Total common equity	Total common equity/total assets	ceq/at
Stockholders equity	Stockholders equity/total assets	teq/at
Equity stock	Equity stock/total assets	cstk/at
Retained earnings	Retained earnings/total assets	re/at
Treasury stock	Treasury stock/total assets	tstk/at
Financing CF	Financing CF/total assets$_{t-1}$	fincf/at$_{t-1}$
Delta debt	Change in total debt/total assets$_{t-1}$	(dlc + dltt - dlc$_{t-1}$ - dltt$_{t-1}$) /at$_{t-1}$
Short-term debt issue	Changes in current debt/total assets$_{t-1}$	dlcch /at$_{t-1}$
Short-term debt issue dummy	=1, if st debt issue is greater than 5%	
Long-term debt issue	(Long-term debt issuance - reduction)/total assets$_{t-1}$	(dltis - dltr) /at$_{t-1}$
Long-term debt issue dummy	=1, if lt debt issue is greater than 5%	
Equity issues (gross)	Sale of common stock/total assets$_{t-1}$	sstk/at$_{t-1}$
Equity issues (gross) dummy	=1, if equity issues (gross) is greater than 5%	
Equity issues (net)	Sale of common stock - dividends - share repurchases)/total assets$_{t-1}$	(sstk-dvc-dvp-prstkc)/at$_{t-1}$
Equity issues (net) dummy	=1, if equity issues (net) is greater than 5%	
Debt-to-equity change (gross)	Short- and long-term debt issue/equity issues (gross)	(dltis + dlcch)/sstk
Debt-to-equity change (net)	Short- and long-term debt issue/equity issues (net)	(dltis + dlcch)/(sstk-dvc-dvp-prstkc)
	DealScan	
All-in-drawn	interest spread over base rate	
Fixed rate dummy	=1, if base rate is a fixed rate	
Seniority dummy	=1, if seniority is senior	
Security dummy	=1, if facility is secured	
No. of managers	number of lenders for one facility	
One manager dummy	=1, if no. of managers is one	
	Mergent FISD	
Security dummy	=1, if security level is SS or SEN	
Convertible dummy	=1, if bond is convertible	
	SDC Platinum and CRSP	
Underpricing	(StockPriceatCloseofOffer1-OfferPrice)/OfferPrice	
Underpricing dummy	=1, if SEO is underpriced	
Discount	-100*(OfferPrice - prc$_{t-1}$)/prc$_{t-1}$	
Discount dummy	=1, if SEO was offered at a discount	
Volume	Average volume/shrout, where the average is over 250 days before the offer date	
Volatility	Volatility of prc over 30 days before the offer date	

Definitions mainly follow Leary and Roberts (2014). Other sources for variable definitions are indicated in the respective section.

1.C Summary statistics

Table 1.20: Summary statistics

	N	Mean	Median	SD	Min	Max
Ln(total assets)	177,253	4.820	4.809	2.398	-1.617	10.389
Size	171,977	4.826	4.981	2.570	-2.476	10.238
Ln(market cap)	177,253	4.711	4.590	2.338	-0.529	10.450
Ln(employment)	169,275	-0.432	-0.357	2.379	-6.215	4.736
Employees	171,200	5.925	0.680	16.258	0.000	113.400
Negative profit	177,252	0.384	0.000	0.486	0.000	1.000
Profitability	176,867	-0.084	0.103	0.784	-5.750	0.406
Profitrate	177,252	-0.232	0.026	1.059	-8.131	0.296
Tangibility	177,013	0.285	0.225	0.234	0.000	0.908
Tobin's q	177,253	3.080	1.429	6.941	0.552	56.081
Book Leverage	177,253	0.270	0.222	0.251	0.000	1.000
SG&A Expenses	171,977	0.485	0.221	1.235	0.000	9.771
R&D Expenses	171,977	0.237	0.000	1.181	0.000	9.658
CAPEX to total assets	171,445	0.082	0.044	0.119	0.000	0.763
Interest Coverage Ratio	177,252	40.554	2.969	1,037.904	-136,848.000	121,212.000
Altmans (1968) Z-Score	171,164	1.140	2.993	21.244	-152.686	55.167
Dividend Dummy	177,253	0.319	0.000	0.466	0.000	1.000
Short-term debt	177,253	0.105	0.021	0.304	0.000	2.381
Long-term debt	177,253	0.191	0.132	0.217	0.000	1.110
ST to LT debt	142,331	2.483	0.170	10.531	0.000	82.750
Equity (ceq)	177,253	0.267	0.470	1.207	-9.063	0.953
Equity (teq)	52,632	-0.210	0.471	3.874	-31.438	0.958
Equity stock	175,509	0.123	0.007	0.471	0.000	3.592
Retained earnings	175,396	-2.222	0.080	10.631	-84.710	0.833
Treasury stock	164,589	0.034	0.000	0.105	0.000	0.690
Total financing CF	126,079	0.351	0.005	1.337	-0.302	10.249
Debt change	172,995	0.046	0.000	0.290	-0.665	1.818
ST Debt issues (net)	77,924	0.029	0.000	0.227	-0.406	1.809
ST Debt issues dummy (net)	177,253	0.621	1.000	0.485	0.000	1.000
LT Debt issues (net)	164,471	0.035	0.000	0.186	-0.337	1.166
LT Debt issues dummy (net)	177,253	0.264	0.000	0.441	0.000	1.000
Equity issues (gross)	169,728	0.205	0.003	0.755	0.000	5.563
Equity issues dummy (gross)	177,253	0.202	0.000	0.401	0.000	1.000
Equity issues (net)	159,952	0.150	0.000	0.660	-0.243	4.856
Equity issues dummy (net)	177,253	0.160	0.000	0.367	0.000	1.000
DtoE change (gross)	54,745	53.444	0.057	246.008	-119.199	1,968.000
DtoE change (net)	59,378	2.039	0.000	53.272	-255.000	338.940

The sample consists of all firm-year observations between 1975 and 2018 for nonfinancial, nonutility, and non-governmental US firms from the Compustat universe. Variables are constructed as described in table 1.19 in the appendix and then, apart from book and market leverage, winsorized at the 1%- and 99%-level. If book or market leverage is below 0 (above 1), the respective observation is replaced with the 0 (1) value.

Chapter 2

How does Competition affect Zombie Firms?

Abstract

This paper analyzes the effects of product market competition on zombie firms in the US using a large sample of publicly traded firms. First, we show that the asset-weighted share of zombie firms at the industry level decreases significantly with more competition. This decrease is mostly pronounced in industries characterized by a low concentration and low margins. Second, neither the exit or default probability, nor the recovery likelihood are significantly affected by changes in competition. Third, at the firm level, zombie firms grow more slowly, reduce their assets and cash holdings, issue less equity, and obtain smaller loans. These findings suggest that zombie firms adapt to higher competition by scaling down the size of the firm.

2.1 Introduction

The existence of insolvent borrowers that are kept alive by subsidized credit, also known as zombie firms, has negative consequences for the economy because of potential negative spillovers on healthy firms. Specifically, existing research demonstrates that zombie firms may distort competition by increasing entry barriers and by distorting prices in product and labor markets (Caballero et al.,

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2008; Acharya et al., 2019; Schivardi et al., 2020, 2021). While the effect of zombie firms on the competitive environment has received considerable attention, little is known about how abrupt changes in competition affect zombie firms themselves. In this paper, we aim to fill this gap by investigating how increased import competition from China affects the existence of zombie firms in the US and how it shapes their financial policies.

The effect of higher product market competition on zombie firms is a priori not clear. On the one hand, more competition reduces average mark-ups in an industry and thus lowers the profitability of firms (e.g., Edmond et al. (2015) and Acharya et al. (2019)). This, in turn, can increase the likelihood that firms become zombies. Hence, more competition can lead to a higher number of zombie firms. On the other hand, more competition can also force zombie firms to either exit the industry or, because of induced efficiency gains, recover from their zombie status. Thus, more competition can also reduce the number of zombie firms in an industry.

Identifying the effect of competition on zombie firms is empirically challenging due to endogeneity concerns. In this paper, we aim at overcoming these concerns by employing the instrumental variable proposed and used by Autor et al. (2019). This approach uses imports from China to eight wealthy countries as an instrument for imports from China to the US. It allows investigating how changes in competition affect the share of zombie firms at the industry level, the recovery and exit probabilities of zombie firms, and their financial choices compared to those of their healthy peers.

We provide evidence on the relation between competition and zombie firms using a large sample of publicly traded US firms operating in manufacturing industries covering the years 1991 to 2014. Following existing literature, we define import penetration as the fraction of imports to total domestic production plus net imports. We use data on imports from Peter Schott, data on US domestic production from the NBER-CES Manufacturing Industry database, and data to calculate the instrumental variable from Autor et al. (2019). Our final sample consists of 5,807 firms, out of which 2,225 are classified as a zombie at least once during our sample period. We identify zombie firms following Acharya et al. (2019). Specifically, in any given year, a firm is classified as a zombie if its interest rate gap is negative, its book leverage is above the industry median, and its Interest Coverage Ratio (ICR), defined as EBIT over interest expenses, is below the industry median. At the industry level, we observe that the equal- and the asset-weighted zombie shares decrease over time, ranging between 5% and 15% (equal-weighted) and between 8% and 20% (asset-weighted), respectively (see, Figure 2.1).

The empirical analysis proceeds in two steps. First, we estimate regressions at the industry level to examine the effect of product market competition on the share of zombie firms. Our results show that a one standard deviation increase in competition reduces the asset-weighted zombie share by 11 percentage points on average. By exploiting the cross-sectional variation in competition across industries, we further show that the effect is less pronounced in concentrated industries, and that the change in import penetration needs to be sufficiently high (above the median) to significantly affect the share of zombie firms.

Second, we turn to firm-level estimations to understand how competition affects zombie firms' exit, recovery, and firms' financial choices. We estimate regressions of exit and recovery indicator variables as well as total assets on imports from China, a zombie indicator variable, and an interaction of these two variables. We find that neither the exit or default probability, nor the recovery likelihood are significantly affected by changes in competition. However, our results show that competition has a negative effect on the asset size of zombie firms. The effect is statistically and economically significant. A one standard deviation increase in competition reduces the size of total assets by almost 3%. This decrease in the size of zombie firms appears to be responsible for the observed decline in the share of zombie firms at the industry level. We further observe that zombie firms grow significantly slower compared to non-zombie firms.

Finally, we investigate how zombie firms adjust their financial policy choices when exposed to higher competition to accommodate the smaller asset size. One financial position that firms can easily adjust is liquid assets. Indeed, we find that relative to non-zombie firms, zombie firms reduce their cash-to-asset ratio significantly with higher competition. We also demonstrate that zombie firms issue significantly smaller amounts of equity and obtain smaller bank loans when they are exposed to higher competition. Collectively, these results are consistent with our evidence that zombie firms are negatively affected by higher foreign competition. They grow more slowly, reduce their holdings of liquid assets, issue smaller amounts of equity, and obtain smaller loans compared to non-zombies.

Altogether, this paper contributes to the literature in several ways. First, it contributes to the literature on zombie firms (see, for instance, Hoshi (2006), Caballero et al. (2008), Acharya et al. (2019), Schivardi et al. (2020), Banerjee and Hofmann (2018, 2022), and Favara et al. (2022)) by empirically examining the zombie phenomenon in the US and specifically the effects of product market competition on zombie firms. Specifically, we show that abrupt changes in competition have significant effects on the share of zombie firms at the industry level and affect financial choices at the firm level. Second, we contribute to the literature examining product market competition and default risk (see, for example, Valta (2012a), Xu (2012), and Chen et al. (2019)), by showing that increased competition does not increase the exit or default probabilities of zombie firms. Finally, we add to the literature investigating firms' financing choices, e.g. Begenau and Salomao (2019), and more specifically the financial policies of zombie firms, e.g. Giannetti and Simonov (2013), by studying how zombie firms react to the increased foreign competition in terms of their equity and debt financing, asset growth, and cash management decisions.

The rest of the paper proceeds as follows. In Section 2.2, we discuss the theoretical background of the relation between zombie firms and the intensity of competition and derive two testable hypotheses. In Section 2.3, we describe the construction of the sample and how we identify zombie firms. In Section 2.4, we explain our empirical strategy and present the empirical results of the effect of competition on zombie firms at the industry level. To gain insights on whether and how zombie firms react to the shocks in competition, we study firm level financing policies in Section 2.5. Section 2.6 concludes.

2.2 The relation between competition and zombie firms

Caballero et al. (2008) show that the existence of zombie firms increases entry barriers and distorts competition in product and input markets. While the effect of zombie firms on product market structure has been analyzed in earlier studies, e.g. Hoshi (2006) and Acharya et al. (2019), the reverse relationship has received little attention. However, abrupt changes in the competitive structure of industries can trigger firm exit and entry, and affect firms along many different dimensions. Our focus lies on two competing hypotheses that describe the effects of competition on zombie firms.

First, existing research shows that an increase in product market competition is associated with lower mark-ups (Bustamante and Donangelo, 2017; Dasgupta et al., 2018), higher cash-flow volatility (Irvine and Pontiff, 2009), higher credit risk (Huang and Lee, 2013), and a higher cost of debt (Valta, 2012a), among others. Through these channels, higher competition is likely to be associated with more zombie firms, with more assets held by zombie firms, and more generally with a higher share of zombie firms at the industry level. We call this view the *contaminating* hypothesis.

Second, lower margins, higher cash flow volatility, and higher costs of capital could also make it more likely for existing zombie firms to finally exit the market. The mechanism at play relates to the process of Schumpeterian creative destruction, a restructuring and factor allocation directed towards more productive and efficient uses (Caballero and Hammour, 2000; Caballero et al., 2008). That is, higher competition could lead to more firm exits and smaller amounts of assets managed by zombie firms. Simultaneously, more competition is associated with lower levels of leverage (Xu, 2012), sales growth and profitability (Hombert and Matray, 2018), and represents a substitute for corporate governance (Giroud and

Mueller, 2011). Thus, through these channels, zombie firms could become more efficient with more competition (McGowan et al., 2018; Banerjee and Hofmann, 2022), implying a negative relation between competition and the share of zombie firms. We refer to this view as the *cleansing* hypothesis.

In the following sections, we take these hypotheses to the data and analyze the effects of competition on zombie firms both at the industry and firm level.

2.3 Data and descriptive statistics

2.3.1 Data

The starting point for our sample is the CRSP/Compustat merged database. We drop all firm-year duplicates and exclude observations with either missing or negative total assets, sales, and equity. Additionally, we drop observations with missing information on interest expenses, short- or long-term debt, and operating income before interest and taxes. We restrict the sample to firms incorporated in the US and exclude firms with headquarters in territories outside of the US. We merge these data for each 3-digit SIC code industry and year with data on US imports and exports from Schott (2008), data on US domestic production provided by the NBER-CES Manufacturing Industry database, and import data from Autor et al. (2019).[1] This narrows down the final sample to manufacturing firms (four-digit SIC codes 2000-3999) over the years from 1991 to 2014. The sample contains over 50'000 firm-year observations from 5'807 distinct firms operating in 116 three-digit SIC manufacturing industries. Next, we deflate all USD denominated variables to USD 2012 values using the GDP deflator from the FRED database and construct the variables for our analysis. Table 2.12 in appendix 2.B contains a description of the variables that we use in the analysis. We winsorize all variables at the 1%- and 99%-level with the exception of leverage, which is bounded between zero and one.

2.3.2 Measuring zombie firms

Following Caballero et al. (2008), Acharya et al. (2019) and Acharya et al. (2020), we define a zombie firm as a low-quality firm that receives subsidized credit at advantageous interest rates. In line with this definition, Caballero et al. (2008) classify a firm as a zombie if it receives subsidized credit. To do so, the actual interest payment made by the firms, R_{it}, is compared to an estimated benchmark,

1. The import-export data is available on Peter Schott's website. We thank Peter Schott and Robert Feenstra for making their trade data publicly available. The data on US HS-level imports and exports (1989-2018) was first used in Schott (2008). We also thank David Dorn for making their data available on his webpage.

R^*_{it}, based on the firm's actual debt structure and an advantageous interest rate expected to be paid by the highest quality borrowers.[2] The difference between the effective interest expenses and the estimated benchmark, $R_{it} - R^*_{it}$, is referred to as the interest rate gap, x_{it}. Firms with a negative x_{it} are expected to receive subsidized credit by their banking counterparts and are categorized as zombie firms.

The obstacle with this approach is that the interest rate data used by Caballero et al. (2008) is not available for the US. We therefore rely on the more recent identification approach by Acharya et al. (2019), which uses the actual interest paid by high-quality (AAA-rated) borrowers as the benchmark and complements the resulting interest rate gap with firms' ratings and operating characteristics to distinguish between zombie and healthy firms. Specifically, a firm is categorized as a zombie if it meets two criteria: *(i)* it has an interest coverage ratio below the median and a leverage ratio above the median (both medians are computed at industry-year level); *(ii)* it obtains credit at very low rates, precisely at a rate below that paid by AAA-rated[3] borrowers with similar debt structure in any given industry-year.

To keep track of the zombie status, we define the dummy variable Z_{it} equal to one if firm i is classified as a zombie in year t, and zero otherwise. Since we are interested in competition, which is typically measured at the industry level, we need to aggregate the zombie status at this level. To do so, we calculate the asset-weighted zombie share as follows:

$$AZ_{jt} = \frac{\sum_N Z_{it} \times at_{it}}{\sum_N at_{it}}, \tag{2.2}$$

2. As from Caballero et al. (2008), R^*_{it}, for firm i in year t, is defined as:

$$R^*_{it} = rs_{t-1}BS_{it-1} + \left(\frac{1}{5}\sum_{j=1}^{5} rl_{t-j}\right)BL_{it-1} + rcb_{\text{min over last 5 years, t}} \times Bonds_{it-1}, \tag{2.1}$$

where BS_{it}, BL_{it}, and $Bonds_{it}$ represent short-term loans, long-term bank loans, and total bonds outstanding (including convertible bonds and warrant-attached bonds), respectively, for firm i at end of year t; while rs_t, rl_t, and $rcb_{\text{min over the last 5 years, t}}$ represent the average short-term prime rate in year t, the average long-term prime rate in year t, and the minimum coupon rate on any convertible corporate bond issued in the last 5 years before t.

3. In addition to S&P credit ratings from Compustat daily updates, we use Aswath Damodaran "synthetic" rating from his website: https://pages.stern.nyu.edu/~adamodar/New_Home_Page/datafile/ratings.htm. The empirical results are not sensible to using either ratings. In the final dataset we rely on the S&P credit ratings whenever available, otherwise the synthetic rating.

where N is the total number of firms i in industry j at time t and at is the total book value of assets. Additionally, we also calculate an equally-weighted zombie share for which we divide the number of zombies in a given industry by the total number of firms in the same industry for each year. Figure 2.1 shows the evolution of asset-weighted and equally-weighted US zombie shares in the manufacturing industries from 1991 to 2014. The asset-weighted share of zombie firms in our sample decreased from 17% at the beginning of the period to roughly 10% in 2014. These numbers are plausible and in line with the study of Favara et al. (2022), even though their data exhibits more fluctuation and a less pronounced downward trend. This may, however, be due to the different zombie classification methods they apply or the fact that they also consider private firms, whereas our sample is limited to firms reporting to the SEC. Comparing Figure a) to Figure b), we conclude that zombie firms appear to be larger, or at least similar, to the average firm in terms of assets.

Figure 2.1: Zombie shares 1990 - 2014

Panel a) shows the unweighted zombie shares over time. Panel b) shows the asset-weighted zombie shares over time. The sample covers manufacturing firms from 1991 until 2014. The data sources and the cleaning are described in section 2.3.1. Zombie firms are defined as in Acharya et al. (2019), more details on the identification process are provided in section 2.3.2.

Given that our most relevant competition measures are only available for manufacturing industries, our analysis is restricted to this set of industries. We acknowledge that this may raise concerns of external validity. Nevertheless, Favara et al. (2022) show that manufacturing industries have the highest number of publicly listed zombie firms in the United States. Therefore, our study focuses exactly on these industries where the zombie phenomenon is mostly pronounced, thus covering a large percentage of zombie firms in the US market.

2.3.3 Measuring product market competition

We use three different proxies for product market competition, all defined at the three-digit SIC level. First, we rely on the Herfindahl-Hirschman Index (HHI), which we calculate using firm sales from Compustat as in Giroud and Mueller (2010). The HHI ranges from 0, i.e., perfectly competitive markets, to 1, i.e., monopoly, and is therefore easy to interpret. Hence, it is widely used to study the relation between competition and firm behavior (Frésard, 2010; Giroud and Mueller, 2010; Valta, 2012a; Xu, 2012; Frésard and Valta, 2015; Covarrubias et al., 2020). However, the HHI neglects foreign competition. According to recent studies, foreign firms have significantly affected the product markets in the US throughout our sample period (Feenstra et al., 2002; Irvine and Pontiff, 2009; Cuñat and Guadalupe, 2009; Acemoglu et al., 2016; Pierce and Schott, 2018; Autor, Dorn, Hanson, Pisano, et al., 2020).

To capture this additional competition, we follow Schott (2008) and use import penetration as second proxy measure for product market competition. In our case, import penetration is defined by the value of imports divided by domestic production plus net imports. Even though this measure allows us to capture foreign competition, it does not address potential endogeneity concerns. Foreign firms will decide whether or not to enter a given product market in the US based on the characteristics of this market, especially domestic competition. As pointed out by Xu (2012), import penetration might also be endogenous with respect to important firm-level variables such as leverage or profitability, which are used to classify zombie firms. To mitigate these endogeneity concerns, we make use of the 2-SLS approach introduced by Autor et al. (2013). They use imports from China to eight developed countries as instrument for imports from China to the US.[4] The idea is to capture the variation in imports from China to the US that solely arises from cost and productivity shocks in China and is thus uncorrelated with industry characteristics in the US. We use the data provided by Autor et al. (2019) on imports from China, which the authors originally scale by the labor force. Since we are interested in industry and firm outcomes, mainly driven by firms' policy choices, we deviate from this approach and scale by total US domestic production plus net imports, similarly to Acemoglu et al. (2016). In line with Autor et al. (2019), we use data from the beginning of the sample period, i.e., 1991, to mitigate potential endogeneity concerns arising from the effects of foreign competition on domestic production.

Figure 2.2 plots the time trend of the described proxies for product market competition and the asset-weighted zombie share. The domestic competition, i.e., 1-HHI, decreases over the sample period from an industry average of 0.26

4. The countries are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland.

in 1991 to 0.33 in 2014. This positive correlation with the zombie share implies that with less domestic competition the number of zombie firms, or their size, decreases on average. However, we face the endogeneity issues already described and neglect foreign competition, which increases substantially during the sample period. The import penetration more than doubles between the beginning and the end of our sample. The increase with respect to China is even more extreme. While in 1991 imports from this single country accounted for less than 0.01% of the domestic production, the fraction rose steadily to 0.04% in 2000. One year later, China joined the WTO and the size of imports increased exponentially amounting to 0.18% of total 1991 US domestic production in 2014. From Figure 2.2 we therefore conclude that: *i*) domestic competition does not capture all relevant product market competition, *ii*) the decrease in domestic competition is offset by a strong increase in foreign competition, and *iii*) both measures of foreign competition are negatively correlated with the asset-weighted zombie share. We interpret these descriptive results as a first indication in support of the *cleansing* hypothesis.

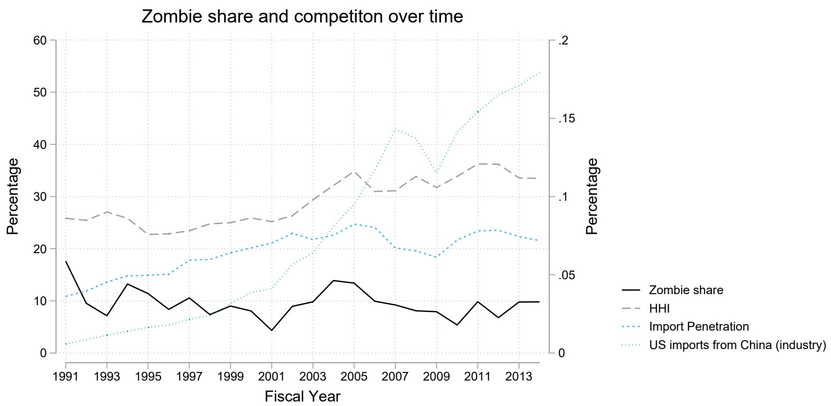

Figure 2.2: Share of Zombie Firms and different proxies for product market competition

This Figure plots the asset-weighted share of US zombie firms from 1990 to 2014 (solid black line) together with three different proxies for product market competition on the 3-digit SIC level. The HHI (dashed grey line) is calculated based on Compustat sales, the import penetration (dashed blue line) is calculated as imports divided by domestic production plus imports minus exports with data from Schott (2008), and import data from China to the US (dotted green line) is from Autor et al. (2019) and scaled by total domestic production plus net imports in 1991. The sample covers manufacturing firms from 1991 until 2014. The data sources and the cleaning are described in section 2.3.1. Nominal values are deflated to 2012 USD. Zombie firms are defined as in Acharya et al. (2019), more details on the identification process are provided in section 2.3.2.

2.3.4 Summary statistics

Panel A of Table 2.1 presents the descriptive statistics for firm-level variables. As most of the variables are commonly used in corporate finance research, we do not describe them in detail but rather note the similarities to studies that use a related dataset, such as Valta (2012a), Xu (2012), Dhaliwal et al. (2014), Hombert and Matray (2018), and Dasgupta et al. (2018), as well as studies that rely on all firms in the Compustat universe (Frank and Goyal, 2009; Leary and Roberts, 2014). Across the whole sample, there are on average 9.3% of firms classified as a zombie each year. This average is consistent with Figure 2.1. The four indicator variables, Exit, Default, M&A, and Recovery are created based on the Compustat item "Reason for deletion" ($DLRSN$). The *Exit* indicator equals one for the last observation of a firm whenever there is non-missing information for this variable and the deletion date is prior to June 2014. In our dataset, 6.8% of the observations match these criteria. The $Default$ indicator equals one if $DLRSN$ is 2 or 3, i.e., bankruptcy or liquidation, and zero otherwise. The $M\&A$ indicator equals one when $DLRSN$ is 4. Finally, the *Recovery* indicator captures observations where a firm is no longer classified as a zombie after having been a zombie in earlier years.

Panel B of Table 2.1 presents industry-level summary statistics for the asset-weighted zombie share and the proxies for product market competition. The HHI shows a sample median of 26.32 and a standard deviation of 26.00, values similar to those reported in Giroud and Mueller (2010) and Guadalupe and Wulf (2010). *Import penetration* has an average value of 19.88%, a median value of 11.54%, and a standard deviation of 23.66%. Both the HHI and import penetration are similar to the statistics reported in previous studies (Valta, 2012a; Xu, 2012). $Imports\ China\ to\ US$ and $Imports\ China\ to\ Other$, show similar statistics in terms of median values, 0.009 and 0.011% respectively, while the mean value for China's imports to the US is a bit larger (0.060%) than imports from China to the eight other high-income countries (0.050%).

2.4 Product market competition and zombie firms

In this section, we present and discuss the main results of the effect of product market competition on the share of zombie firms at the industry level. According to Figure 2.2, the asset-weighted zombie share is positively correlated with domestic competition, but negatively correlated with the two proxies of foreign

Table 2.1: Summary Statistics

	N	Min	P25	P50	Mean	P75	Max	SD
				Panel A: firm level variables				
Interest Coverage Ratio	44,588	-544.742	-2.286	3.116	1.638	11.294	569.828	135.464
Book Leverage	50,051	0.000	0.016	0.156	0.194	0.316	0.953	0.186
Market-to-Book Ratio	46,239	0.529	1.121	1.578	2.364	2.556	14.072	2.329
Cash Flow to Assets	45,347	-1.126	-0.030	0.065	-0.015	0.118	0.393	0.273
Log(Total Assets)	50,051	0.073	3.368	4.824	4.971	6.515	10.371	2.231
Tangibility	50,029	0.001	0.084	0.180	0.221	0.316	0.919	0.175
Asset growth	45,596	-0.535	-0.069	0.032	0.160	0.183	3.289	0.556
Cash Holdings	50,050	0.000	0.027	0.113	0.224	0.335	0.925	0.258
Equity issues (gross)	44,752	0.000	0.000	0.005	0.139	0.029	2.394	0.410
Equity issues (net)	40,830	-0.219	-0.018	0.000	0.088	0.012	2.128	0.360
Equity issues dummy (gross)	50,073	0.000	0.000	0.000	0.184	0.000	1.000	0.387
Equity issues dummy (net)	50,073	0.000	0.000	0.000	0.135	0.000	1.000	0.341
Zombie Dummy	50,073	0.000	0.000	0.000	0.093	0.000	1.000	0.291
Exit Dummy	50,073	0.000	0.000	0.000	0.068	0.000	1.000	0.252
Acquisition or merger	50,073	0.000	0.000	0.000	0.039	0.000	1.000	0.193
Default Dummy	50,073	0.000	0.000	0.000	0.003	0.000	1.000	0.057
Recovery Dummy	29,997	0.000	0.000	0.000	0.090	0.000	1.000	0.286
				Panel B: industry level variables				
Asset-weighted zombie share	2,573	0.000	0.000	0.000	10.769	8.491	100.000	22.354
HHI	2,573	3.150	16.321	26.320	35.133	45.818	100.000	25.995
Import Penetration	2,573	0.001	4.370	11.538	19.880	24.520	100.000	23.662
Imports China to US	2,551	0.000	0.001	0.009	0.060	0.039	2.402	0.179
Imports China to Others	2,551	0.000	0.002	0.011	0.050	0.039	1.469	0.127

Panel A shows summary statistics at the firm-year level, whereas Panel B shows summary statistics for variables at the three-digit SIC industry level. The sample covers manufacturing firms from 1991 to 2014. The data sources are described in section 2.3.1. Table 2.12 in the Appendix contains definitions of all variables. Nominal values are deflated to 2012 USD. Zombie firms are defined as in Acharya et al. (2019). More details on the identification process are provided in section 2.3.2.

competition. We take this descriptive analysis a step further and estimate the following regression model:

$$ZombieShare_{j,t} = \alpha + \beta Competition_{j,t-1} + \gamma' X_{j,t-1} + \mu_t + \nu_j + \epsilon_{j,t}, \qquad (2.3)$$

Subscripts j and t represent industry and year, respectively. The dependent variable, $ZombieShare_{j,t}$, is the asset-weighted share of zombie firms. Our main interest lies in examining the marginal effect of competition on the zombie share (β). The vector $X_{j,t-1}$ includes industry-year averages of firm-level variables that are known to have an effect on the likelihood of becoming a zombie firm (market-to-book ratio, cash flow-to-assets ratio, firm size, book leverage, and tangibility).[5] To account for time-invariant industry-specific effects, we include industry fixed effects (ν_j) at the three-digit SIC industry-level. We capture time-specific shocks, e.g. demand shocks, by including year fixed effects (μ_t). We calculate standard errors adjusted for heteroskedasticity and within three-digit SIC industry clustering.

In column 1 of Table 2.2, the HHI is unrelated to the share of zombie firms. Once we add the control variables in column 2, the relation becomes negative. That is, an increase in domestic competition is associated with an increase in the zombie share in the next year. However, for both specifications, the associations are not statistically significant. To account for foreign competition, we use import penetration in columns 3 and 4. The coefficient estimate of import penetration is negative and statistically significant in both columns (with and without control variables). In terms of economic magnitude, a one standard deviation increase of import penetration is associated with a 3.5 percentage points reduction of the asset-weighted zombie share. These results are in line with the *cleansing* hypothesis as well as the descriptive evidence from Figure 2.2.

Even tough import penetration accounts for foreign competition, it is likely to be affected by reverse causality. The choice of foreign firms to enter a given industry is affected by the structure of the industry itself, i.e., product market competition, and therefore also indirectly by the share of zombie firms. In fact, the model by Caballero et al. (2008) shows that higher barriers to entry due to more zombie firms affect the entry likelihood of new competitors. Additionally, import penetration might also be endogenous with respect to firm-level characteristics such as profitability, as shown by Xu (2012).

To address these endogeneity concerns, we rely on an established instrumental variable approach from the international trade literature (see, for instance, Autor et al. (2013)).

2.4.1 Instrumental variable approach

Following China's entry to the WTO in 2001, the US has seen an increase in imports from China of more than 1000% in real terms (see, Figure 2.2). This additional competition has significant consequences for the US economy. For example, for the domestic labor market (Autor et al., 2013; Acemoglu et al., 2016; Autor et al., 2019), the political polarization (Autor, Dorn, Hanson, and Majlesi,

5. The choice of control variables is consistent across all tables and motivated by the literature on zombie companies and firm performance in general (see, for instance, Hoshi (2006), McGowan et al. (2018), Acharya et al. (2019), and Banerjee and Hofmann (2022)).

Table 2.2: Product market competition and the share of zombie firms

	(1)	(2)	(3)	(4)
HHI	-0.0000	-0.0004		
	(0.001)	(0.001)		
Import Penetration			-0.0013*	-0.0012*
			(0.001)	(0.001)
Market-to-book		-0.0006		-0.0005
		(0.006)		(0.006)
Cash flow to assets		0.1744**		0.1646**
		(0.070)		(0.070)
Log assets		0.0027		0.0032
		(0.008)		(0.009)
Book Leverage		-0.2179**		-0.2079**
		(0.085)		(0.083)
Tangibility		-0.0596		-0.0600
		(0.110)		(0.108)
YearFE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	1,622	1,618	1,622	1,618
Adjusted R^2	0.160	0.173	0.163	0.175
F	0.001	2.903	3.224	3.290

The dependent variable in all columns is the asset-weighted zombie share. HHI is calculated based on Compustat sales and import penetration is imports divided by domestic production plus imports minus exports with data from Schott (2008).The sample covers manufacturing firms from 1991 to 2014. The data sources are described in section 2.3.1. Table 2.12 in the Appendix contains definitions of all variables. Nominal values are deflated to 2012 USD. Zombie firms are defined as in Acharya et al. (2019). More details on the identification process are provided in section 2.3.2. Standard errors of the OLS regressions are adjusted for heteroscedasticity and clustered at the three-digit SIC industry level, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

2020), mortality rates (Pierce and Schott, 2020), and the housing market (Xu et al., 2019). At the firm level, existing studies by Hombert and Matray (2018) and Autor, Dorn, Hanson, Pisano, et al. (2020) show that China's accession to the WTO had negative effects on firms' profitability, sales, and R&D expenditures.

Simply using imports from China to the US as a proxy for product market competition is not going to mitigate our endogeneity concerns since Chinese firms might decide whether or not to enter a product market based on industry structure or firm characteristics such as profitability (see, for instance, Hombert and Matray (2018)). In addition, imports from China to the US might be correlated with demand shocks in the US (Autor et al., 2013). Therefore, we follow Autor et al. (2013) and use imports from China to eight other developed countries as instrument in an IV analysis. Those countries are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland. We scale trade data with total US domestic production plus net imports in 1991 to ease interpretation.[6] The underlying idea behind this IV approach is to use only the effect arising from productivity and trade shocks in China to identify changes in competition in the US, i.e., to isolate the effect of higher competition from Chinese firms.[7] Empirical evidence by Brandt et al. (2017) suggests that Chinese firms indeed experienced a productivity shock after the trade liberalization.

The instrument has to satisfy the relevance and exclusion restrictions. The relevance condition requires that the instrument is sufficiently correlated with the endogenous variable, i.e., imports from China to the US. Using the data provided by Autor et al. (2013), we calculate an increase of imports from China to the US of 1451% in real terms, and of 1114% from China to the other eight countries over our sample period. Also, the correlation between exports from China to the US and to the other countries is 0.93 and statistically significant at the 1%-level. In column 3 of Panels A and B of Table 2.3, we present first-stage estimates of the 2-SLS approach (with and without controls). In both specifications, the adjusted R^2 is very high, suggesting that the variation of the endogenous variable is well explained by the variation of the instrumental variable. In addition, the F-Statistic has a value of about 50, which is well above the critical value of 10 (Stock and Yogo, 2005), reducing concerns of a weak instrument bias and further supporting the validity of the relevance condition.

The exclusion condition requires the instrument to affect the dependent variable only via the endogenous variable. In our setting, this implies that the imports from China to the other countries only affect the outcome variable, i.e., the share of zombie firms in the US, through its effects on the imports from China to the US. We believe that this condition is likely to be satisfied. In particular, recent studies show that the US zombie share follows a different trend compared to Europe and the rest of the world (see, e.g., De Martiis et al. (2022) and Favara et al. (2022)). Additionally, the same instrument has been widely used in the literature in order to establish causal results in settings which are similar to ours,

6. We also show in Table 2.11 that we obtain similar results when we use absolute values.

7. See, Bloom et al. (2016) for a similar identification strategy where the authors examine the impact of Chinese import competition on patenting, IT, and productivity in Europe.

e.g. Acemoglu et al. (2016), Autor et al. (2019), and Hombert and Matray (2018).

In columns 1 and 2 of Table 2.3, we show the endogenous and reduced form model, followed by the first and second stages of the 2-SLS model in columns 3 and 4. In Panel A, we do not include any control variables apart from the fixed effects, whereas in Panel B we control for the previously used determinants of zombie firms. Consistent with the results from Table 2.2, more competition in terms of imports from China to the US negatively correlates with the asset-weighted zombie share. In economic terms, a one standard deviation increase in import penetration from China to the US reduces the asset-weighted zombie share by 13 percentage points. In the reduced form model (column 2), we find almost the same effect in terms of statistical and economic significance as in column 1. Column 3 shows the results of the first stage, i.e., the estimates of the regression of the imports from China to the US on the imports from China to the other eight countries plus the fixed effects and the controls (in Panel B). The coefficient estimate is statistically significant and the F-Statistic is sufficiently large. Comparing Panel A to B, the control variables do not seem to matter much as neither the size of the effect, the statistical significance, nor the F-Statistic are affected by the inclusion of the additional variables. Finally, column 4 shows the estimates of the second stage. The results support our previous findings. An increase in the comparative advantage of Chinese firms translates into a statistically lower asset-weighted zombie share in the same industry in the US.[8] The results support the idea that more competition increases the pressure on all firms within an industry and forces them to become more efficient, i.e., the results favor the *cleansing* hypothesis.

In the next section, we use cross-sectional variation in industry structure to improve our understanding of the economic forces at play.

8. The negative effect is not due to our scaling approach as we show by using absolute values of imports in Table 2.11 in appendix 2.A.

Table 2.3: Foreign competition and the share of zombie firms

	Endogenous (1)	Reduced (2)	First Stage (3)	Second Stage (4)
	Panel A: without controls			
Imports China to US	-0.0727***			-0.0700**
	(0.026)			(0.029)
Imports China to Others		-0.0944**	1.3486***	
		(0.043)	(0.191)	
YearFE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	1,616	1,616	1,616	1,616
Adjusted R^2	0.163	0.163	0.942	0.003
F	7.638	4.926	49.970	5.878
	Panel B: with controls			
Imports China to US	-0.0685**			-0.0659**
	(0.027)			(0.029)
Imports China to Others		-0.0889**	1.3490***	
		(0.043)	(0.190)	
Market-to-book	-0.0022	-0.0018	-0.0042**	-0.0021
	(0.006)	(0.006)	(0.002)	(0.006)
Cash flow to assets	0.1677**	0.1647**	0.0481**	0.1679**
	(0.070)	(0.070)	(0.021)	(0.071)
Log assets	0.0036	0.0036	-0.0012	0.0035
	(0.009)	(0.009)	(0.003)	(0.009)
Book Leverage	-0.2111**	-0.2153**	0.0643*	-0.2111**
	(0.084)	(0.084)	(0.035)	(0.084)
Tangibility	-0.0631	-0.0609	-0.0334	-0.0631
	(0.113)	(0.113)	(0.047)	(0.113)
YearFE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	1,612	1,612	1,612	1,612
Adjusted R^2	0.176	0.175	0.943	0.014
F	3.464	3.007	50.668	3.171

The dependent variable in all columns is the asset-weighted zombie share. Imports from China to the US and imports from China to the eight other countries are scaled by total US domestic production plus net import in 1991 with data from Autor et al. (2019). As in Autor et al. (2019) we use the imports from China to the eight other countries to predict the exogenous part of imports from China to the US in the first stage. Those eight other countries are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland. The sample covers manufacturing firms from 1991 to 2014. The data sources are described in section 2.3.1. Table 2.12 in the Appendix contains definitions of all variables. Nominal values are deflated to 2012 USD. Zombie firms are defined as in Acharya et al. (2019). More details on the identification process are provided in section 2.3.2. In column 4, the reported R^2 is the centered R^2. Standard errors are adjusted for heteroscedasticity and clustered at the three-digit SIC industry level, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

2.4.2 Heterogeneity across industries

Not all manufacturing industries are equally competitive. To better understand the negative effect of competition on the share of zombie firms documented so far, we exploit the cross-sectional variation in our sample. As Table 2.4 shows, there is substantial heterogeneity in all three measures of competition at the beginning (Panel A) as well as at the end (Panel B) of our sample period. In 1991 the interquartile range of the HHI is 16.40 percentage points and the standard deviation amounts to 16.78. In the same year, the level of import penetration ranges from 0.01% to 69.84%, and imports from China to the US range from 0 to 0.09%. 23 years later, the cross-sectional heterogeneity is even higher. In terms of time series variation, Table 2.4 and Figure 2.2 reveal that the level of domestic competition decreases over time as the median HHI increases from 21.95 to 24.18. This decrease is mentioned and discussed by Autor, Dorn, Katz, et al. (2020). At the same time, the median of import penetration increases by almost 50% to 11.85%, and the median of imports from China to the US increases to 0.05%.

In Panel C of Table 2.4, we start by exploiting the cross-sectional variation of competition. More specifically, we calculate the three year median level of competition for each industry-year combination. Using the one year lag, we then divide the industries into two equally large groups and estimate the same 2-SLS regression as in Table 2.3 separately for each group. To compare levels of competition and not to be left with many industries without any foreign competition in one group, we only consider industries with import penetration greater than 0.1%, or with imports from China accounting for more than 0.001% of domestic production. Columns 1 and 2 of Panel C show that the effect of competition on the share of zombie firms is more pronounced in less concentrated industries (low HHI). We find similar results for import penetration in columns 3 and 4. The coefficient estimate of Imports from China to US is negative and statistically significant when import penetration is already high. Similarly, the coefficient estimate is negative in column 6, where Imports from China to US are above the median. Finally, when we split industries according to the increase of competition from China from $t-2$ to $t-1$, the results show that the effect is negative and significant for large increases. This suggests that large increases in competition are driving the negative effect on the asset-weighted zombie share.

Our results in Panel C indicate that the level of competition needs to be sufficiently high before the competitive shock has a significant effect on the share of zombie firms. This result is reasonable, as the canonical model of competition suggests that a more competitive environment drives down firms' mark-ups and therefore profits (Edmond et al., 2015). This makes it more likely for firms to become zombies in the first place. At the same time, the shock also needs to be sufficiently large to impact the dynamics of the asset-weighted zombie share.

In Panel D of Table 2.4, we further divide industries based on typical industry characteristics. The first two characteristics are total factor productivity (TFP) and the Cost of Goods Sold (COGS). A competitive environment is often characterized by a high TFP and a low COGS margin (Chhaochharia et al., 2016; Dasgupta et al., 2018). The results in columns 1 and 2 are thus not surprising and underline our findings from panel C. With respect to industry size, as measured by capital and employees, columns 5 to 8 do not reveal any significant differences. In sum, investigating the cross-sectional variation across industries reveals that a positive shock to competition has only a statistically significant negative effect on the asset-weighted zombie share in industries that are characterized by a higher level of competition, a higher TFP, and lower margins at the time of the shock.

Table 2.4: Summary statistics on cross-sectional variation

	Min	P5	P25	Median	P75	P95	Max	SD
				Panel A: 1991				
HHI	5.433	7.340	13.674	21.946	30.075	65.818	71.252	16.677
Import Penetration	0.012	0.154	2.864	6.743	14.567	34.344	69.841	12.092
Imports China to US	0.000	0.000	0.000	0.001	0.003	0.034	0.091	0.014
				Panel B: 2014				
HHI	3.862	7.307	15.641	24.181	37.674	92.748	100.000	25.994
Import Penetration	0.075	0.429	4.097	11.847	27.713	86.775	100.000	25.650
Imports China to US	0.000	0.000	0.009	0.047	0.180	0.721	2.314	0.387

Panel C: Industry cross section competition

	HHI		Import Penetration		US imports		Δ US imports	
	Low	High	Low	High	Low	High	Low	High
Imports China to US	-0.0797***	-0.0211	0.8250	-0.0972***	-0.1152	-0.0885***	0.1305	-0.1331***
	(0.025)	(0.085)	(0.514)	(0.030)	(0.586)	(0.030)	(0.080)	(0.036)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	826	782	793	789	630	627	696	715
Centered R^2	0.045	0.005	0.012	0.051	0.005	0.048	0.019	0.022

Panel D: Industry cross section characteristics

	TFP		COGS margin		Employment		Capital	
	Low	High	Low	High	Low	High	Low	High
Imports China to US	0.1729	-0.1202***	-0.0919***	-0.0380	-0.2004	-0.0433	-0.0785	-0.0466
	(0.116)	(0.033)	(0.033)	(0.033)	(0.132)	(0.030)	(0.100)	(0.035)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	800	777	798	783	778	830	766	844
Centered R^2	0.040	0.024	0.014	0.023	0.016	0.018	0.015	0.025

Panel A and B display summary statistics for our three measures of product market competition for two different years, 1991 and 2014. The HHI is calculated based on Compustat sales, the import penetration is calculated as imports divided by domestic production plus imports minus exports with data from Schott (2008), and import data from China to the US is from Autor et al. (2019) and scaled by total domestic production plus net imports in 1991. The sample covers manufacturing firms from 1991 to 2014. The data sources are described in section 2.3.1. In Panel C and D, industries are split on different characteristics as indicated for each column. For the first three characteristic in Panel C, we calculate the three year median from $t-4$ to $t-1$ and then split the industries in each year in two groups based on this median. For import penetration, we only consider industry-year combinations with a median larger than 0.1% and larger than 0.001% for imports from China to the US. In panel B the industries are split based on the value of the characteristics in $t-1$. The dependent variable in all columns in Panel C and D is the asset-weighted zombie share. Parameters are estimated using 2SLS. Zombie firms are defined as in Acharya et al. (2019). More details on the identification process are provided in section 2.3.2. Standard errors are robust to heteroskedasticity and clustered at the three-digit SIC level in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

2.4.3 Firm-level evidence

So far, our results show that the asset-weighted zombie share decreases after a competitive shock and therefore support the *cleansing* hypothesis. As pointed out in Section 2.2, the negative effect is consistent with fewer zombie firms that belong to an industry or with zombie firms that decrease in size. For the number of zombie firms to decrease, some zombies need to exit the industry and be replaced by more productive non-zombie firms. Alternatively, higher competition could force zombie firms to become more efficient and productive, such that they recover from their zombie status. Therefore, we analyze in a next step firm level dynamics to better understand what drives the effect at the industry level. More specifically, we adjust our estimation model from equation 2.3 to the firm-level:

$$\begin{gathered} y_{i,j,t} = \alpha + \beta Competition_{i,j,t-1} + \gamma ZombieDummy_{i,j,t-1} + \\ \lambda Competition_{i,j,t-1} \times ZombieDummy_{i,j,t-1} + \mu_t + \nu_i + \epsilon_{i,j,t} \end{gathered} \tag{2.4}$$

Subscripts i, j, and t refer to firm, industry, and year, respectively. The dependent variable $y_{i,j,t}$ is a firm level outcome. It can be a dummy variable or a continuous variable. All regressions include firm-specific control variables (market-to-book ratio, cash flow-to-assets ratio, and firm size), year fixed effects (μ_t) to account for aggregate shocks that affect all firms, and firm fixed effects (ν_i) to account for unobserved firm heterogeneity. We estimate the model in reduced form (i.e., using the instrument as an exogenous regressor) and with the 2-SLS approach. We cluster standard errors at the three-digit SIC industry level to account for common responses of firms in the same industry. λ is the coefficient of interest. It captures the effect of competitive shocks on zombie firms relative to their healthy peers.

We start by investigating if zombie firms have a different exit probability or a higher recovery likelihood when competition increases. Table 2.5 presents the results.

In column 1, the dependent variable is an indicator variable equal to one when a firm exits before the end of the sample period.[9] Neither the coefficient on competition, nor the coefficient on the interaction with the zombie indicator variable are statistically significant. Note that the zombie dummy variable also does not have a statistically significant effect on the exit probability. This may be surprising. However, recall that the definition of zombie firms includes the immediate support by stakeholders to stay alive.

9. More specifically, the indicator is one if the deletion date ($DLDTE$) is prior to June, 2014 and there is non-missing data in the variable reason for deletion $DLRSN$

Table 2.5: Foreign competition, firm exit, entry, and default

	Exit	Exit	Default	Default
	(1)	**(2)**	**(3)**	**(4)**
Imports China to Others	0.0115		-0.0003	
	(0.018)		(0.003)	
Imports China to US		0.0096		-0.0003
		(0.013)		(0.002)
Zombie dummy	-0.0050	-0.0050	-0.0012	-0.0012
	(0.008)	(0.008)	(0.002)	(0.002)
Imports China x Zombie dummy	0.0036	0.0024	0.0031	0.0025
	(0.013)	(0.010)	(0.005)	(0.004)
Market-to-book	-0.0048***	-0.0048***	-0.0003***	-0.0003***
	(0.001)	(0.001)	(0.000)	(0.000)
Cash flow to assets	-0.0114	-0.0114	-0.0038**	-0.0038**
	(0.010)	(0.010)	(0.002)	(0.002)
Log assets	-0.0112***	-0.0112***	-0.0019**	-0.0019**
	(0.004)	(0.004)	(0.001)	(0.001)
Book Leverage	0.0827***	0.0827***	0.0133***	0.0134***
	(0.015)	(0.015)	(0.003)	(0.003)
Tangibility	0.0363**	0.0361**	0.0044	0.0044
	(0.016)	(0.016)	(0.006)	(0.006)
YearFE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	30,739	30,739	30,739	30,739
Adjusted R^2	0.115	0.004	0.131	0.002
	Acquisition	Acquisition	Recovery	Recovery
	(5)	**(6)**	**(7)**	**(8)**
Imports China to Others	0.0112		0.0041	
	(0.010)		(0.020)	
Imports China to US		0.0092		0.0034
		(0.007)		(0.017)
Zombie dummy	-0.0102*	-0.0102*		
	(0.005)	(0.005)		
Imports China x Zombie dummy	0.0192	0.0148		
	(0.021)	(0.014)		
Market-to-book	-0.0029***	-0.0029***	-0.0013	-0.0013
	(0.001)	(0.001)	(0.001)	(0.001)
Cash flow to assets	0.0074	0.0074	-0.0742***	-0.0742***
	(0.005)	(0.005)	(0.011)	(0.011)
Log assets	-0.0006	-0.0006	0.0015	0.0015
	(0.004)	(0.004)	(0.004)	(0.004)
Book Leverage	0.0215*	0.0215*	0.6179***	0.6179***
	(0.013)	(0.013)	(0.018)	(0.018)
Tangibility	0.0119	0.0118	0.0755*	0.0754*
	(0.020)	(0.020)	(0.042)	(0.042)
YearFE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	30,739	30,739	16,684	16,684
Adjusted R^2	0.111	0.001	0.048	0.063

The dependent variables are dummy variables. The *Exit* dummy is equal to one for the last observation of a given firm within the sample if this firm has non-missing information for the reason of deletion (*DLRSN* in Compustat). We consider a firm as defaulted if *DLRSN* is equal to 2 or 3, i.e. bankruptcy or liquidation, and the corresponding dummy is one for the last year. The *Acquisition* dummy is one for the last observation of a firm with *DLRSN* equal 4. Finally, the *recovery* dummy is equal to one in the first year a previous zombie firm is not classified as a zombie. The first column for each dependent variable shows the result of the reduced model whereas the second displays the result of the 2SLS regressions. The sample covers manufacturing firms from 1991 to 2014. The data sources are described in section 2.3.1. Table 2.12 in the Appendix contains definitions of all variables. Nominal values are deflated to 2012 USD. Zombie firms are defined as in Acharya et al. (2019). More details on the identification process are provided in section 2.3.2. Standard errors are adjusted for heteroscedasticity and clustered at the three-digit SIC industry level, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

In columns 2 and 3, we only consider firms with *DLRSN* equal to 2 or 3, i.e., bankruptcy or liquidation as reasons for exit. As for column 1, competition has no effect on the probability of default. If a firm is acquired in a reverse acquisition, Compustat reports the value 4 for *DLRSN*. Columns 4 and 5 present results where an acquisition indicator variable is the dependent variable. The results do not reveal any statistically significant effect. In the last two columns, the dependent variable is an indicator variable equal to one for the first observation that the firm is no longer classified as a zombie and has recovered.[10] In line with the previous findings, competition does not significantly affect the probability of recovery. Overall, Table 2.5 suggests that shocks to the competitive environment do not affect zombie firms' exit, default, or recovery probability.

In a second step, we analyze if zombie firms shrink their balance sheet as a response to a competitive shock. We estimate the model described in equation 2.4 with the natural logarithm of total assets as dependent variable. Table 2.6 presents the results.

Column 1 shows the results of the reduced form regression. Column 2 presents the results of the 2-SLS estimation. In both columns, the coefficient on the interaction between competition and the zombie indicator variable is negative and statistically significant. This suggests that the total assets of zombie firms are decreasing significantly more compared to non-zombies when both types of firms are exposed to higher competition. This finding is consistent with our evidence at the industry level. Moreover, the coefficient on the zombie indicator variable is positive but not statistically significant, suggesting that total assets of zombie firms are similar in size compared to the total assets of non-zombie firms.

Overall, our results of this section suggest that: *i*) a change in foreign competition has a negative effect on the asset-weighted zombie share, in particular in competitive industries, for large changes in foreign competition, and for industries with low margins; *ii*) the size of zombie firms decreases significantly in the aftermath of a competitive shock relative to non-zombie firms, whereas the likelihood of exit or recovery is not affected.

10. Note that the zombie dummy variable and the interaction term are not identified due to perfect collinearity in this model.

Table 2.6: Foreign competition and asset size

	(1)	**(2)**
Imports China to Others	-0.2360***	
	(0.0794)	
Imports China to US		-0.1956***
		(0.0699)
Zombie indicator	0.0295	0.0283
	(0.0213)	(0.0216)
Imports China to Others x Zombie	-0.2546***	
	(0.0381)	
Imports China to US x Zombie		-0.1923***
		(0.0317)
Market-to-book ratio	0.0163**	0.0162**
	(0.0068)	(0.0068)
Cash flow-to-assets	0.5116***	0.5115***
	(0.0360)	(0.0359)
Book leverage	0.5957***	0.5949***
	(0.0603)	(0.0602)
Tangibility	-0.4036***	-0.4010***
	(0.0818)	(0.0819)
Year FE	Yes	Yes
Firm FE	Yes	Yes
Observations	30,739	30,739
Adjusted R2	0.94	0.04

This tables shows estimates of regressions of the natural logarithm of total assets on foreign competition, a zombie firm indicator variable, and the interaction of these two variables. The first column shows the result of the reduced model whereas the second displays the result of the 2SLS regression. The sample covers manufacturing firms from 1991 to 2014. The data sources are described in section 2.3.1. Table 2.12 in the Appendix contains definitions of all variables. Nominal values are deflated to 2012 USD. Zombie firms are defined as in Acharya et al. (2019). More details on the identification process are provided in section 2.3.2. Standard errors are adjusted for heteroscedasticity and clustered at the three-digit SIC industry level, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

2.5 Zombie firms' policy choices and competition

So far, we find evidence that higher product market competition is associated with a lower zombie share at the industry level, and that zombie firms reduce their asset size. An open question is what policy choices accompany the shrinking process and how specific positions of the balance sheet of zombie firms are affected. In this section, we therefore analyze how zombie firms grow their assets, manage their liquidity, and raise external funds in the wake of higher competition.

2.5.1 Asset growth

In this section, we analyze asset growth at the firm level. We expect that zombie firms grow more slowly compared to non-zombie firms when faced with higher competition. Table 2.7 presents the results for the reduced form (column 1), and 2-SLS regressions (column 2).

Overall, the coefficient on Imports China to US is negative and significant in both columns, suggesting that foreign competition has a negative effect on asset growth. This result is consistent with evidence in Frésard and Valta (2015), who show that firms invest less when they are exposed to competitive shocks. Moreover, zombie firms have similar asset growth compared to non-zombie firms, as shown by the negative but not significant coefficient estimate on the zombie indicator variable. Importantly, the coefficient on the interaction between competition and the zombie indicator variable is negative and statistically significant, implying that the asset growth rate of zombie firms is significantly lower compared to non-zombie firms when faced with higher competition. The effects are also economically large. A one standard deviation increase in foreign competition leads to a decrease in zombie firms' asset growth of 5.32% compared to 3.47% for non-zombie firms. These results are consistent with the idea that zombie firms reduce their scale with higher competition.

2.5.2 Cash holdings

Next, we explore, which policy choices accompany the shrinking process. Specifically, we analyze how cash holdings of zombie firms respond to higher competition. Cash is a natural candidate to analyze, as firms can quickly adjust this balance sheet position. We expect that zombie firms reduce their cash holdings with higher foreign competition compared to non-zombie firms. We estimate regression model 4 with the cash-to-assets ratio as the dependent variable. Table 2.8 presents the results.

Table 2.7: Foreign competition and asset growth

	(1)	(2)
Imports China to Others	-0.1644***	
	(0.0193)	
Imports China to US		-0.1431***
		(0.0336)
Zombie indicator	-0.0011	-0.0016
	(0.0119)	(0.0117)
Imports China to Others x Zombie	-0.0875**	
	(0.0413)	
Imports China to US x Zombie		-0.0654**
		(0.0256)
Tobin's Q	0.0100***	0.0098***
	(0.0033)	(0.0033)
Cash flow-to-assets	0.0905***	0.0904***
	(0.0271)	(0.0270)
Log(total assets)	-0.2181***	-0.2182***
	(0.0113)	(0.0112)
Book leverage	-0.0967***	-0.0973***
	(0.0416)	(0.0416)
Tangibility	-0.0100	-0.0076
	(0.0513)	(0.0519)
Year FE	Yes	Yes
Firm FE	Yes	Yes
Observations	25,440	25,440
Adjusted R2	0.13	0.07

This tables shows estimates of regressions of asset growth on foreign competition, a zombie firm indicator variable, and the interaction of these two variables. The first column shows the result of the reduced model whereas the second displays the result of the 2SLS regression. The sample covers manufacturing firms from 1991 to 2014. The data sources are described in section 2.3.1. Table 2.12 in the Appendix contains definitions of all variables. Nominal values are deflated to 2012 USD. Zombie firms are defined as in Acharya et al. (2019). More details on the identification process are provided in section 2.3.2. Standard errors are adjusted for heteroscedasticity and clustered at the three-digit SIC industry level, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Both, foreign competition and the zombie indicator variable are not significantly related with firms' cash holdings. However, the interaction between foreign competition and the zombie indicator variable is negative and statistically significant in both columns. Thus, relative to non-zombie firms, zombie firms reduce their cash-to-assets ratio significantly with higher foreign competition. This finding is consistent with our earlier results on zombie firms' reduced asset size.

Table 2.8: Foreign competition and cash holdings

	(1)	**(2)**
Imports China to Others	0.0121*	
	(0.0067)	
Imports China to US		0.0101
		(0.0074)
Zombie indicator	-0.0003	-0.0002
	(0.0035)	(0.0036)
Imports China to Others x Zombie	-0.0277***	
	(0.0095)	
Imports China to US x Zombie		-0.0225*
		(0.0116)
Tobin's Q	0.0066***	0.0066***
	(0.0012)	(0.0012)
Cash flow-to-assets	-0.0519***	-0.0519***
	(0.0055)	(0.0055)
Log(total assets)	-0.0187***	-0.0187***
	(0.0056)	(0.0056)
Book leverage	-0.1342***	-0.1342***
	(0.0074)	(0.0074)
Tangibility	-0.3325***	-0.3328***
	(0.0563)	(0.0562)
Year FE	Yes	Yes
Firm FE	Yes	Yes
Observations	30,739	30,739
Adjusted R2	0.79	0.09

This tables shows estimates of regressions of cash holdings on foreign competition, a zombie firm indicator variable, and the interaction of these two variables. The first column shows the result of the reduced model whereas the second displays the result of the 2SLS regression. The sample covers manufacturing firms from 1991 to 2014. The data sources are described in section 2.3.1. Table 2.12 in the Appendix contains definitions of all variables. Nominal values are deflated to 2012 USD. Zombie firms are defined as in Acharya et al. (2019). More details on the identification process are provided in section 2.3.2. Standard errors are adjusted for heteroscedasticity and clustered at the three-digit SIC industry level, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

2.5.3 Equity issues

Next, we analyze how competition affects zombie firms' ability to raise outside equity capital. We expect that zombie firms experience problems in raising outside equity capital, implying that they raise less equity when exposed to higher competition. To investigate the effects of competition on equity issues, we estimate the regression model 4 with equity issuance as the dependent variable. We use two alternative definitions of equity issuance: (i) gross equity issues scaled by lagged assets (*Gross equity issuance*) as in McLean (2011) and (ii) gross equity issuance minus dividends and share repurchases scaled by lagged assets (*Net equity issuance*). Table 2.9 presents the results. In columns 1 and 2, the dependent variable is *Gross equity issuance*, and in columns 3 and 4, the dependent variable is *Net equity issuance*.

In column 1 of Table 2.9 (reduced form regression using the instrument as an exogenous regressor), competition has a marginally significant negative effect on gross equity issues, while the zombie indicator variable is positive but not significant. The interaction term between competition and the zombie indicator is negative and statistically significant with a coefficient estimate of -0.056. This result suggests that zombie firms raise significantly smaller amounts of equity capital when they are exposed to higher competition compared to non-zombie firms. We obtain very similar results in column 2, which contains the 2-SLS estimates. The interaction term is also significantly negative with a coefficient of -0.0439. The results in columns 3 and 4 (net equity issuance) are very similar, too. The interaction term between the zombie indicator and competition is negative and statistically significant in both columns. Overall, the results show that zombie firms raise significantly smaller amounts of equity when exposed to competition. This finding is consistent with the idea that such firms are shrinking in size and allocate their capital more efficiently.

2.5.4 Loan size

Finally, we analyze whether the reduced asset size is also visible in the firms' debt financing. We merge our data set with loan data from DealScan and create a cross sectional loan data set. We then estimate regressions using the natural logarithm of the loan amount as the dependent variable. Table 2.10 presents the results.

Table 2.9: Foreign competition and equity issues

	Gross Eq. (1)	Gross Eq. (2)	Net Eq. (3)	Net Eq. (4)
Imports China to Others	-0.0202*		-0.0368***	
	(0.0103)		(0.0073)	
Imports China to US		-0.0167**		-0.0304***
		(0.0065)		(0.0073)
Zombie dummy	0.0050	0.0049	0.0060	0.0059
	(0.0057)	(0.0059)	(0.0046)	(0.0047)
Imports China to Others × Zombie dummy	-0.0560***		-0.0357***	
	(0.0132)		(0.0111)	
Imports China to US × Zombie dummy		-0.0439***		-0.0264***
		(0.0132)		(0.0082)
Tobin's Q	0.0573***	0.0573***	0.0492***	0.0492***
	(0.0074)	(0.0074)	(0.0067)	(0.0067)
Cash flow-to-assets	-0.1860***	-0.1860***	-0.1775***	-0.1775***
	(0.0142)	(0.0142)	(0.0252)	(0.0252)
Log(total assets)	-0.1386***	-0.1386***	-0.1146***	-0.1146***
	(0.0368)	(0.0367)	(0.0255)	(0.0255)
Book leverage	0.2455***	0.2455***	0.2634***	0.2633***
	(0.0444)	(0.0444)	(0.0395)	(0.0395)
Tangibility	0.1570	0.1571	0.1236	0.1240
	(0.0975)	(0.0974)	(0.0765)	(0.0764)
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	30,135	30,135	27,292	27,292
Adjusted R2	0.42	0.18	0.43	0.17

This tables shows estimates of regressions of equity issues on foreign competition, a zombie firm indicator variable, and the interaction of these two variables. The dependent variable is Gross equity issues in columns 1 and 2, and Net equity issues in columns 3 and 4. The first column for each dependent variable shows the result of the reduced model whereas the second displays the result of the 2SLS regressions. The sample covers manufacturing firms from 1991 to 2014. The data sources are described in section 2.3.1. Table 2.12 in the Appendix contains definitions of all variables. Nominal values are deflated to 2012 USD. Zombie firms are defined as in Acharya et al. (2019). More details on the identification process are provided in section 2.3.2. Standard errors are adjusted for heteroscedasticity and clustered at the three-digit SIC industry level, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Foreign competition has a statistically significant positive effect on the loan size for all firms on average. Additionally, the zombie indicator variable is negative, but not statistically significant. Importantly, the interaction term between the zombie indicator variable and foreign competition is negative in both columns, implying that banks indeed reduce the loans to zombie firms after a shock to competition. The decrease in the loan amount is therefore consistent with the idea that zombie firms reduce the size of their balance sheet. Collectively, these results are consistent with our evidence that zombie firms are negatively affected by higher foreign competition. They grow more slowly, reduce their holdings of liquid assets, issue smaller amounts of equity, and obtain smaller loans.

Table 2.10: Foreign competition and loan size

	(1)	**(2)**
Imports China to Others	0.3281**	
	(0.143)	
Imports China to US		0.2757***
		(0.086)
Zombie dummy	-0.0894	-0.0827
	(0.068)	(0.068)
Interaction	-0.5545**	-0.5044*
	(0.277)	(0.254)
Tobin's Q	0.0507**	0.0508**
	(0.020)	(0.020)
Cash flow to assets	0.6579***	0.6581***
	(0.122)	(0.123)
Log assets	0.7285***	0.7284***
	(0.017)	(0.017)
Book Leverage	-0.2351	-0.2405
	(0.193)	(0.194)
Tangibility	0.1384	0.1320
	(0.175)	(0.175)
YearFE	Yes	Yes
Firm FE	Yes	Yes
Observations	8,338	8,338
Adjusted R^2	0.697	0.607

For this analysis we merge our data set with data on loans from DealScan and end up with a loan cross sectional data set with loans originating from 1991 until 2014 granted to manufacturing firms. The dependent variable in all columns is the natural log of the loan amount. The first column shows the result of the reduced model whereas the second displays the result of the 2SLS regression. The data sources are described in section 2.3.1. Table 2.12 in the Appendix contains definitions of all variables. Nominal values are deflated to 2012 USD. Zombie firms are defined as in Acharya et al. (2019). More details on the identification process are provided in section 2.3.2. Standard errors are adjusted for heteroscedasticity and clustered at the three-digit SIC industry level, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

2.6 Conclusions

This paper analyzes the relationship between product market competition and zombie firms in the US. We provide robust evidence of a negative effect of competition on the share of zombie firms in an industry. We establish this result using an instrumental variable approach, where we use imports from China to eight high-income countries as instrument for imports from China to the US. Furthermore, we show that the negative effect mainly arises in already competitive industries, for sufficiently large increases in foreign competition, and is driven by a decrease in zombie firms' size. In our sample, competition does not have statistically significant effects on the exit or recovery probabilities of zombie firms. Finally, we show that competition has a negative effect on the asset growth and cash holdings of zombies, and that such firms raise less outside capital. Overall, our findings suggest that zombie firms scale down their size and adjust their financial policies in the wake of higher competition.

Our analysis shows that abrupt changes in competition significantly affect zombie firms. Given that these type of firms are prevalent in other economies, future research could extend the analysis to other countries. Moreover, we remain agnostic about the exact channels through which competition reduces the scale of zombie firms. For example, higher competition could provide incentives to the management of zombie firms to reduce the scale of the firm and allocate capital internally more efficiently. Alternatively, capital providers could reallocate capital away from zombie firms as they fear that the status quo would increase the default likelihood of such firms, and as such enforce a smaller scale. We look forward to future research addressing these open questions.

2.A Robustness

Table 2.11: Foreign competition and zombie shares - USD values

	Endogenous (1)	Reduced (2)	First Stage (3)	Second Stage (4)
	Panel A: without controls			
Imports China to US	-0.0023***			-0.0022**
	(0.001)			(0.001)
Imports China to Others		-0.0030**	1.3486***	
		(0.001)	(0.191)	
YearFE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	1,616	1,616	1,616	1,616
Adjusted R^2	0.163	0.163	0.942	0.003
F	7.638	4.926	49.970	5.878
	Panel B: with controls			
Imports China to US	-0.0021**			-0.0021**
	(0.001)			(0.001)
Imports China to Others		-0.0028**	1.3490***	
		(0.001)	(0.190)	
Cash flow to assets	0.1677**	0.1647**	1.5315**	0.1679**
	(0.070)	(0.070)	(0.661)	(0.071)
Market-to-book	-0.0022	-0.0018	-0.1323**	-0.0021
	(0.006)	(0.006)	(0.054)	(0.006)
Tangibility	-0.0631	-0.0609	-1.0641	-0.0631
	(0.113)	(0.113)	(1.499)	(0.113)
Book Leverage	-0.2111**	-0.2153**	2.0459*	-0.2111**
	(0.084)	(0.084)	(1.107)	(0.084)
Log assets	0.0036	0.0036	-0.0391	0.0035
	(0.009)	(0.009)	(0.107)	(0.009)
YearFE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	1,612	1,612	1,612	1,612
Adjusted R^2	0.176	0.175	0.943	0.014
F	3.464	3.007	50.668	3.171

The dependent variable in all columns is the asset-weighted zombie share. Imports from China to the U.S. and imports from China to the eight other countries are scaled by total U.S. domestic production in 1991 with data from Autor et al. (2019). Those eight other countries are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland. As in Autor et al. (2019) we use the imports from China to the eight other countries to predict the exogenous part of imports from China to the U.S. in the first stage. The sample covers manufacturing firms from 1990 until 2014. The data sources and the cleaning are described in section 2.3.1. All variables are constructed according to table 2.12 in the appendix and nominal values are deflated to 2012 USD. Zombies are defined as in Acharya et al. (2019), more details on the identification process are provided in section 2.3.2. In column 4, the reported R^2 is the centered R^2. Standard errors are robust to heteroskedasticity and clustered at the 3-digit SIC level in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

2.B Variable Definition

Table 2.12: Variable definition

Variable	**Construction**	**Construction Compustat**
Interest Coverage Ratio	EBIT / Interest Expenses	ebit/xint
Book Leverage	Short + Long-term Debt / Total Assets	(dlc+dltt)/at
Market-to-Book Ratio	Market Value of Assets / Book Value of Assets	(at-ceq+prcc_f*csho)/at
Cash Flow Ratio	(EBITDA - interest expenses - taxes - dividends) / Total Assets$_{t-1}$	(oibdp-xint-txt-dvc)/at$_{t-1}$
Log assets	Log(Total Assets)	ln(at)
Tangibility	Property, Plant, and Equipment / Total Assets	ppent/at
Asset growth	(Total Assets - Total Assets$_{t-1}$) / Total Assets$_{t-1}$	(at-at$_{t-1}$)/at$_{t-1}$
Cash holdings	Cash / Total Assets	che/at
Equity issue (gross)	Sale of Common Stock / Total Assets$_{t-1}$	sstk / at$_{t-1}$
Equity issue (net)	(Sale of Common Stock - Dividends - Purchase of Common Stock) / Total Assets$_{t-1}$	(sstk-dvc-dvp-prstkc)/at$_{t-1}$
Zombie dummy	1, if a firm is classified as a zombie	
Exit dummy	1 for the last observation, if a firm exits before the end of the sample period and has non-missing values in $DLRSN$	
Default dummy	1 for the last observation, if a firm exits before the end of the sample period and has $DLRSN$ equal to 2 or 3	
M&A dummy	1 for the last observation, if a firm exits before the end of the sample period and has $DLRSN$ equal to 4	
Recovery dummy	1 in the first year a firm exits its zombie status	

Note: All USD values are deflated to 2012-USD using the GDP deflator. All variables, apart from leverage which is forced to lie between zero and one, are then winsorized at the 1% - and 99%-level. Time subscripts of the current time period are dropped for convenience.

Chapter 3

Heterogeneity in Returns to Wealth

Evidence from Swiss Administrative Data

Abstract

In this paper, we address how returns on financial assets vary across the population. Exploiting rich administrative data, we can neatly describe the heterogeneity across all parts of the distribution of wealth. We find compelling evidence that the rich benefit from higher returns. Likely, this is due to two different effects that have been called *scale dependence* and *type dependence*. The former is due to an observed positive correlation between net worth and returns. The latter describes a high persistence of returns for each individual, most possibly due to better information and market access advantages. In our first set of results, we find evidence that both channels play an essential role. Conceptually, this paper contributes by investigating the interaction of type and scale dependence. As returns are persistent, we identify low and high-type investors across the distribution of returns. Thus, modeling the latter allows us to document the scale dependence for many different types. We find that net worth has a larger positive effect on returns for high types, highlighting a previously undocumented channel through which wealth inequality reinforces itself.

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3.1 Introduction

Since Pareto (1896) it is well known that both income and wealth are highly unequally distributed and very right-skewed ((see Piketty and Saez (2003), Piketty (2014), Saez and Zucman (2016), and Zucman (2019)). Many researchers such as Krusell and Smith (1998), Quadrini (2000), Benhabib et al. (2011) or Chien et al. (2011) tried to replicate this tail inequality with a variety of modelling choices. Benhabib et al. (2011), for example, use heterogeneity in returns to wealth and their persistence to match the fat tail of the wealth distribution. More recently, Gabaix et al. (2016) provided a theoretical setting, which is not only able to match the distribution of the tail but can also explain the fast rise of income and wealth inequality. They label the underlying forces, which lead to the fast transition, *scale* and *type dependence*. The former dependence corresponds to a high correlation between net worth and returns to wealth, whereas the latter describes individual specific skills that lead to persistent differences in levels of returns. The two theoretical ideas by Benhabib et al. (2011) and Gabaix et al. (2016) are brought to the data on wealth by Fagereng et al. (2020) and Bach et al. (2020). The authors show empirically that returns to wealth feature a scale and type dependence. However, they focus on the average effect on returns and thus neglect the possibility that the effect of wealth may vary across different levels of return.

The goal of this paper is to further investigate the empirical evidence for scale and type dependence. More specifically, we scrutinize whether the scale dependence varies across the distribution of returns, i.e. if there is a heterogeneous effect of wealth for different return levels. Or, put differently, whether there is an interaction between the two dependencies. To do so, we model the full distribution of the returns to wealth using distributional regressions techniques introduced by Chernozhukov et al. (2013). This method allows us to obtain the entire distribution of returns for different quantiles of net worth, conditional on all other observables. In the next step, we obtain the unconditional distribution of returns, which only depends on the level of net worth. This allows us to isolate the pure effect of net worth while accounting for the impact of observables, i.e., socio-demographics and portfolio choices. As a result, we can explicitly document the scale dependence across different returns. Conditional on the full set of individual-specific characteristics we interpret the distribution of returns as the set of distinct investor types. This enables us to estimate the interaction between scale and type dependence. To give an intuition on scale dependence, consider two investors of the same type with high and low wealth. The wealthier investor may have the opportunity to invest in private equity or hedge funds, both known to require high initial investments. Likewise, they may afford a family office in which investment professionals manage their wealth portfolio. These factors can lead to higher returns for people with a higher level of wealth, therefore, leading to a self-reinforcing increase in wealth inequality. Another potential explanation for scale dependence is the observation that investors with more wealth tend to reduce irrational investment behavior (e.g. Vissing-Jorgensen (2003) or Calvet et al. (2009b)) or invest a higher share in risky assets with high return (Guiso et al., 1996). In comparison, type dependence describes individual specific skills that lead to higher returns throughout the wealth distribution and can thus explain the fast rise of wealth inequality. Serial entrepreneurs such as Elon Musk, Richard Branson, or successful mutual fund managers are typical examples of type dependence. Theoretical settings that feature type dependence are, for example, the work by Guvenen (2009) or Kacperczyk et al. (2019).

To make our hypothesis easier to understand, we give the following example: Suppose there are two investors, and there are riskless (e.g. bank deposits), and risky assets (e.g. stocks) available. One investor has a higher sophistication than the other one and is, therefore, able to generate higher returns on average. Potential reasons herefore may be due to better stock picking or by suffering less from irrational trading behavior. Put differently, the first investor profits from type dependence. Further, suppose that both investors would increase their shares in the risky portfolio equally if they experience windfall gains. Since they both invest more in the risky asset, their average returns would both increase. As a result, we would observe scale dependence. At the same time, however, the more sophisticated investor would pick the better stocks and generates an even higher return than the other investor. Consequently, the investor with the higher level of sophistication profits from the higher level of wealth *and* from his capability to make better investments. Our simple example relies on two building blocks. First, the two investors must be different concerning their capability of generating returns. Existing literature in financial economics mentions many different reasons for such differences in investment types. Theoretical work suggests that investor sophistication (Kacperczyk et al., 2019), limited participation in the stock market (Guvenen, 2009), limited liability (Chien and Lustig, 2010), or trading technologies (Chien et al., 2011) may explain those constant differences in the level of returns across investors. Some of these factors are also based on empirical evidence, e.g. Calvet et al. (2009a), Graham et al. (2009), Gao and Huang (2019), and others. Second, both investors need to allocate additional wealth into the risky asset to generate higher returns on average. Several micro-founded theories suggest that this will be the case. For instance, the presence of utility functions with a decreasing relative risk aversion as suggested by Ogaki and Zhang (2001) would cause the investors to behave accordingly. Similarly, if the level of wealth changes the risk aversion as in Tversky and Kahneman (1991), additional wealth would be invested into the riskier asset.

The data we use for our analysis is provided by the tax authorities of the canton of Bern, Switzerland. Several factors make our data set suitable for addressing our goal. First, the data set covers the entire population above 18 from 2002 – 2017. The large panel structure is a necessary component to measure the effect of type dependence on the returns on wealth. Additionally, because we cover the entire population, we have reliable data for the full distribution of wealth, including the top, who are generally under-represented in survey data. Second, Switzerland knows a wealth tax, making it mandatory for the households to give a detailed description of their wealth composition. This feature is often missing in other large panel structured data sets. Last, because we are using administrative data, measurement error and underreporting of wealth information are much less severe, as tax authorities have a strong incentive to control for such effects.

We split our empirical analysis into two parts. First, we follow Fagereng et al. (2020) and estimate the average effects of net worth, asset shares, leverage ratio, and socio-demographic variables on the return to financial wealth. We find evidence for scale dependence. Further, we find that type dependence plays an essential role in explaining heterogeneity. Next, we exploit a unique feature for a subgroup of our data set, namely the information about the amount of financial wealth invested in equity, bonds, and bank deposits. Doing so allows us to show that scale dependence and type dependence play a more critical role in explaining returns on equity and bonds than returns from bank deposits. Overall, the results of the first two parts are in line with the existing empirical literature by Fagereng et al. (2020) and Bach et al. (2020) and support the theoretical predictions made by Benhabib et al. (2011) and Gabaix et al. (2016). In a second step, we apply distribution regression techniques by Chernozhukov et al. (2013) to estimate the size of scale dependence for different types. Controlling for the effect of net worth, asset shares, and socio-demographic characteristics, we interpret each distinct level of return as a specific investor type. We find that the effect of net worth strongly varies throughout the distribution of types, with high types benefitting the most from windfall gains. These results remain significant even if we control for the individual's risk appetite, captured by the allocation of the financial portfolio.

The rest of this paper proceeds as follows. In section 3.2 we discuss the economic intuition and theoretical background that explains the interaction between scale and type dependence. In section 3.3, we describe the data set that we are using, present an overview of the individuals we observe, and report some descriptive statistics as well as a simple portfolio composition for the distribution of net worth. In section 3.4 we discuss the average effect of socio-demographic variables on the return on financial wealth and assess the importance of scale and type dependence in our data. Finally, in section 3.5 we model the entire distribution of returns and estimate the scale dependence for different types of investors and conclude with section 3.6.

3.2 Economic Intuition for the Interaction between Scale and Type

This paper examines whether there is evidence for an interaction between *type* and *scale* dependence concerning returns to wealth. This research question is related to two different strands of the literature. The first stems from the financial economics literature and investigates why some individuals can generate higher returns on investments than others. The second is related to the portfolio choice and provides evidence that individuals increase their share in a risky asset once they obtain a higher level of wealth. In the following, we will present existing evidence on these two building blocks to use as an intuition for our hypothesis that scale dependence interacts with an investor type. In short, high-type investors tend to invest more in risky assets and thus profit more from additional wealth since they earn higher returns on those additional investment shares.

From a theoretical perspective, different models which incorporate *type* differences between investors are brought forward. A prominent example is a model by Chien et al. (2011), in which agents differ regarding their trading technologies. Their model can match the skewness and the kurtosis of the wealth distribution, the volatility of returns, and the risk-free rate. A different approach, discussed by Kacperczyk et al. (2019), uses investor sophistication as a source of heterogeneity between agents. They show that capital income inequality is increasing with the level of aggregate information technology. This is due to a higher demand for risky assets in states with a high level of information technology, which crowds out unsophisticated investors. Guvenen (2009) induces heterogeneity in returns by introducing limited participation and shows that this leads to reasonable high equity risk premia, flat interest rates, and a low wealth level for non-participants. For many of those factors, there also exists empirical evidence. For instance, Calvet et al. (2009a) find that well-educated households are more likely to rebalance their portfolio and, according to Goetzmann and Kumar (2008), are better diversified. Similarly, Bilias et al. (2010) find that college graduates have a significantly lower probability of investment inertia.[1] Graham et al. (2009) provide empirical evidence for a *competence effect* as their results suggest that those investors also trade more and suffer less from a *home bias*.[2] Using different (socio-) demographic characteristics as proxies for investor sophistication, Dhar and Zhu (2006) document that more sophisticated investors are less affected by the disposition effect.[3] Apart from the previously mentioned factors, many other exist and Calvet et al. (2009b) provide a well-executed overview. Beyond education or so-

1. Investment inertia describes the tendencies to not trade over a long period.

2. The term *home bias* was introduced in French and Poterba (1991) and describes the tendency of private investors only to hold domestic stocks.

3. Keeping stocks which performed worse in the past in the portfolio while selling well-performing stocks is often described as the disposition effect.

phistication, the access to superior information of favorable trading technologies may allow some investors to earn constantly higher returns than others. In their article, Gao and Huang (2019) investigate the effect of the implementation of a new online database for firm information on individuals investor trading activities. They find that access to the database positively impacts future stock returns, highlighting that informativeness has a relevant effect on performance. Overall, there is vast theoretical and empirical evidence on the existence of type-specific factors concerning investment behavior and, in turn, also to realized returns. However, these observations alone are not sufficient to support our hypothesis that *scale dependence* is affected by the *type* of an individual.

As a next step, we discuss the theoretical and empirical evidence on our second building brick, the increase in the shares invested in the risky asset with higher levels of wealth. Potentially, there are many reasons why individuals behave accordingly. For our purposes, it suffices to highlight two examples of underlying forces causing a shift towards a riskier asset once more wealth is available. On the one hand, individuals may have an indirect utility function of wealth with decreasing relative risk aversion (DRRA).[4] In this case, they will always allocate more of their wealth share to the risky asset the higher their wealth level is (see Ogaki and Zhang (2001) and Meyer and Meyer (2005)). Even though not commonly used in canonical models, there is empirical evidence for such DRRA utility functions.[5] Early studies on these issues, such as Friend and Blume (1975) and Jianakoplos and Bernasek (1998), find support for DRRA function if wealth is measured more inclusively, e.g., includes also human capital and real estate wealth. Similarly, Kessler and Wolff (1991), Guiso et al. (1996), and Calvet et al. (2009a) find evidence for a positive correlation between wealth and the share of risky assets in portfolios held by households using data sets from different countries. On the other hand, individuals' loss aversion may change with higher levels of wealth as described in Tversky and Kahneman (1991). For instance, one could imagine that the rich value losses and gains more equally as even substantial losses do not jeopardize their living standards. Once again, this would imply that individuals shift more of their portfolio shares to risky assets once their level of wealth increases.

Based on the previous arguments, we expect investor types to be prevalent and that investors may increase their investment in the risky asset once they obtain additional wealth. However, how would those two blocks lead to an interaction between type and scale dependence concerning returns? Suppose that there are two investors (H and L) with identical indirect utility functions of wealth with DRRA or decreasing loss aversion, holding the same level of net worth and access

4. Note that implies that the individual also has a DRRA utility function for consumption. See Meyer and Meyer (2005) for a detailed discussion of the interaction between the functional forms of the two utility functions.

5. An exception is Kim and Omberg (1996).

to two asset classes: a riskless asset and a class of risky asset, where the risky assets generate, on average, higher returns than the riskless asset. Additionally, suppose that investor H can generate persistently higher returns if she invests in the class of risky assets. This may be due to a higher level of sophistication or access to superior trading technologies. If both investors receive the same windfall gain in net worth, they will invest more into the risky asset due to the functional form of their utility function. Since the average return of the risk asset is higher than the return of the riskless asset, they will both generate higher average portfolio returns than before. This corresponds to the scale effect. However, the more sophisticated investor will be able to generate higher returns from her additional investment in the risk asset. Put differently, investor H also profits from her type. Overall, the high-type investor, therefore, profits more from the windfall gains than the low-type investor due to the combination of the type and the scale effect.

3.3 Data

We use an extensive data set with administrative tax records of individual households as our primary data source. The data covers all taxpayers in the canton of Bern, Switzerland, from 2002 to 2017. Starting at the age of 16, residents have to hand in a detailed tax return that includes all income sources and all components of their wealth and debt. These returns are processed by the tax authorities and build the basis of our analysis. A list of factors renders this data attractive for our purposes. First, individuals can be tracked over time, allowing us to tackle our analysis from a panel perspective. Second, we observe the entire population. This is crucial as it enables the precise analysis of wealth and its returns at the very tails of the distribution. Third, the data covers a long period enabling us to estimate precise individual effects. Finally, measurement error and unreliable observations are rare exceptions since the data is checked by the tax authorities to determine the tax payments of each individual. The tax data is available at the household level, i.e., married individuals hand in only one tax record. To facilitate an individual-specific analysis that allows us to track individuals even if their marital status changes, we follow the method by Fagereng et al. (2020) and duplicate all observations where two individuals are married and split up the income and wealth equally between the two partners. As our data covers the whole population, the results are not jeopardized by any selection biases. The only changes in the sample composition are due to migration and mortality. It is improbable these causes induce a selection bias. Concerning external validity, the canton of Bern is roughly representative of Switzerland, which is confirmed by the similar portfolio compositions reported in Martínez (2020a), which covers roughly half of Switzerland's population, and the data on household finance throughout Switzerland provided by Swiss National Bank (2019). Subsequently, we start describing our data by characterizing our main variables. Later, we describe the preparation of our data. Last, we briefly discuss the individual's summary statistics and present the portfolio composition across the net worth distribution.

3.3.1 Variable Description

Wealth and Its Components

Our data set consists of five different wealth components: Financial wealth (w_{it}^f), real estate (w_{it}^r), business wealth, wealth from self-employment and additional wealth (w_{it}^a). The latter category captures wealth that is not well categorized by the remaining components such as vehicles, art, and cash holdings. These components are all separately reported from financial wealth.[6] In the following discussion, we will aggregate business wealth and wealth from self-employment to one category, named business wealth (w_{it}^b), as the distinction between the two components is mainly based on the legal construction of the enterprise. For a subsample of our population, we can decompose financial wealth into three subcomponents: Bank deposits (w_{it}^d), equity (w_{it}^e) and bonds (w_{it}^o).[7] For most individuals, financial assets make up for the largest share of their fortune, followed by real estate and additional wealth. Finally, a small number of taxpayers own shares of private companies. On the one hand, this includes shares in limited partnerships, construction companies, and business buildings. On the other hand, business wealth incorporates equity capital invested in self-owned businesses. For tax purposes, real estate is priced at a hypothetical value that underestimates the market price. We adjust for the undervaluation using a study from the tax authorities of the canton of Bern (Steuerverwaltung des Kantons Bern, 2020). The study estimates the average difference between market value and tax value for each of the 346 municipalities of the canton, looking at all housing transactions in the canton of Bern between 2013 and 2016. This allows us to adjust the real estate value on a municipality level to find a proxy for the market value of each individual's real estate wealth. We observe financial wealth on a gross level and a separate category for debt (d_{it}), which is negative if the individual has outstanding debt. Apart from mortgages, debt captures credits, loans, and consumption debt. In the following, we will refer to an individual's *gross wealth* (w_{it}^g) as the sum of all wealth components

$$w_{it}^g = w_{it}^f + w_{it}^r + w_{it}^b + w_{it}^a$$

6. The full list consists of cash, gold, vehicles, boats, horses, art, and shares at heritage trust funds.

7. From 2015 onwards, this decomposition is possible for individuals filling in their tax reports online. Roughly 45% of the residents use these online tools.

and *net worth* to be the total gross wealth net of outstanding debt

$$w_{it}^n = w_{it}^g + d_{it}.$$

Income and transfers

The focus of the present paper lies on returns to wealth, defined as income from period t divided by the average wealth between period $t-1$ and t.

$$r_{it}^x = \frac{y_{it}^x}{\frac{1}{2}(w_{it}^x + w_{it-1}^x)}, \quad x \in \{f, d, e, o\}.$$

We use the average wealth level as the denominator to account for the fact that an asset receives an income flow during the year, while we only observe the end of period levels of wealth. As a result, we underestimate the return if an asset was bought in period t after dividend and interest payments on the underlying asset and overestimate returns if the asset was sold in period t but after the cash flows of the same period are realized. The numerator y_{it}^x is the pecuniary income stream of asset x in period t. In terms of taxes, this sort of income constitutes a part of the taxable income. Note that income from financial wealth is either subject to withholding taxes or not. For our analysis, we will aggregate the gross values, i.e., the income plus the withholding taxes, since this represents the effective income from wealth.[8] At its core, financial income captures interest to deposits, bonds as well as dividends. Note that capital gains are not part of the taxable income in Switzerland and therefore not available in our data. Since we only observe the total wealth at the end of each tax period and have no information about purchases and/or sales within the period, we cannot compute the precise capital gains and hence do not include them in our definition of income. While there are ways to estimate capital gains based on asset market performance, we withstand from doing so for this paper. The reason is that capital gains are subject to high risk until the underlying asset is sold. Additionally, estimating the portfolio performance would be determined greatly by the overall asset market performance. Thus there would surely be a mean reversion within our data set, and individual performance would not be captured adequately. Finally, Fagereng et al. (2019) show that capital gains are relatively more important for the top of the wealth distribution. Therefore, our measure of returns will yield conservative results with respect to heterogeneity. Beyond these forms of income from wealth, our data covers a large range of other income sources such as labor income, income from self-employment, and pension income.

8. Assets excluded from withholding taxes include foreign equity or bonds and interest on private loans. This makes up for roughly one-third of all returns on financial wealth.

Socio-demographics

Our data set is anonymized, nevertheless, we observe the year of birth, the marital status (single, married, separated, divorced, widowed), the number of children, and the place of residence for each individual. Since some of those variables are potentially correlated with net worth, it is essential to control for them in the empirical analysis. For example, Martínez (2020a) finds that age is positively correlated with wealth in Switzerland.

3.3.2 Data construction

To ensure the reliability of our estimates, we take six steps to homogenize the data. First, we exclude roughly 7.3% of our observations because they are fundamentally different than normal taxpayers. These include (*i*) individuals going abroad or returning from abroad (1.9%), (*ii*) individuals who forgot to hand in a record (2.8%) and (*iii*) individuals younger than 18 or older than 100 (2.6%).[9] Second, we exclude individual-year duplicates, which make up 0.3% of the observations. These duplicates mainly exist for an individual right after marriage or after separation/divorce. Third, we drop individuals with impossible changes in their marital status, e.g., from widowed to single. This cleaning step affects 0.3% of our sample. Forth, we exclude cases where individuals mistype their records. In about 0.7% of all observations, we observe that income from wealth exactly equals the level of wealth.[10] These records can not be trusted, however, we do not have to exclude all observations of such an individual as these mistakes seem to be uncorrelated over time. Fifth, there may be substantial financial or aggregate wealth changes, e.g., caused by marriage or heritage.[11] In such years, it would be delicate to calculate any returns to wealth. Thus, we keep these observations but do not calculate returns in such years. Overall, about 0.3% of all observations fall into that criterion. Finally, we label implausibly high returns as such.[12] Besides interests and dividends, payments from liquidations and gifted assets count as financial returns. These special incomes can not be compared to standard returns on wealth. However, we can not separate them in the data. As these forms of incomes are causing implausibility, our main results in sections 3.4 and 3.5, and additional results in section 3.C of the appendix are derived without these

9. If an individual forgets to hand in their tax report they are taxed with a substantial mark-up based on their previous year's tax report.

10. The tax authorities in Bern have confirmed that these are individual mistakes made by the taxpayer.

11. We define a substantial change to be higher than 500'000 CHF in absolute terms, and to be either a relative change of -66% or +200% compared to the previous year.

12. We label returns higher than +/- 30% as implausibly high. Note that it is practically infeasible to get a return above that level by only holding deposits, bonds, and equity. For returns to business wealth, we set the bar at +/- 100% as business wealth is more volatile.

observations. In total, roughly 0.8% of our data are unreliable due to immense returns.

3.3.3 Summary Statistics

In Table 3.1 we report the summary statistics of our data set, pooling the observations from all years. We report the mean, standard deviation and a few selected percentiles of the variables of interest. The data set consists of around 12 million observations from 2002 until 2017 and includes data from 1,070,884 distinct individuals. The observations are almost equally distributed across years, with a slight positive time trend. Panel A shows basic socio-demographic characteristics. The sample is well balanced across gender and marital status. Panel B gives an overview of the individual's income. Total income captures all taxable income after deductions. The main source is labor income, with an average of around 33,942 CHF. Social security payments and pension income are ranked second in terms of their average importance. Our main focus lies on financial income and its subcomponents used to compute the returns on the individual assets. Around 80% of the observations report a positive level of financial income. Financial income is not the most important source of income, nevertheless, it accounts on average for almost 5% of the total income. In panel C, we report the statistics for all components of wealth. On average, the most important assets held by an individual are financial wealth and real estate. More than half of the observations report no wealth in real estate. This is typical for a Swiss data set as the majority of the population does not own real estate but is renting instead.[13] We find business wealth to be the least important asset on average, and less than 10% of the observations report a positive entry for that asset class. Looking at the individuals for whom we have detailed information about their financial wealth (2015 – 2017), we observe that the median taxpayer holds no financial assets apart from bank deposits.[14] Finally, panel D displays the return on different assets. Within our sample, the average return to financial wealth is 0.91% across the entire sample period. There is a large heterogeneity within the sample, as the percentile range between the 10th and the 90th percentile with 5.14 percentage points shows. As one would expect, this is mainly driven by the significant differences in returns to business wealth and equity. Interestingly, as we find in unreported results, the large variation in total financial wealth is almost equally shared between and within individuals. In contrast, for business wealth, the main driver of the variation is the between variation. Overall, we note that our summary statistics are similar to the one previously found for Switzerland (Martínez, 2020a; Swiss National Bank, 2019).

13. See Martínez (2020a) for similar results.

14. In total we have 1,115,278 observations with detailed data from 436,022 distinct individuals. As in the main data set, the observations are almost equally distributed across years.

Table 3.1: Summary statistics on individual level

	Mean	**SD**	**P10**	**Median**	**P90**	**P99**	**Obs.**
			Panel A: socio-demographics				
Age	49.89	18.59	25.00	49.00	76.00	90.00	11,962,563
Female (%)	52.38	49.94	0.00	100.00	100.00	100.00	11,962,563
Married (%)	53.71	49.86	0.00	100.00	100.00	100.00	11,962,563
Number of Children	0.48	0.92	0.00	0.00	2.00	3.00	11,962,563
			Panel B: income				
Total Income	47,461	96,322	14,152	43,420	80,624	165,212	11,962,563
Total Labor Income	36,835	41,523	0	34,961	77,970	149,662	11,962,563
Additional Income	-1,697	42,175	-5,905	0	40	22,000	11,962,563
Pension Income	3,814	10,625	0	0	15,614	49,372	11,962,563
Social Security Income	6,603	10,117	0	0	21,468	29,064	11,962,563
Total Financial Income	2,043	76,802	0	101	2,498	25,837	11,962,563
Bank Deposits	362	7,540	0	24	356	5,786	1,115,278
Bonds	37	840	0	0	0	813	1,115,278
Equity	1,009	129,063	0	0	370	10,859	1,115,278
Real Estate Income	-494	14,966	-3,750	0	2,452	20,481	11,962,563
Business Income	358	11,677	0	0	0	1,136	11,962,563
			Panel C: wealth				
Total Wealth	355,902	5,468,635	2	88,124	746,600	3,155,332	11,962,563
Total Financial Wealth	138,796	4,629,607	0	25,756	243,111	1,383,371	11,962,563
Bank Deposits	85,713	337,118	2,127	30,073	192,925	803,642	1,115,278
Bonds	1,671	21,397	0	0	0	42,528	1,115,278
Equity	29,543	998,596	0	0	30,135	444,931	1,115,278
Real Estate	199,753	1,094,191	0	0	522,748	1,837,412	11,962,563
Additional Wealth	10,005	265,316	0	0	9,100	164,030	11,962,563
Business Wealth	9,482	143,540	0	0	0	239,414	11,962,563
Debt	-90,841	419,768	-269,500	0	0	0	11,962,563
			Panel D: returns on wealth				
Financial Wealth (%)	0.91	17.37	0.04	0.55	1.76	5.18	8,959,646
Bank Deposits (%)	0.33	29.81	0.00	0.07	0.48	2.18	648,732
Bonds (%)	2.15	7.39	0.39	1.47	3.83	11.43	15,213
Equity (%)	2.81	13.66	0.00	1.50	4.55	26.17	175,152
Business Wealth (%)	6.10	37.80	0.00	0.03	1.84	160.37	679,218

The summary statistics cover the entire population in the canton of Bern, Switzerland, above the age 18 pooling data from 2002 – 2017. We exclude specially taxed people, i.e. individuals going abroad or returning from abroad, people who forgot to hand in their tax report, and people with obvious mistakes in their tax report.

3.3.4 Portfolio Composition

Figure 3.1 shows the portfolio composition of the average individual across different percentiles of net worth, including the very top of the distribution. The figure shows the average asset position as a share of the average gross wealth held by an individual at a specific percentile of net worth. Individuals at the 10th percentile hold, on average, around zero net worth. A median person of our data set has an average net worth of approximately 60k CHF and a gross wealth of around 110k

CHF. Approximately 40% of its gross wealth is invested in financial assets. For the bottom half of the distribution, the majority of its wealth is held in financial assets. However, even at the bottom half of the distribution, we find a relatively large share of the portfolio is invested in real estate but accompanied by sizeable outstanding debt. For individuals around the median net worth, real estate is, on average, the most important asset of their portfolio. They hold smaller mortgages on their house than the bottom half of the distribution. Financial wealth, on the other hand, becomes less critical. This observation remains true until we reach the very top of the distribution. For individuals at the top of the net worth distribution, financial assets make up the largest share of their portfolio, and debt plays only a minor role. Interestingly, in our data set, business wealth is irrelevant for the average person at each percentile of the distribution. However, for an individual observation, it may be a large share of its portfolio. Note that we cannot differentiate between public equity and private equity, thus, financial wealth is a mix of both. As a result, the share of business wealth may be underestimated for the richest individuals who hold larger, more complicated legal enterprises in their financial portfolios. In addition to the overall portfolio composition, we can decompose the financial portfolio into three broad categories (equity, bonds, and bank deposits) for a subsample of our data. We report the allocation of financial assets in section 3.A of the appendix.

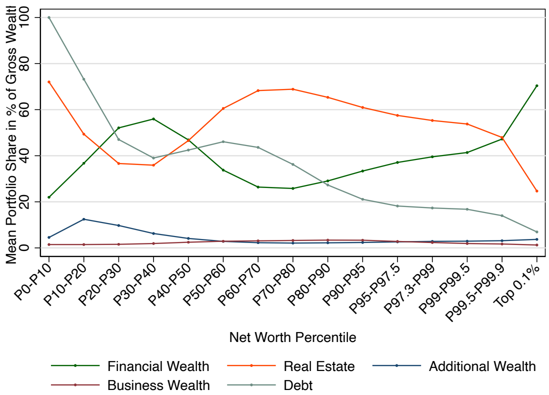

Figure 3.1: Portfolio Composition across the Net Worth Distribution

This figure displays the portfolio allocation of the average individual across the different percentiles of net worth.

3.4 Modelling Average Effects on Returns to Wealth

In this section, we aim at modeling individual returns on wealth for financial assets. We now introduce formal models to analyze how returns depend on observables. In the first step, we use classical OLS techniques to identify average effects on returns. In the spirit of Fagereng et al. (2020), we regress returns on different assets r_{it} of individual i in year t on a set of covariates denoted by X_{it}. The latter includes information on marital status, gender, age, number of children, the logarithm of total net worth, portfolio composition, and yearly indicator variables.[15] Based on the results in Fagereng et al. (2020), we suspect that the level of net worth is a strong predictor for high returns. This would correspond to scale dependence, that is, higher wealth correlates with higher returns. However, it is a priori unclear whether this relation holds once we control for the socio-demographic variables. Formally, the linear regression model is presented in the following equation.

$$r_{it} = X_{it}'\beta + \epsilon_{it}. \tag{3.1}$$

Beyond scale dependence, Gabaix et al. (2016) suggest that type dependence, i.e. the presence of high growth types, is a determining factor of returns. We tackle this issue by including individual fixed effects into the regression model from equation (3.1). In essence, individual fixed effects account for the persistence of returns. Comparing the two types of models, with and without individual fixed effects, we can get an idea of which type of dependence is prevalent in the data. Note that socio-economic factors such as age are typically not regarded as affecting your type as their impact may change over time. Further, all time-invariant variables are omitted once we control for individual fixed effects. However, we keep net worth as a predictor because potential changes in wealth may drive returns. For our baseline exercise we choose r_{it} to be the return on financial wealth (r_{it}^f). In addition, we run the same exercise for the three broad categories of financial wealth that we can identify. In particular, this covers the return on bank deposits (r_{it}^d), equity (r_{it}^e) and bonds (r_{it}^o). Accordingly, Table 3.2 presents the estimates of the baseline model with and without fixed effects and Table 3.3 for the subgroups of financial wealth.

As shown in column (1) of Table 3.2, the year fixed effects only explain roughly 5.2% in the variation of the return on financial wealth. Moving to column (2), we see that net worth not only has the expected positive impact but is also of sizeable economic relevance. A 1 percentage point increase in net worth would predict an increase in financial returns by more than ten basis points on average. In addition to net worth, the most relevant predictors for financial returns are the individual portfolio compositions. A larger share in financial wealth predicts an increase in returns; the same is true for a higher leverage ratio, computed as the ratio of

15. We use the logarithm as the net worth is highly skewed to the right as described in the previous sections. This has the drawback that we can only use individuals with positive net worth. As a robustness check we do the same exercise using the net worth percentile ranks, which allows us to use the full data set. The results are qualitatively unchanged and reported in Table 3.5 of the appendix.

Table 3.2: Average effects: scale and type dependence

	Without individual FE			Including individual FE		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
ln(Net Worth (CHF))		0.00176***	0.00057***		0.00093***	0.00013***
		(0.000)	(0.000)		(0.000)	(0.000)
Share in w_{it}^f		0.00264***	0.00033***		0.00122***	0.00019
		(0.000)	(0.000)		(0.000)	(0.000)
Share in w_{it}^r		-0.00249***	-0.00135***		-0.00094***	0.00011
		(0.000)	(0.000)		(0.000)	(0.000)
Share in w_{it}^b		-0.00024***	-0.00040*		-0.00001	-0.00042
		(0.000)	(0.000)		(0.000)	(0.001)
Leverage Ratio		0.00324***	0.00112***		0.00133***	0.00028
		(0.000)	(0.000)		(0.000)	(0.000)
Equity Share			0.01629***			0.00639***
			(0.000)			(0.000)
Bonds Share			0.01055***			0.00527***
			(0.000)			(0.000)
Socio-Demographics	no	yes	yes	no	yes	yes
Year FE	yes	yes	yes	yes	yes	yes
Ind. FE	no	no	no	yes	yes	yes
R^2	0.052	0.105	0.142	0.398	0.412	0.685
adj. R^2	0.052	0.105	0.142	0.335	0.349	0.512
N	8,875,289	8,462,780	950,626	8,816,922	8,401,047	885,441

The outcome variable is individual returns on financial wealth r_{it}^f in all columns. The explanatory variables in all models are portfolio and socio-demographic characteristics, a constant and fixed effect. Standard errors clustered at the individual level in parentheses, *** $p < 0.001$ ** $p < 0.01$, * $p < 0.05$. The data set is cleaned as described in section 2.

total debt to gross wealth. We find the opposite effect for real estate and business wealth, while the latter has only a small economic relevance. There are different possible reasons for this finding. First, individuals may have more sophisticated portfolios if they invest a large share of their net worth in financial assets. In particular, these individuals are likely to have better-diversified portfolios, which leads to higher returns on average. Second, individuals with high financial shares might choose to seek riskier investment opportunities because they have a smaller demand for liquidity since they are less exposed to the risk of unexpected damage to the house or their own business. Last, it may be that some effect that is due to scale dependence may be captured by the share in financial assets, which is positively correlated with net worth. Similar explanations may cause the negative effect of real estate shares. Individuals with high exposure in real estate may choose to hold less risky financial assets to satisfy the demand for liquid assets.[16] Regarding the leverage ratio, we reason that households with more long-term

16. We can control for the risk exposure of the financial portfolio using only a subsample of the data set. The coefficients for the share in both financial assets and real estate are significantly

debt can exploit the low nominal interest rates to invest in riskier financial assets. Consequently, these individuals earn higher returns on their financial wealth while financing it with relatively cheap borrowings. In addition, high leverage ratios are negatively correlated with high net worth and may capture some of the effects due to scale dependence.

As previously mentioned, the data contains additional information on the financial asset allocation for a subsample of our observations. We have a detailed description of the financial portfolio for roughly half of the population, allowing us to divide total financial wealth into three broad asset categories. Using this information, we can control for the risk attitude of the individual. More precisely, we include both equity and bond shares into the list of control variables captured by X_{it}. As expected, both equity and bond shares are significant predictors for high returns and yield the most considerable explanatory power. Overall the qualitative results are similar to the one we obtain without conditioning on the portfolios risk exposure. However, as shown by Bach et al. (2020), some part of the variation in return is clearly due to the riskiness of the portfolio. Comparing the magnitude of scale dependence (i.e., the coefficient for the logarithm of net worth), we show that the size of the coefficient is significantly lower when we condition on the shares in financial asset classes. Nevertheless, we find a clear indication that scale dependence is a significant and economically relevant factor for the variation in returns even after controlling for the level of net worth by including individual fixed effects.

Before we turn to the regression with fixed effects, we briefly discuss the role played by the socio-demographic variables. While all socio-demographic variables except age are statistically significant, only marital status is economically relevant. For a more detailed discussion of these variables and their impact, we refer the reader to section 3.C of the appendix. Married individuals have, ceteris paribus, an average return that is ten basis points higher than their single counterparts. Like the argument we have stated previously, we consider the demand for liquidity to be the most critical factor driving these results. Single households are more exposed to income shocks and have higher fixed costs (such as rent and insurance payments) than married households. This is likely causing them to hold less risky assets and invest a higher share of their financial wealth in bank deposits.

Shifting our attention to columns (4) to (6), we first need to discuss what individual fixed effects capture. In this regard, Fagereng et al. (2020) present three different categories that the fixed effect may capture: (*i*) the persistent difference in risk tolerance, (*ii*) the persistent disparities in net worth, and the positive effect of wealth on returns (Piketty, 2014) and (*iii*) the persistent difference in financial sophistication, ability to access information on financial markets

smaller in absolute terms. This indicates that the demand for liquid financial assets such as bank deposits is inversely related to the share in financial wealth.

and other constant individual characteristics (such as intertemporal discounting). Further, as we have a mixture of public and private equity as part of the financial assets, we may also capture persistent differences in entrepreneurial skills. All of the aforementioned persistent differences may affect the return of an individual portfolio, conditioning on the size of their net worth. Given the large increase in the explained variation of the returns (measured by the adjusted R^2), our data suggest that the three effects coexist. Indeed, even after controlling for the persistent difference in net worth, the scale of the portfolio positively correlates with high returns. Once we add the bond and equity shares, we find that the overall portfolio composition is no longer significant. Only the allocation of financial assets and the changes in net worth are significant predictors of the individual's return. One interpretation might be that the positive correlation between shares in financial wealth and shares invested in equity was previously captured by the former. The true channel driving the increasing returns was through the latter. Last, we find that controlling for the financial asset allocation yields a significant increase in the predictive power of the full model. Including equity and bond shares into the regression increases the adjusted R^2 by almost 50% in both model specifications, indicating that the financial investment decision is a strong channel for predicting returns and should not be neglected whenever possible. We take this as evidence that financial sophistication and access to private equity positively affect individual returns as it would otherwise be hard to justify the large difference in the adjusted R^2. Taken together, the results in Table 3.2 indicate that both, type and scale dependence are prevalent and drive returns to financial wealth.

Using the subsample of our data set, we redo our previous regression analysis using the return on deposits, on bonds, and equity as dependent variables. Note that in this case, the fixed-effect models are equal to a cross-sectional first difference. The results of this analysis are displayed in Table 3.3.[17] The results for all three types of returns confirm the findings for the overall portfolio above. This indicates that even after controlling for the riskiness of an asset, the size of net worth plays a vital role in predicting an individual's return. The coefficient of net worth is weakest for the return on bank deposits. There are two reasons for that. First, bank deposits yield on average the lowest return, and second, there is little that the investor can do to impact the return on bank deposits. This is reflected in the smaller increase in the explained variation after including fixed effects. Indeed, investors can only choose the bank they want to work with and how much wealth to invest in a saving account rather than in a checking account. After controlling for the individual fixed effect, the only covariate that is a significant predictor for high returns is the individual's level of net worth, a strong indication that scale dependence is an essential factor that drives the

17. We do not report the entire table including all socio-demographics as they do not yield any additional information.

Table 3.3: Average effects: scale and type dependence for returns on different asset classes

	r_{it}^d		r_{it}^e		r_{it}^o	
	(1)	(2)	(3)	(4)	(5)	(6)
ln(Net Worth (CHF))	0.00039***	0.00011*	0.00323***	0.00135**	0.00361***	0.00350**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Share in w_{it}^f	0.00025**	0.00032	0.00097	-0.00030	0.00495*	0.02754
	(0.000)	(0.000)	(0.001)	(0.002)	(0.002)	(0.014)
Share in w_{it}^r	-0.00101***	0.00015	-0.00561***	-0.00174	0.00024	0.01900
	(0.000)	(0.000)	(0.001)	(0.002)	(0.003)	(0.014)
Share in w_{it}^b	-0.00054**	-0.00020	0.00721***	0.00084	0.01381**	0.00905
	(0.000)	(0.001)	(0.002)	(0.005)	(0.005)	(0.027)
Leverage Ratio	0.00102***	0.00050*	0.00580***	0.00061	0.00924***	0.00748
	(0.000)	(0.000)	(0.001)	(0.002)	(0.002)	(0.006)
Socio-Demographics	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes
Ind. FE	no	yes	no	yes	no	yes
R^2	0.006	0.691	0.020	0.807	0.034	0.842
adj. R^2	0.006	0.381	0.020	0.613	0.033	0.683
N	609,738	547,880	168,620	148,826	15,060	12,240

The table displays the results of regressing the returns of the assets on portfolio and socio-demographic characteristics, a constant and fixed effects as indicated. Standard errors clustered at the individual level in parentheses, *** $p < 0.001$ ** $p < 0.01$, * $p < 0.05$.

return on financial assets. Compared to the benchmark case in Table 3.2, we find a more substantial increase in the adjusted R^2 for the different asset classes. This suggests that conditional on the level of net worth and the risk exposure of the individual, financial sophistication is crucial for the returns.[18] An observation which is in line with previous findings such as Graham et al. (2009), Calvet et al. (2009b) and Dhar and Zhu (2006).

Overall, the simple regression analysis shows that both scale and type dependence coexist and are crucial factors to determine the return of different investment vehicles. These results are consistent with the previous findings of Bach et al. (2020) and Fagereng et al. (2020), who do a similar exercise with a Swedish and Norwegian data set, respectively. In principle, the effects presented so far may vary across different levels of the returns. If so, we would neglect this heterogeneity by only running ordinary regressions. Thus, we introduce a more flexible and comprehensive approach in the following, allowing us to answer our research question, namely whether there is an interaction between scale and type dependence.

18. Note that when the dependent variable is the return of a specific asset, we implicitly control for the riskiness of the asset.

3.5 Heterogeneity of Scale Dependence across Types

As pointed out in chapter 3.2, existing theoretical and empirical evidence suggests that an interaction between the two dependencies is likely to be prevalent. High-type investors may benefit more from an increase in net worth than low types. For example, this may be due to higher investment sophistication or access to superior trading technologies (see Dhar and Zhu (2006) and Guvenen (2009)). To uncover this possible interaction, we need to model the full distribution of returns conditional on the covariates. In essence, we are isolating the effect of net worth on the returns on financial wealth throughout the distribution of the latter. Thereby, we will control for the same set of regressors as in the previous section. By controlling for the set of observables, we interpret the quantiles of returns as an approximation for the individual's type. While this approach does not perfectly capture the individual's type, we believe it to be a close approximation to the true differentiation across types as we can control for sociodemographic characteristics and risk attitude captured by the portfolio choice of the individual. Note that this assumption would be invalid if individuals would migrate through the return quantiles over time. We calculate binned scatterplots for the first and the second lag of the return quantiles to verify this assumption. According to Figure 3.2, it is indeed the case that individuals remain in their respective bins over time.

(a) First Lag (b) Second Lag

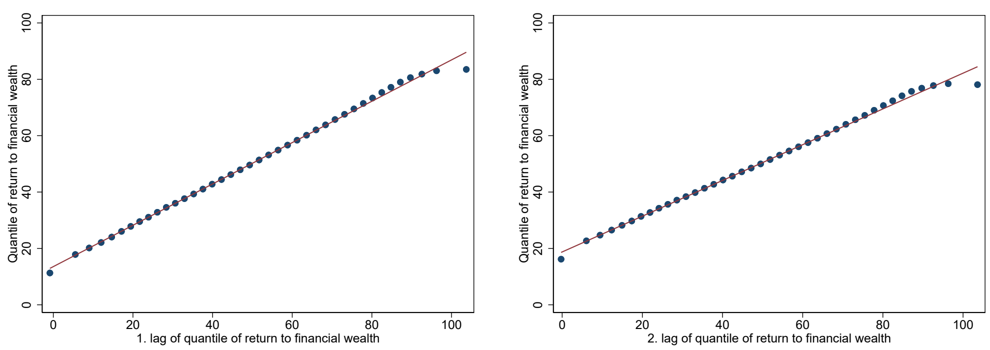

Figure 3.2: Binned scatterplots for the quantile of return to financial wealth and its lags

The figure shows the relative mobility of individuals across return quantiles over time. Individuals are separated into quantiles based on their returns each year and then binned into 40 bins according to their residuals. The residuals are obtained from regressing the return on the respective lag and the control variables as in column (2) in Table 3.2.

We will model the conditional distribution of returns using Distribution Regression (DR) techniques developed by Chernozhukov et al. (2013). Formally, equation (3.2) introduces this approach.

$$F_{r_{it}|X_{it}}(y) = \Lambda(X_{it}'\beta(y)), \tag{3.2}$$

where $F_{r|X}(y)$ denotes the cumulative distribution function (CDF) of r_{it} conditional on a matrix of regressors X_{it} at a threshold y, Λ is a parametric link function (e.g. logit or probit) and $\beta(y)$ is a coefficient vector. The estimated coefficients in (3.2) provide information on how a covariate shifts the CDF of returns at a certain threshold. Note that this is a semi-parametric approach in the sense that $\beta(y)$ varies with the thresholds. This is, we allow the effects of the regressors to vary across the distribution of r_{it}, which generates a high degree of flexibility. Compared to other methods that aim at distributional effects, DR does not require the outcome to be continuous. For a more profound documentation of DR, the reader may consider the influential work by Chernozhukov et al. (2013).

Conceptually, our goal is to draw conclusions on the effect of net worth only. Therefore, we need to translate effects at the conditional distribution of r_{it} into unconditional effects. Equation (3.3) derives the unconditional CDF from the conditional one in equation (3.2).

$$F_{\langle r|w_{it}^n=\cdot\rangle}(y) = \int_{\mathcal{X}} F_{r_{it}|X_{it}}(y)dF(\mathcal{X}). \tag{3.3}$$

In a nutshell, we integrate over the covariates to eliminate the effects of all regressors in X_{it} apart from net worth, w_{it}^n. With respect to the latter, we artificially set w_{it}^n to specific values to get the distribution of returns which then only depends on w_{it}^n. We denote this modified covariate distribution by $\mathcal{X}$. For instance, $F_{\langle r|w_{it}^n=10,000\rangle}(y)$ denotes the CDF of returns on financial wealth provided that all individuals would hold 10'000 CHF of net worth. Setting net worth to its values at the unconditional quantiles $q \in (.01, .99)$ we obtain a distribution of returns at every quantile of net worth. As these distributions are hypothetical, we will refer to them as counterfactuals hereafter. In essence, we model the distribution of returns for each quantile of net worth. Note that, while our focus lies on the effect of additional net worth across types, it would be possible to isolate any effect of an observable. However, our method will enable us to estimate the importance of scale dependence across the different types. In the following, we will present two sets of results. In subsection 3.5.1, we elaborate on how the distribution of returns to financial wealth depends on net worth. In a second step, we will discuss in subsection 3.5.2 how different sets of covariates, or equivalently how different definitions of an investor's type, alter the effect of net worth on the returns.

3.5.1 Distribution of Returns by Net Worth

The analysis in this subsection relies on the full sample and a benchmark model including the same covariates as the OLS regression model presented in Table 3.2. In a first step, Figure 3.4 describes the distribution of returns for three different levels of net worth: The 10th (2,646 CHF), 50th (105,325 CHF), and 90th (685,381 CHF) quantile of net worth.[19] Both panels of Figure 3.4 present functionals of the counterfactual distributions in equation (3.3). We obtain the quantile function by taking the left inverse of the distribution function. To get the probability mass function (PDF) we differentiate the CDF with respect to the support.[20] At this point, we want to stress that the following results are only due to changes in net worth and not due to other observables, as we control for the full set of covariates in our data. Starting with the right panel of Figure 3.4, the PDF illustrates that the full distribution is shifted to the right as we increase the level of net worth held by an individual. In other words, we find that low returns become less likely and higher returns become more frequent. This finding is qualitatively the same as the one we described in section 3.4 - higher net worth leads to higher returns on financial wealth. In the left panel, we observe that the quantile function of returns is shifted upwards. However, the shift is stronger for top quantiles of returns, indicating that, while all returns are positively affected by net worth, high returns seem to be affected more strongly. Thus, we find a positive interaction between the individual's type and the ability to increase returns with a higher level of net worth.

In the following, we consider the full distribution of returns at all quantiles of net worth. The left panel of Figure 3.5 visualizes how specific quantile values of the returns change depending on net worth. This Figure implies two patterns. For higher levels of net worth, the distribution of returns is (*i*) more widespread and (*ii*) more skewed. Both suggest that net worth changes the distribution of returns. If we interpret each quantile of the distribution of returns to be a separate type of investor, (*i*) implies that the scale effect changes across the distribution of types. If scale dependence were linear across types, we would observe a linear increase in the returns on financial wealth, and the variance would stay constant. However, our results show that the variance in returns increases substantially for higher levels of net worth. This shows that, while all types are able to generate higher returns with additional net worth, high type individuals do so with much more success. This result becomes more prominent as we look at the very highest types of investors in panel (b) of Figure 3.5. Even for moderate levels of net worth, the high type investors can generate very high returns and continue increasing their returns as they get access to more net worth. From observation (*ii*), we find

19. For the counterfactual distributions, we use the percentile values of 2017.

20. Note that the PDF is consistently estimated but at a lower rate of convergence. For more details on this issue, see Rothe and Wied (2020).

Figure 3.3: Distribution of Returns for Specific Values of Net Worth

(a) Quantile Function (b) PDF

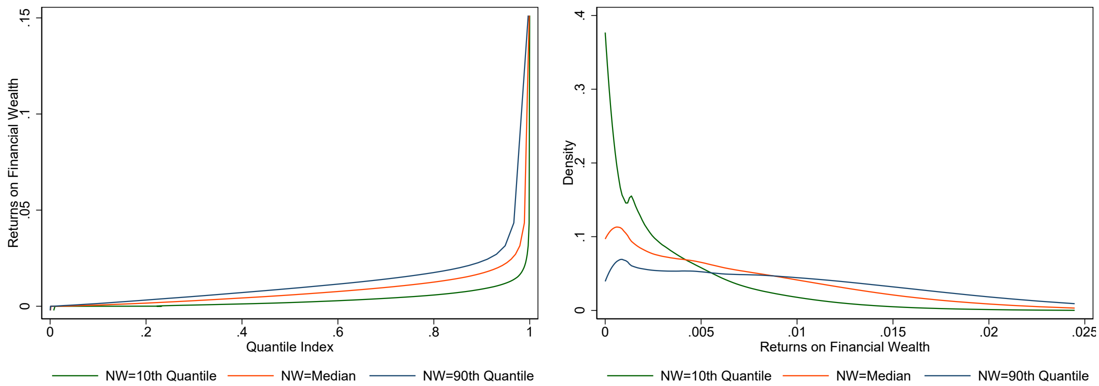

Figure 3.4: Distribution of Returns for Specific Values of Net Worth

The figures displays the unconditional quantile and probability density function of returns to wealth on net worth.

that scale dependence varies for all types across the distribution of net worth. We observe a relatively small and linear impact of net worth for moderate levels of net worth, which changes drastically once an individual surpasses a net worth that is larger than the 90th percentile of the distribution. Individuals at the top of the wealth distribution can generate much larger marginal effects on their financial returns.

Both observations (*i*) and (*ii*) are in line with our hypothesis formulated in chapter 3.2 and in line with the existing literature too. The positive effect of investor sophistication on the level of capital income is modeled in Kacperczyk et al. (2019) whereas Calvet et al. (2009a) summarise the empirical evidence in this regard. Guvenen (2009) proposes a model with limited stock market participation that leads to a disparity in capital income. So far we did not control for differences in the risk attitude of individuals. Wealthier individuals may be able to take higher risks which leads to higher performance of their portfolio or enables them to better diversify the risk. In addition, individuals at the top of the distribution may no longer have a motive for precuationary savings, which enables them to invest all of their additional net worth in risky assets. However, we show later in this section that differences in risk attitude cannot fully explain these observations once we use a subsample of our data to control for the financial portfolio decisions.

Taken together, our findings provide two novel insights. (*i*) A larger stock of net worth increases returns more strongly for high-type investors. (*ii*) The increase in returns is largest at the top quantiles of net worth. Both results are in line with the explanations of existing literature. First, investor sophistication

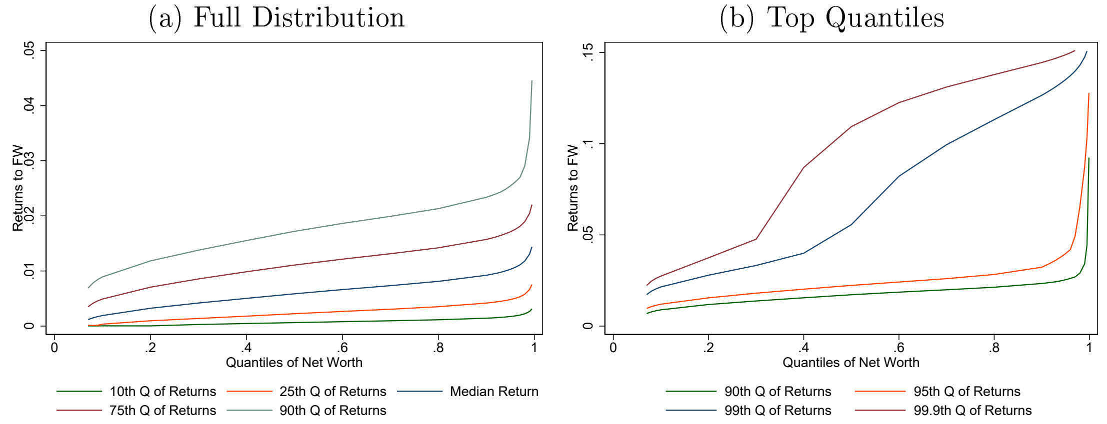

Figure 3.5: Distribution of Returns by Quantile of Net Worth

The left figure plots the full distribution of returns at all quantiles of net worth whereas the right figure shows the distribution only for top quantiles.

could be a key element. High-type investors can more easily acquire information on investment opportunities, leading to a stronger increase in returns as they move along the distribution of net worth. Second, limited participation in private equity and similar asset classes may explain the high returns for the individuals at the very top of the wealth distribution. An additional explanation could be the saving behavior of the individuals. Once individuals acquire a high enough net worth buffer, they may invest a larger share in high-risk assets, leading to a sharp increase in the marginal effect of net worth on financial returns.

3.5.2 Robustness Checks to Capture the True Type

In the previous subsection, we showed a strong interplay between type and scale dependence. In particular, we showed that high type investors are much more successful at increasing the marginal impact of net worth on financial returns. To assess the validity of our results, we perform different robustness checks to our definition of an individual's type. More precisely, we focus on how net worth changes the distribution of returns if we use different sets of covariates to capture the type of an individual. We try to convince the reader that while different methods to isolate the type of an investor alter the quantitative results, the qualitative relations stay the same. This subsection relies on information about the composition of the financial portfolio. Thus, we only use the sample period from 2015 to 2017, which incorporates these characteristics. This allows us to have a more precise estimate of the type by controlling for the individual's risk attitude.

We start discussing our results by comparing the average return across types for different levels of net worth. Figure 3.6 shows how different specifications of the type alter this relationship. We consider three specifications by adding sets of control variables: (*i*) Demographic variables, (*ii*) shares of wealth classes of gross wealth, and (*iii*) shares of bonds and equity of total financial wealth. The demographic variables include age, gender, number of children, and marital status. Further, we include the following shares of total wealth: business wealth, real estate wealth, financial wealth, and leverage ratio. Note that in this setting, including covariates is equivalent to different definitions of an individual's type. For example, a model that only controls for socio-demographic characteristics has the implicit assumption that these variables fully capture a type. By equation (3.3), we compute the distribution of returns that only depends on net worth. Thus, the presented results do no longer explicitly depend on the included control variables. Instead, a large difference between the models would imply that the included covariates correlate with net worth and thus alter the unconditional effect of the latter.

(a) Average Return by Quantile of NW (b) Average Marginal Effect

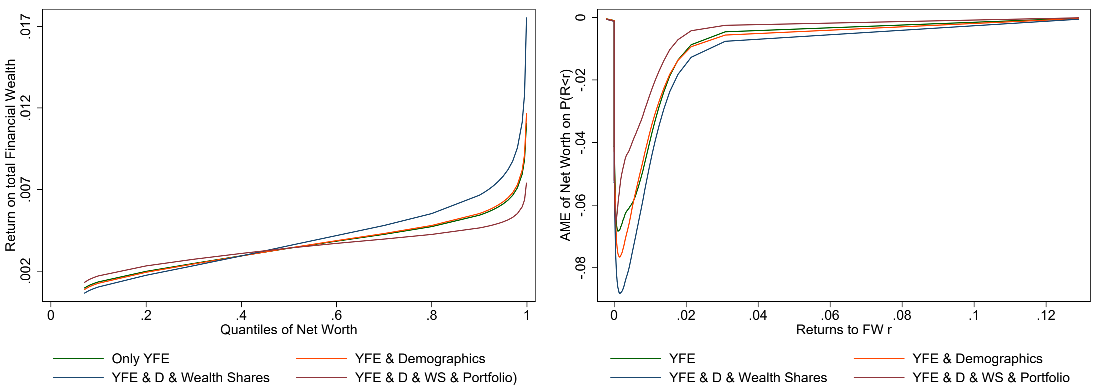

Figure 3.6: 4 Models for the Unconditional Effect of Net Worth

The figures show the average return by quantile of net worth as well as the average marginal effect for four different models. The first model only features year fixed-effects, for the second model we add socio-demographic variables, in the third model we additionally include wealth shares, and for the forth we add the portfolio asset shares.

The left panel of Figure 3.6 shows that net worth increases the average return to financial wealth irrespective of the model specifications. Thus, we observe a scale effect of net worth even when we account for other channels driving the returns. Yet, the heterogeneity in returns depends on the included covariates. While the demographic variables do not significantly alter the effect of net worth, the contrary is true for the wealth shares and portfolio composition. First, we consider the inclusion of the wealth shares. The results from section 3.4 implied that (*i*) a larger share of real estate wealth decreases returns at the average and (*ii*) a larger share of financial wealth increases returns. While the more flexible approach we apply here allows these effects to differ across types, we find that, on average, the impact of net worth is dampened if we include wealth shares to capture the true type of an individual. From the discussion of the portfolio composition in section 3.3.4 we know that the share in real estate wealth has a positive correlation, and the share in financial wealth has a negative correlation with net worth. Thus, not including the wealth shares underestimates the immediate effect of net worth. The converse is true once we control for the shares of equity, bonds, and bank deposits. Wealthier individuals hold larger shares in equity and bonds, which boosts returns. The direct effect of net worth across types is thus lower as part of the higher returns stems from a beneficial portfolio composition and higher risk-taking induced by additional net worth.

Next, we turn to the marginal effect of net worth. Compared to standard regression models, this parameter represents the analog to an OLS slope coefficient. The right panel of Figure 3.6 illustrates how net worth affects the probability to gain a return lower than r, the value on the x-axis. Intuitively, a higher value of net worth leads to a lower likelihood for low returns. Thus, individuals with high net worth are less likely to end up with a low return. Being in line with the implications from the left panel of Figure 3.6, the negative effect of net worth is most substantial once we control for the wealth shares. Accounting for the effects of the financial portfolio shares weakens the immediate effect of net worth. Based on Figure 3.6, we observe that several covariates alter the channels through which net worth drives returns. In the following, we investigate whether these patterns vary across the distribution of returns.

In the previous Figure 3.6, we discussed the average return by quantile of net worth for different specifications of an investor's type. In contrast, we will now model the 10th, 50th, and 90th quantile of returns. In addition, we present the returns computed by values in CHF to ease the interpretation of Figure 3.6. Figure 3.8 shows qualitatively the same results we discussed in the benchmark definition of types shown in Figure 3.5 but shows the differences as we change the specification of a type. The results suggest two conclusions. First, the discussed impact of net worth across types is qualitatively independent of the type specification. In other words, for all specifications of an individual's type, we find a positive a clear scale dependence, which is more pronounced for high types. In addition, the marginal impact of net worth on returns increases for very high levels of net worth. Second, the type specification matters most at the top values of net worth. To see this, consider the returns predicted by the model with all but the financial portfolio composition (blue line) and the full model (red line). An individual holding 100'000 CHF (median) gains roughly the same return throughout all model specifications. Yet, an individual holding three million CHF gains up to 2.6 times higher returns according to the model that abstracts from the risk attitude of the portfolio (i.e., does not consider the financial portfolio composition). Thus, for high levels of net worth, adequately controlling for all channels is crucial. Surprisingly, the model specification has roughly the same relative effect at the 10th, 50th, and 90th quantile of the returns. For this purpose, consider the return predicted by the model, including all variables but the financial portfolio composition relative to the return predicted by the full model. The relative value is almost identical for individuals holding 100,000 CHF: .99 at the 10th quantile, 1.02 at the median, and 1.01 at the 90th quantile. This fraction is remarkably close even for wealthier individuals holding one million CHF (1.10, 1.33, 1.32). The predicted values differ substantially only at the very top of the distribution of net worth.

Figure 3.7: Distributional Effect of Net Worth for Different Quantiles of the Returns

(a) 10th Quantile of Returns (b) Median Return (c) 90th Quantile of Returns

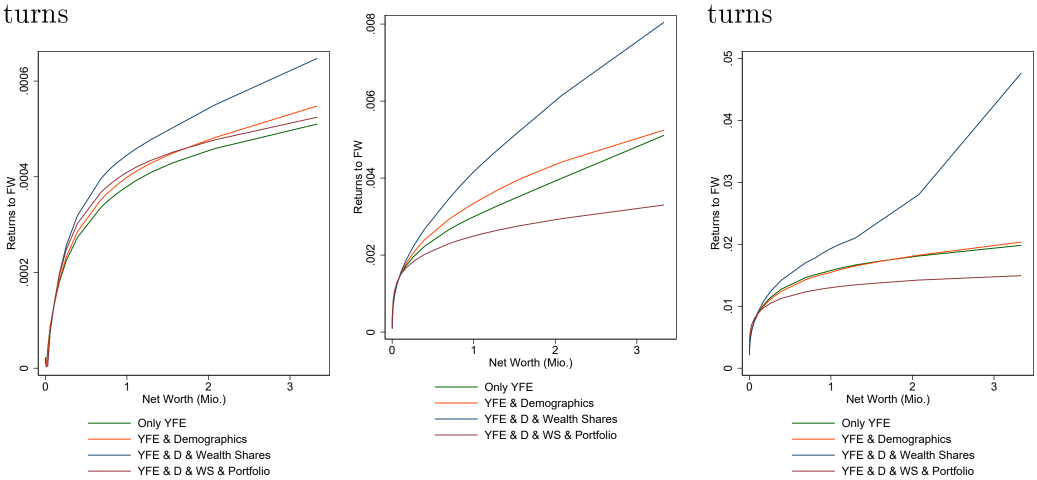

Figure 3.8: Distributional Effect of Net Worth for Different Quantiles of the Returns

The left figure plots the full distribution of returns for three selected return quantiles and for different types captured by return quantiles.

In subsection 3.5.2, we draw two main conclusions. (i) The heterogeneous effect of net worth on the returns is intensified because the wealthy hold lower shares in real estate. In contrast, part of the heterogeneity is due to the risk attitude and not due to net worth. This is a strong indication that portfolio allocations should be considered when we try to find a quantitatively accurate estimate of scale dependence across types. (ii) We find that the qualitative relations hold for all types of investors with only minor changes independent of how we define an individual's type.

3.6 Conclusion

This paper contributes to the ongoing research about the connection between net worth and the heterogeneity in returns. We use high-quality administrative tax data from the canton of Bern, Switzerland, to show that the returns on financial wealth increase with net worth even after we control for the individuals' risk-taking. Building on the recent empirical findings by Fagereng et al. (2020) and Bach et al. (2020) we further investigate the heterogeneity in returns across individuals and confirm that scale and type dependence play a crucial role as the empirical and theoretical literature suggest. In contrast to the previous work, we focus on the interaction between scale and type dependence. We show that the two drivers of returns are not additively separable and that scale dependence becomes more influential for high-type investors. Our results suggest that investors increase their share in risky assets with growing net worth, which plays to the advantage of high-type investors who are more successful at picking assets with a high return.

The existing literature focuses on modeling the average return, yet, the impact of additional net worth may differ substantially across the distribution of types. We prevent a similar misspecification problem by using a flexible approach that allows the effects of the covariates to vary throughout the distribution. Methodologically, we contribute in two ways. First, modeling the distribution of returns provides valuable information on higher-order moments such as the top quantiles and the variance. Second, aiming at the immediate effect of net worth on different investor types, we derive the unconditional distribution of returns where the latter solely depends on net worth. Once we control for the full set of observable characteristics, we interpret each quantile of returns as a distinct investor type. This allows us to estimate the direct relation between net worth and the type of an individual. Taken together, our Distribution Regression results are twofold: (i) we find that the *scale* effect of net worth is prevalent and is strongest for high type investors. In particular, net worth substantially boosts the top quantiles of the returns. (ii) We use different definitions of an investor's type to see how these adjustments alter the relation between scale and type dependence. We find that not controlling for an individual's asset allocation (financial, real estate, and business wealth) underestimates the relationship between scale and type dependence. Mainly, this is because the share in real estate, an asset typically lowering the returns on financial wealth, is positively correlated with net worth. Further, our analysis shows that not accounting for the risk behavior, meaning the shares invested in risky assets such as equity, substantially overestimates the impact of scale dependence as a large portion of the heterogeneity in returns is driven by different portfolio allocations. Thus, not considering the asset and portfolio allocation of the individual draws a misleading image of the true relation between scale and type dependence.

Overall our results suggest that there is a strong link between investor types and the scale effect. However, to the best of our knowledge, a theoretical foundation of this heterogeneous effect is missing. In this regard, our empirical results may help to formalize the interaction between type and scale dependence. We hope that future work may focus more strongly on a household's financial portfolio composition and how the level of net worth impacts this decision.

3.A Data

Using around half of the individuals from 2015 – 2017 we can deconstruct the overall financial wealth into three asset classes: Equity, bonds and bank deposits. Figure 3.9 reports the asset allocation of the financial portfolio for a few selected cohorts of the net worth distribution with a focus on the wealthiest individuals. The figure reports the average investment allocation for each group of interest, where we ranked individuals according to their net worth position in a given year. Throughout most of the distribution the majority of financial assets are invested in bank deposits, differing only for the top 0.1% of the net worth distribution. This is a striking observation and shows the high risk aversion of the individuals, given that the median household possesses on average financial wealth around 24k CHF and invests only 10% in risky assets. Throughout the full distribution bond holdings are close to irrelevant for the average individual. However, given that we are, to the best of our knowledge, the first to show a detailed financial portfolio composition for a Swiss data set we are cautions to what extent our results are representative for the entire population of Switzerland.

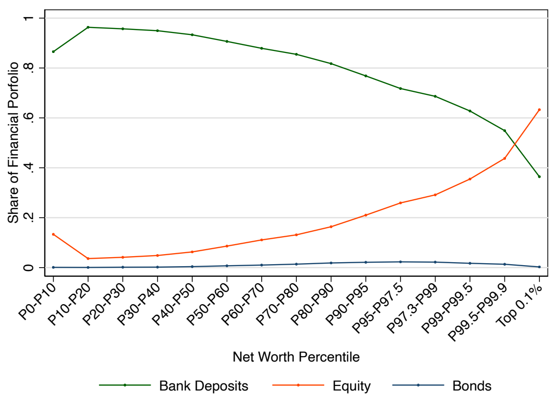

Figure 3.9: Financial Portfolio Composition across the Net Worth Distribution
This figure displays the allocation of the financial portfolio for a few selected cohorts of the net worth distribution.

3.B Modelling Average Effects on Returns to Wealth

In this section we provide additional information to section 3.4 and present some robustness checks to the previously discussed results.

Table 3.4 is an extension to table 3.2 discussed in section 3.4 including the coefficients for socio-demographic variables. Note that while all except marital status are significant for predicting individual returns, they contain only little economic relevance. The exception to the former can be found for married individuals. On average the model predicts an increase in returns of around ten basis points (both in the model with and without fixed effects).

Table 3.4: Average effects: scale and type dependence

	Without individual FE			Including individual FE		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
ln(Net Worth (CHF))		0.00176***	0.00057***		0.00093***	0.00013***
		(0.000)	(0.000)		(0.000)	(0.000)
Share in w_{it}^f		0.00264***	0.00033***		0.00122***	0.00019
		(0.000)	(0.000)		(0.000)	(0.000)
Share in w_{it}^r		-0.00249***	-0.00135***		-0.00094***	0.00011
		(0.000)	(0.000)		(0.000)	(0.000)
Share in w_{it}^b		-0.00024***	-0.00040*		-0.00001	-0.00042
		(0.000)	(0.000)		(0.000)	(0.001)
Leverage Ratio		0.00324***	0.00112***		0.00133***	0.00028
		(0.000)	(0.000)		(0.000)	(0.000)
Female		0.00003*	0.00007**		0.00000	0.00000
		(0.000)	(0.000)		(.)	(.)
Married		0.00111***	0.00039***		0.00124***	0.00012
		(0.000)	(0.000)		(0.000)	(0.000)
Widowed		-0.00030***	-0.00014**		-0.00092***	0.00022
		(0.000)	(0.000)		(0.000)	(0.000)
Divorced		-0.00014***	-0.00017***		0.00078***	-0.00000
		(0.000)	(0.000)		(0.000)	(0.000)
Separated		0.00001	0.00003		0.00060***	-0.00020
		(0.000)	(0.000)		(0.000)	(0.000)
Children		0.00009***	0.00003		0.00006***	0.00007
		(0.000)	(0.000)		(0.000)	(0.000)
Age		-0.00000	-0.00001***		-0.00057***	-0.00040***
		(0.000)	(0.000)		(0.000)	(0.000)
Equity Share			0.01629***			0.00639***
			(0.000)			(0.000)
Bonds Share			0.01055***			0.00527***
			(0.000)			(0.000)
Year FE	yes	yes	yes	yes	yes	yes
Ind. FE	no	no	no	yes	yes	yes
R^2	0.052	0.105	0.142	0.398	0.412	0.685
adj. R^2	0.052	0.105	0.142	0.335	0.349	0.512
N	8,875,289	8,462,780	950,626	8,816,922	8,401,047	885,441

The outcome variable is individual returns on financial wealth r_{it}^f in all columns. All models additionally include a constant. Standard errors clustered at the individual level in parentheses, *** $p < 0.001$ ** $p < 0.01$, * $p < 0.05$. The data set is cleaned as described in section 2.

In addition to the benchmark model of section 3.4 we provide the results for a slightly differnt specification. Table 3.5 shows the result of the model we previously discussed but replacing the logarithm of net worth the individual's percentile rank of net worth denoted by $P(w_{it}^n)$. This specification brings the advantage that we can use the full number of observations including the individuals with negative or zero net worth. However, the drawback of this approach is that there is no clear interpretation what it means to jump one percentile rank in the distribution and the difference in CHF between percentile ranks at the top of the distribution is much larger compared to the bottom. For these reasons we consider the results in tabel 3.2 to be economically more meaningful. We find that there is no qualititative difference between the two models and that both models give clear evidence for the existence of *scale* and *type dependence*.

Table 3.5: *Robustness:* average effects: scale and type dependence

	Without individual FE			Including individual FE		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
$P(w_{it}^n)$		0.00014***	0.00005***		0.00008***	0.00002***
		(0.000)	(0.000)		(0.000)	(0.000)
Share in w_{it}^f		0.00266***	0.00032***		0.00115***	0.00026*
		(0.000)	(0.000)		(0.000)	(0.000)
Share in w_{it}^r		-0.00309***	-0.00198***		-0.00136***	-0.00002
		(0.000)	(0.000)		(0.000)	(0.000)
Share in w_{it}^b		-0.00032***	-0.00059***		-0.00023*	-0.00060
		(0.000)	(0.000)		(0.000)	(0.000)
Leverage Ratio		0.00411***	0.00183***		0.00179***	0.00050***
		(0.000)	(0.000)		(0.000)	(0.000)
Equity Share			0.01587***			0.00647***
			(0.000)			(0.000)
Bonds Share			0.01015***			0.00531***
			(0.000)			(0.000)
Socio-Demographics	no	yes	yes	no	yes	yes
Year FE	yes	yes	yes	yes	yes	yes
Ind. FE	no	no	no	yes	yes	yes
R^2	0.052	0.104	0.136	0.398	0.401	0.672
adj. R^2	0.052	0.104	0.136	0.335	0.338	0.493
N	8,875,289	8,875,289	1,002,801	8,816,922	8,816,922	939,009

The outcome variable is individual returns on financial wealth r_{it}^f in all columns. All models additionally include a constant. Standard errors clustered at the individual level in parentheses, *** $p < 0.001$ ** $p < 0.01$, * $p < 0.05$. The data set is cleaned as described in section 2.

3.C Empirical Regularities and the Influence of Socio Demographics

In this section, we present some empirical regularities within our data set that accompany and motivate the modelling approach in the section 3.4 of the main body. First, we discuss the heterogeneity in returns on financial wealth across different percentiles of net worth. We then show that even within narrow asset classes there is a strong correlation between net worth and financial returns. Later, we discuss the connection between socio-demographic variables and financial returns and argue why it is important to control for these variables when modelling the returns on financial wealth.

3.C.1 Average Returns Increase with Total Net Worth

In Table 3.6 we report the average return on specific asset classes of financial wealth for selected percentiles of net worth, using the entire data set from 2002 – 2017 or 2015–2017, respectively. For each asset class returns are computed for all individuals who hold at least 500 CHF in the corresponding asset at $t-1$ and t. Individuals are ranked in every year based on their net worth, conditional that they surpassed the minimum level of wealth for the asset of interest. We report the average return across individuals and year within the given percentile. Note that while this procedure yields more meaningful results because we only look at individuals invested in the asset, it makes it difficult to compare the returns between different asset classes. This follows from the fact that individuals may change their relative rank in the net worth distribution because the overall sample of individuals differs across asset classes. This is true in particular when comparing the returns between bonds and the remaining assets as only a small share of individuals are invested in bonds, with high net worth individuals being overrepresented for that asset class.

Table 3.6: Average return for selected percentiles of net worth

	Total Financial Wealth (%)	Equity (%)	Bonds (%)	Bank Deposits (%)
$P(w_{it}^n) = 5$	0.4	1.6	1.4	0.2
$P(w_{it}^n) = 25$	0.6	1.9	1.5	0.2
$P(w_{it}^n) = 50$	0.8	2.0	2.1	0.2
$P(w_{it}^n) = 75$	0.9	2.4	2.0	0.2
$P(w_{it}^n) = 90$	1.1	2.8	2.5	0.3
$P(w_{it}^n) = 95$	1.3	3.3	2.2	0.3
Top 1%	1.8	3.3	3.5	0.6

Percentiles are computed for each asset seperately, conditional on an invidual holding an average level of wealth above 500 CHF. The reported returns are the average within each group.

In the main body of this paper in section 3.3 we document in Table 3.1 that the average before-tax return on financial wealth is 0.91%, with substantial heterogeneity. We observe a standard deviation of 17.37 and the median return is given by 0.55% compared to a return of 5.18% for the 99th percentile of the distribution. Considering the net worth of an individual, column 1 of Table 3.6 shows a first empirical regularity, namely a strong positive correlation between net worth and financial returns. A similar finding has previously been documented by Fagereng et al. (2020) and Bach et al. (2020) using a similar data set with Norwegian and Swedish tax payers respectively. The top 1% in our data set make a return on financial wealth that is more than two times the size of the median household, and almost five times larger than the bottom 5%. These differences are substantial, and imply that if an average household in the top 1% of the distribution invests 1 CHF in financial assets at the age of 25, her investment will have a level that is more than 50% higher at her retirement age of 65 compared to the median household.

Part (a) of Figure 3.10 is the graphical counterpart to Table 3.6 and shows the average return on financial wealth across all quantiles of total net worth. We find the typical shape of returns on financial wealth previously documented by Fagereng et al. (2020) and Bach et al. (2020). In part (b) of Figure 3.10 we show the evolution of returns within the observed period from 2003 – 2017. The most predominant observation that we make, is that the average return on financial wealth steadily decreased over the past few years, this is in line with the LIBOR rate going to zero and the subsequent fall of the nominal interest on long term investments. This led to a more important role of public and private equity, an asset that is mostly held by the wealthier household (see Figure 3.9 in appendix 3.A), while, at the same time, increasing the prices of equity due to lower discount rates. We find that the heterogeneity in returns has decreased between 2003 and 2017 for the households up to the 80th percentile of total net worth. However, in the same time period, the difference in returns at the top of the distribution has increased heavily, leading to a situation where the top 5% of the distribution earn a return that is about four times higher than the return earned by the 80th percentile of the distribution. As we mentioned in section 3.3 of the main body of the paper all returns are computed by realized returns, without capital gains. Considering that the SPI (a Swiss Stock Index, covering the most important listed companies in Switzerland) had an average yearly return of around 7.5% during the same time period, our results can serve as a lower bound for the true heterogeneity. This is based on the fact that the average share of equity and bond holdings strictly increase as we move further to top of the net worth distribution, implying that the richest would be more affected by the inclusion of capital than the bottom of the distribution.

3.C.2 Systematic Risk Taking Plays an important Role

Focusing on a more detailed description of the returns on financial wealth, we turn our attention to the most important subcomponents of financial wealth holdings. Given the data set at hand we can divide the total financial assets into three

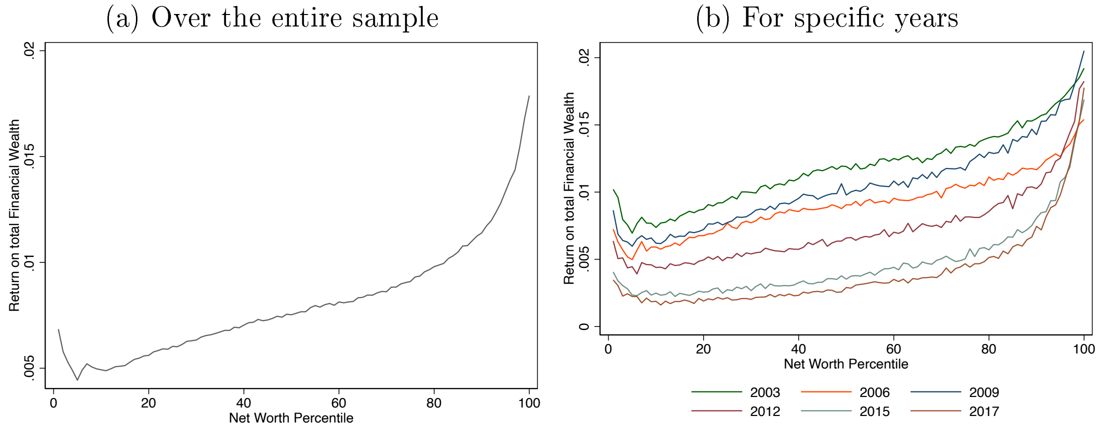

Figure 3.10: Average Return on Financial Wealth across the Financial Wealth Distribution

Part (a) shows the average return on financial wealth across all quantiles of total net worth. Part (b) shows the evolution of returns within the observed period from 2003 – 2017.

broad categories: Equity, Bonds and Bank Deposit. We use this information to shed more light on the source of heterogeneity in returns to financial wealth we reported in section 3.C.1.

Columns 2 – 4 of Table 3.6 report the returns for the three subgroups of financial wealth for a few selected percentiles of net worth. Overall, equity yields the highest return, compared to bonds and bank deposits although the top 1% of the net worth distribution have similar returns for both equity and bonds.[21] While some of the heterogeneity in financial returns can be explained through the different portfolio compositions we have displayed in Figure 3.1 there is still a strong correlation between net worth and returns on individual asset classes. The two effects combined yield the strong heterogeneity in returns that we report in column one of Table 3.6. The median individual holds on average less than 20% of its financial wealth in equity compared to the top 1% who hold more than half in either public or private equity. In addition, wealthier households make a significantly larger return on their risky asset. This is an indication that, while some of the differences may be explained based on different risk attitudes, a non-negligible contribution may be due to the better performance of high net worth individuals across all investment opportunities. Figure 3.11 gives a more detailed insight to the heterogeneity in returns on the different components of financial wealth. The Figure looks very similar compared to the returns on total financial wealth, though the levels of return vary across the different groups. We

21. Note that only a small portion of the individuals hold bonds with the majority in the top end of the net worth distribution. As we compute the percentiles conditional on an individual holding on to at least 500 CHF of the specific asset the different groups are not perfectly comparable.

find that even for the safest asset of the three, bank deposits, wealthy individuals are able to generate a higher return. A possible explanation may be that wealthy households have a smaller liquidity constraint, enabling them to invest into saving accounts rather than checking accounts.

(a) Equity (b) Bonds (c) Bank Deposits

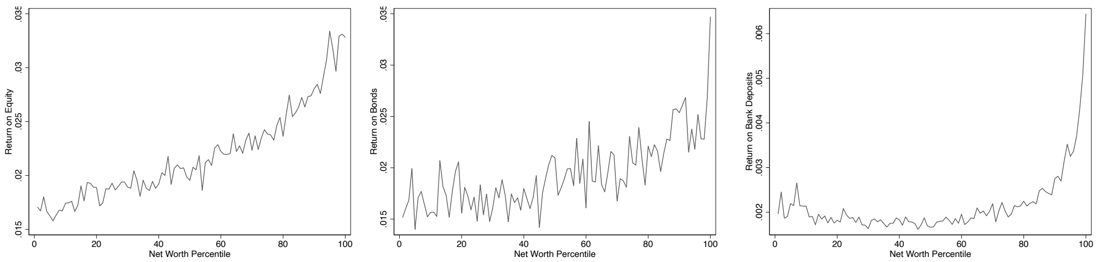

Figure 3.11: Average Return on specific assets across the Financial Wealth Distribution

On the x-axis we show all quantiles of the financial wealth distribution, conditional that the household holds the specific asset. Displayed are always the returns of the respective asset class.

3.C.3 Differences across Marital Status

In Figure 3.12 we report the differences in returns on total financial wealth for single and married individuals. We find that married individuals are able to achieve a higher return on average for all percentiles of the net worth distribution. However, looking at separate years individually we notice that the difference in returns has shifted over the years. While married individuals in the lower part of the distribution were able to generate a higher return in the years before 2010, this difference has perished over time. For the most recent year, we find that both single and married individuals generated the same level of return with an average return of around 0.25%. The opposite is true for the top of the distribution. It seems that married individuals generated a higher return in 2010 and 2017. A possible reason for the observed difference is the long term horizon for married individuals. Singles are exposed to more risk as they are unable to share income shocks between each other. This makes them vulnerable for sudden changes in income which may restrict their investment horizon on different assets. Put differently, single individuals with low financial wealth are unable to take the same risk as their married counterparts which might lead to the observed difference in returns.

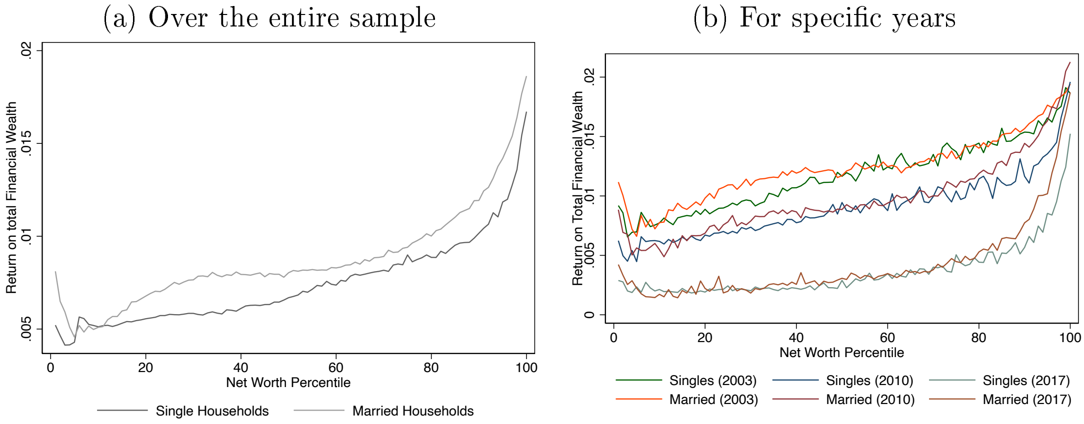

Figure 3.12: Average Return on Financial Wealth for Single and Married Households across the Financial Wealth Distribution

The figures display the differences in returns on total financial wealth for single and married individuals across the financial wealth distribution.

3.C.4 Differences across Age Groups

We divide the population into four distinct groups conditional on their age. For that purpose, we chose three thresholds by which we separate our sample population: All individuals below the age 35 (*young*), between 35 and 49 (*middle aged*), between 50 and 64 (*senior workers*), and individuals from 65 and older (*retired*). In Figure 3.13 we plot the four groups together. We find almost no difference in returns across all age cohorts which suggests that age is not a suitable indicator for financial experience. The biggest difference, we find is between the top net worth individuals who are middle aged and retired. The explaining factor may the different investment horizons of the separate groups. While middle aged workers are saving for their retirement they may choose to invest in volatile assets as they are less exposed to short term price changes. On the other hand retired individuals have generally little to no labor income which makes them rely more heavily on their financial portfolio to finance consumption. This makes them more exposed to sudden changes in asset prices which may lead to a more conservative portfolio allocation. This factor is less prominent for individuals at the lower part of the net worth distribution due to their financial restrictions. In particular for middle aged and young individuals at the lower part of the distribution the liquidity constraint may be a more important driver for their portfolio allocation. Given their age they may be saving for costly durable goods such as real estate or vehicles which restricts them from investing into long term investments. Overall, we document only small differences in financial returns across the four different age groups.

Figure 3.13: Average Return on Financial Wealth for Different Age Groups

The figures graphically shows the differences in returns to wealth across the financial wealth distribution for different age classes. Specifically, we divide the population into four groups: individuals below the age of 35, from 35 to 49, from 50 to 64 and above the age of 64. We control for separate years, when constructing the net worth percentiles and show the average return for each percentile.

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I hereby declare that I have written this thesis independently and have not used any sources other than those indicated. I have marked all co-authorships as well as all passages taken verbatim or in spirit from sources as such. I am aware that otherwise the Senate is entitled to withdraw the title awarded on the basis of this thesis in accordance with Article 36 paragraph 1 letter o of the Law of September 5, 1996 on the University.

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Bern, 03. Juli 2023

Marc Brunner