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Essays in Corporate and Household Finance

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Abstract

The first chapter of this dissertation develops a moral hazard model to study how *specialized distressed investors*, who privately bail out financially distressed firms, can negatively impact credit rationing ex ante. The model is then used to derive implications on value creation, capital structure, and project choice. The second chapter uses transaction-level data from a Portuguese bank to analyze a large-scale debt forbearance program implemented during COVID-19. The results inform on the heterogeneous effects of debt relief and how observable household characteristics can help to better design debt-relief policies. The final chapter uses a matched employee-employer dataset from Portugal to investigate how the employer capital structure can affect employee consumption and saving decisions. The effects are rationalized using a Diamond-Mortensen-Pissarides model, and suggest that financial distress and bankruptcy costs are partially shifted to employees.

Keywords: financial distress; bankruptcy; debt relief; household consumption and saving

To Maria.

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Contents

List of Tables

List of Figures

Introduction

This dissertation comprises three essays on financial distress, bankruptcy, and debt relief, focusing on the ex ante lending effects of private corporate bailouts, the heterogeneous response of households to forbearance, and the impact of capital structure on employee consumption and saving behavior.

The first chapter, co-authored with Fernando Anjos and Irem Demirci, extends the canonical moral hazard model in corporate finance to study how *specialized distress investors* (henceforth, SDIs) can affect the traditional lending relationship between banks and firms. As a consequence of no commitment by the initial lender, we show that the initial bank may find it ex post optimal to sell its stake to an SDI, possibly reducing pledgeable income and thereby leading to credit rationing. Under some conditions, value-enhancing SDIs can tighten initial financing, suggesting that private bailouts may produce negative spillovers in upstream lending markets. Moreover, even if financing is feasible, we show that the initial lender may find it optimal ex post to sell its stake to a value-destroying SDI, thereby reducing the project NPV. Finally, we use the model to show how SDIs can alter project selection in the context of endogenous entry. Specifically, the entrepreneur can modulate SDI entry and its associated effects by modifying fundamental characteristics of the project, such as project duration, or by adjusting firm leverage.

The second chapter, co-authored with Manuel Adelino and Miguel Ferreira, uses transaction-level data from a Portuguese bank to evaluate the impact of a large-scale debt forbearance program during COVID-19. We find evidence of an unintended resource allocation: only a small fraction of eligible households entered the program, while most households in forbearance were ineligible. Households in forbearance were already financially fragile before the pandemic, with ineligible households being the most fragile group. Nonetheless, we observe a large effect on consumption out of postponed payments, especially among ineligible households. Our findings also indicate that households do not immediately adjust their newly acquired consumption habits once the program ends. Overall, these results suggest that optimally designed policies should consider the strategic behavior of ineligible households. On the one hand, the self-selection of households with high marginal propensities to consume enhances the policy's stimulative effect. On the other hand, this selection effect implies that such programs may inadvertently worsen debt burdens among already fragile households.

The third chapter studies how a firm's capital structure affects employee consumption and saving behavior. Using a comprehensive employee-employer matched dataset from Portugal, I find evidence of precautionary saving, as households employed by highly leveraged firms exhibit lower marginal propensities to consume. This effect is larger for households facing higher expected costs of unemployment and those working in publicly listed companies, where information asymmetries are arguably lower. Moreover, I find that this response is driven by non-essential goods and services. Using exogenous industry-wide shocks, I find that in affected industries only employees of high-leverage firms reduce consumption, even though there is no differential effect on wages. Finally, I develop a Diamond-Mortensen-Pissarides model incorporating risk aversion and wage bargaining frictions, and calibrate it to the Portuguese economy. Consistent with my empirical findings, the model demonstrates how leverage can simultaneously lead to a wage discount and precautionary savings. Taken together, these results suggest that bankruptcy and financial distress costs are partially shifted to employees, who, in turn, help propagate such shocks across the economy.

1

Do Specialized Distress Investors Undermine Firms Ex Ante?

1.1 Introduction

In recent times, a specific group of lenders has become a more prominent player in corporate debt markets. These investors, mostly hedge funds and private equity groups, specialize in acquiring the control of distressed firms and potentially generate efficiency gains in several ways: reducing secured creditors' liquidation bias, replacing underperforming managers, retaining key employees, or providing additional financing. Distress investors are more flexible than other investors, such as banks and mutual funds, in that they can hold concentrated and illiquid positions and are not subject to regulatory restrictions with respect to ownership and management of non-financial corporations.[1]

There is a considerable amount of empirical and theoretical work investigating the role of specialized investors in the reorganization of distressed firms.[2] This literature notwithstanding, we know little about how the ex post emergence of SDIs might have ex ante effects on a firm's relationship with its initial investors. We take a first step in

[1] A notable example of such investors is Eddie Lampert's activist hedge fund, ESL Investments, that invested into unsecured notes and bank debt of distressed Kmart in 2004. Once the company's Chapter 11 reorganization was complete, ESL Investments emerged as Kmart's largest shareholder, owning more than 50 percent of the shares (Gilson and Abbott, 2009). This investment strategy is called "loan-to-own" and involves identifying debt securities that are likely to be converted into equity in the newly restructured firm (i.e., fulcrum security). Distress investors who follow such a strategy do not sell their equity shares immediately after the restructuring; instead, they are actively involved in the management and operations of the firm during and after the reorganization.

[2] E.g., Jiang, Li and Wang (2012), Lim (2015), and Hotchkiss and Mooradian (1997).

bridging this gap by developing a model of SDI spillovers. Specifically, we investigate how potential SDI entry might affect the firm's access to credit, the attractiveness of the project to the entrepreneur, and the entrepreneur's project and capital structure choices. We find that under certain conditions the presence of SDIs will worsen the original agency problem and, concomitantly, credit rationing. What makes the result non-obvious is that it can hold even when SDIs create value ex post, and moreover, even though the initial lender needs to agree to the SDI entering the firm. In addition to the credit rationing result, we also show that the expectation of SDI entry can lead to underinvestment by reducing the entrepreneur's surplus, even when the SDI improves firm value ex post and reduces credit rationing. In contrast to these negative spillovers, we also show that sometimes SDIs can have beneficial ex ante effects, even if they destroy value ex post.

We now turn to the model in more detail, which extends the canonical moral hazard workhorse in corporate finance (Holmstrom and Tirole, 1997; Tirole, 2006) by allowing for the entry of a distress investor in case of failure. The model entails a project with two phases, where an entrepreneur (or "borrower") is initially funded by a lender (or "bank"), which we consider as a traditional financial institution operating in a competitive market. At the end of the first phase, if the project is successful, then the borrower pays down the debt and enjoys the continuation value of the firm. Conversely, if the borrower becomes distressed (i.e., the project fails in phase 1), then an SDI potentially appears. The type of SDI we have in mind is relatively hands-on, has a long investment horizon, and is involved in the management and operations of the firm.[3] Phase-1 success depends on the effort exerted by the entrepreneur, and herein lies the moral hazard problem. The severity of the problem is high whenever the entrepreneur has a relatively high payoff following failure. This happens if the entrepreneur is critical for managing the firm during continuation or is entitled to a sizable exit pay after restructuring.

[3] Distress investors may vary with respect to their investment strategies and investment horizons. For example, passive distress investors do not have any direct influence on the distressed firm and have relatively short investment horizons. Their strategy involves identifying underpriced distressed securities and exploiting the future price appreciation. On the other hand, active and controlling distress investors are more hands-on and have longer investment horizons (the focus of our model).

We analyze two different cases. In the first case, which we term “high-leverage”, after failure, the firm becomes insolvent (i.e., the face value of debt is higher than the firm’s continuation value). If the project fails, then the initial lender takes over the control of the firm and possibly sells its stake to a distress investor. In the second case, which we term “low-leverage”, the default still occurs after phase-1 failure but the firm remains solvent. In such low-leverage firms, entrepreneurs remain in control and are the ones negotiating directly with distress investors. The two cases have some similarity in terms of the effect of distress investors on credit rationing. Specifically, in our model, both the initial lender and the entrepreneur have no commitment, meaning that they will accept desirable SDI offers ex post even if such offers reduce pledgeable income and possibly make initial funding unfeasible. The only difference is that in the high-leverage case, where the initial lender is in control, an SDI may actually compress the entrepreneur’s payoff during restructuring (e.g., by providing an alternative to the original management team when continuing the company), which would imply an improvement with regard to the credit-rationing problem instead of a worsening. Naturally, this only applies to certain types of SDI, which we term “disciplining”, a trait that is not necessarily correlated with the SDI’s ability to create value ex post.

Besides the effect on credit rationing, we also analyze what happens to project NPV as SDIs become more pervasive. Here, there is more of a difference between high- and low-leverage firms. With the latter, since the entrepreneur is in control, she only accepts those SDI offers that create value following failure/distress, which feeds back positively into NPV. In contrast, for high-leverage firms, it is the initial lender who is in control following interim failure, which sometimes leads the lender to strike deals with SDIs that are value-destroying but improve the lender’s stake (i.e., the entrepreneur is expropriated). In such cases, increasing the likelihood of SDI appearance negatively affects the project NPV. Obviously, these NPV results also critically depend on our assumption that the initial lender does not have any commitment.

In addition to the first-order effects of SDI presence described above, we also show that SDIs can affect which types of projects entrepreneurs choose. In the model, SDI entry is endogenous and the equilibrium frequency of SDI appearance is determined by the payoff these agents expect from becoming involved with a distressed firm. It turns out that if entrepreneurs have some control over the types of projects they look for, then they can modulate the (contingent) attractiveness of their firm to SDIs. For example, projects with longer duration (i.e., higher continuation value relative to phase 1 returns) naturally make it more appealing for SDIs to participate. Therefore, if SDIs becoming more pervasive is problematic—e.g., by reducing pledgeable income—, then entrepreneurs could mitigate such a negative effect by picking shorter-duration projects.

Besides using project characteristics strategically, entrepreneurs who are not overly financially constrained can also decide whether it is worthwhile adding debt beyond a critical threshold, namely, the threshold where following failure/distress, control is lost to the initial lenders. We show in the model that the optimal capital structure hinges on the magnitude of the (initial) loan renegotiation costs, relative to how "disciplining" SDIs are. It is perhaps interesting to draw a parallel between this result and Jensen's classic argument (Jensen, 1986). In our case, using debt beyond the aforementioned critical threshold has a desirable disciplining effect on the entrepreneur/manager not because debt service requires the firm to generate a minimum amount of cash flow, but instead because high leverage entails the potential appearance of a distress investor who has more power than the initial lender to compress the manager's payoff following failure.

Our paper relates to several strands of the literature. First, it complements the empirical and theoretical literature on the topic of distressed lending by investigating the potential spillovers associated with this investment. Jiang, Li and Wang (2012) find that the presence of hedge funds during bankruptcy increases the likelihood of a successful reorganization. In a related study, Lim (2015) documents that hedge fund involvement is associated with a higher probability of pre-packaged restructurings, shorter duration of distress, and greater reduction of debt. The study concludes that activist hedge funds can create value by enabling efficient contracting. Hotchkiss and Mooradian (1997) show that the active participation of vultures in the restructured company is associated with a more pronounced improvement in post-restructuring operating performance. Dou, Wang and Wang (2022) argue that there is an undesirable underprovision of distress investors in the economy, yet do not study ex ante spillovers, which we claim are important for a broader efficiency assessment. Noe and Rebello (2003) model a vulture's reputation for toughness and then analyze how this reputation affects distress negotiations, in particular how it helps to extract concessions from stockholders in debt restructurings. Baranchuk and Rebello (2024) model hedge fund involvement in bankruptcy using a two-sided information asymmetry framework. Burkart, Lee and Vladimirov (2024) introduce distress investors in a model where coordination failure is the key friction in distressed restructuring.

Our model does not aim to study distress resolution under frictions such as information asymmetries or coordination problems. Instead, using a very simple canonical setting of moral hazard, our model analyzes the impact of distress investors that may appear in a downturn on the ex ante relationship between a firm and its lender, and the attractiveness of the project for the entrepreneur. Our model is different from existing models that study the participation of distress investors in at least two ways. First, none of the existing models investigate the SDI effect within the context of ex ante effort provision. Second, to our knowledge, we are the first ones to model the spillover effects between ex post distress financing and ex ante lending relationships; in particular, how SDIs might change the availability of credit and the entrepreneur's willingness to take up a project.

Our work also links with theories about the role of liquidation threats in corporate finance. It is well understood that the threat of liquidation (or, more generally, withholding financing) can play an important role in eliciting desirable behavior from borrowers. For example, Bolton and Scharfstein (1990) show how the threat of not funding a later stage project after a report of poor performance is sometimes enough to overcome the perverse incentive to under-report interim cash flows. Dynamic agency models also employ firm size and liquidation as mechanisms that help in curbing moral hazard (e.g., Peter DeMarzo and Michael Fishman, 2007 and Peter DeMarzo and Yuliy Sannikov, 2006). The spirit of our model is perhaps closer to Hörner and Samuelson (2016), where the principal/lender does not have a commitment. Essentially, the idea is that when short-term compensation is not high-powered enough, the principal can use the fate of the firm as an additional tool to motivate the agent. We contribute to this literature by asking what happens to "interim disciplining devices" (such as liquidation following failure) when a third player intervenes in the financing and production dynamics.

Finally, our paper relates to the literature on bailouts, a topic of significant interest not only for academics but also for policy makers. Much of the received wisdom suggests that bailouts can worsen moral hazard. By softening the cost of failure, bailouts may exacerbate incentives for ex ante risk shifting and/or low effort provision.[4] In contrast, we contribute to the literature by asking whether and how *private* bailouts, i.e., the intervention of a new investor who is skilled at distress investing, may generate undesirable spillovers or can provide efficiency gains. Private bailouts have been hitherto ignored in the public debate, but it is plausible that they are relevant and potentially warrant attention on the part of policy makers. Unlike governments, SDIs that consider investing into a distressed firm are not concerned about the tax and unemployment consequences of letting the firm fail.[5] Therefore, inefficient continuation could prima facie appear to be less of an issue when distressed firms are rescued by private parties. However, as our model shows, even if the firm's stakeholders are the ones who decide on SDI entry (as opposed to the government), welfare-reducing SDIs might still enter the firm.

The paper is organized as follows. Section 1.2 presents the general framework of our corporate finance model with initial lending and specialized distress investors. Section 1.3 studies the case of severe financial distress where in the down state the initial loan becomes undercollateralized and hence the firm has negative net worth. Section 1.4 presents the case where the firm has a positive net worth if the project fails and the loan is overcollateralized. Finally, section 1.5 concludes. The Appendix contains all proofs.

[4] See, for example, Cordella and Yeyati (2003), Farhi and Tirole (2012), Chari and Kehoe (2016), and Dell'Ariccia and Ratnovski (2019). The standard arguments notwithstanding, Philippon and Wang (2023) show that it is possible to design a bailout mechanism that does not worsen moral hazard.

[5] For instance, it is estimated that the bailout of General Motors saved 1.2 million jobs and $39.4 billion in personal and social insurance taxes (McAlinden and Menk, 2013).

1.2 Model

1.2.1 Setup

We build on the standard model of entrepreneurial moral hazard proposed in Holmstrom and Tirole (1997) and Tirole (2006). To investigate how distress affects incentives, we add a second phase to the game, where we allow for the entry of specialized financiers who may acquire distressed claims and participate in the firm. There are three players: an entrepreneur (the borrower), an initial lender (sometimes referred to as "bank"), and a specialized distress investor (SDI). The entrepreneur, with cash on hand W, has a project that requires an initial fixed outlay of I to be paid at $t = 0$; the amount $I - W$ is financed by the bank. If the first phase of the project is successful, it yields a verifiable payoff of $R > 0$ and zero otherwise. The success probability of phase 1 is p if the entrepreneur exerts effort and $p - \Delta$ if she shirks. The entrepreneur obtains private benefit $B > 0$ from shirking.

At $t = 0$, the lender makes a competitive offer to the entrepreneur, which is determined by the lender's participation constraint. The loan contract specifies, in case of success, how phase-1 profit (R) is shared between the entrepreneur and the lender. The borrower and the lender receive R_b and $R_l = R - R_b$ (i.e., face value), respectively. The entrepreneur is protected by limited liability such that $R_b \geq 0$. At $t = 1$ we have the project's second phase (or continuation), which we represent in more reduced-form (i.e., no explicit moral hazard problem). We assume that the lender and the borrower are unable to write contracts at $t = 0$ for the sharing of phase-2 output (i.e., there is no long-run debt).[6] The overall project is assumed to be unfeasible under phase-1 shirking (see Assumption 1, presented later, for the formalization).

The outcome of phase 1 determines which subgame the initial lender and the borrower play in the second phase. If phase 1 is successful, then the entrepreneur is able to fulfill her debt obligations, is fully in control of the firm, and captures the entirety of the continuation value (denoted by V). If phase 1 fails, then the borrower defaults on the loan, which does

[6] Our model is only interesting if there is the possibility of default at the interim date, hence some short-term debt is necessary. We fully rule out long-term debt for expositional simplicity.

not necessarily imply that the firm is to be liquidated. Instead, the entrepreneur lacks the liquidity necessary to meet the debt obligation on time and, therefore, may lose control over the firm.[7] While the firm is always illiquid, the transfer of control rights depends on whether the firm is solvent or not. In particular, if the firm is insolvent with negative net worth, then the control rights are fully transferred to the creditor.

In our setting, the SDI appears in phase 2, conditional on phase-1 failure, with endogenous probability q (detailed later). We assume that SDI entry takes the form of the SDI acquiring the initial lender's claim. The initial lender can accept or reject the distress investor's offer but cannot commit ex ante to a course of action with respect to said offers. If an SDI takes over the debt claim, the continuation value of the firm is given by V^e (the "entry" scenario); otherwise, the initial lender keeps the debt claim and the value of the firm is V^n (the "no entry" scenario). We assume that both V^e and V^n are net of direct and indirect costs of bankruptcy.

The SDI faces cost C_s if he attempts to enter the firm, where C_s is a uniform random variable in the interval $[0, \overline{C}_s]$; C_s is observed by the SDI prior to the decision to enter. Entry costs for the SDI might take the form of legal, transaction and information acquisition costs, as well as any additional funding that might be essential for the continuation of the firm. For instance, under Chapter 11 legal bankruptcy, an SDI may provide debtor-in-possession (DIP) financing.

We allow the entrepreneur's phase-2 payoff upon failure to differ depending on whether an SDI participates in the company or not. The entrepreneur's payoff in case of SDI entry is denoted by u_b^e and otherwise by u_b^n. We refer to these reduced-form payoffs as the *borrower's continuation rent* and they are a critical piece of our model. The borrower's continuation rent can be thought of as capturing the following economic effects: (i) phase-2 agency rents, i.e., minimum payments that need to be made to the entrepreneur such that she provides an appropriate amount of effort during continuation; (ii) how critical the en-

[7] If the firm defaults on its debt, then there are multiple possible outcomes which for now we do not explicitly model. For instance, the initial lender might accept to exchange its existing debt for a new debt security with a different maturity, coupon, etc. Similarly, the lender might also be willing to participate in a private workout where its debt is exchanged for equity. Finally, the firm might be reorganized or liquidated through the legal bankruptcy process.

trepreneur's human capital is for continuation, which impacts the surplus she can bargain for; (iii) any and all entrepreneurial outside options that arise during phase 2, which also impact the entrepreneur's ability to bargain; (iv) the technology and bargaining power that is available both to the bank and the SDI; for example, the SDI can have a superior monitoring technology or his management team could have skills that are substitutes to the entrepreneur's.

The borrower's continuation rent plays an important role in shaping phase-1 incentives. Since this payoff accrues to the entrepreneur following failure, there is more scope for moral hazard during phase 1. The borrower's continuation rent thus amplifies the canonical one-period agency problem, being similar to an increased private benefit associated with shirking. The question is whether this effect is worsened or not by SDI presence.

It is important to note that what we characterize in the model as "entrepreneur" can in practice refer to any and all firm associates that are critical for the operations of the business and need to be properly incentivized. One of the important aspects of Chapter 11 bankruptcy of the U.S. is the key employee retention or incentive plans (KERPs). Management turnover during reorganization can be disruptive and costly, and such plans are designed to persuade key employees with firm-specific knowledge to stay with the bankrupt firm. According to Goyal and Wang (2015), 40% of the large public firm bankruptcies in the U.S. between 1996 and 2013 involved KERPs. Moreover, they show that KERPs are more frequently adopted by firms that have DIP financing and activist investors, which are both measures of the strength of creditor control over the bankruptcy process. In the context of our model, given that SDIs are new to the company, retaining key employees might become even more critical. Nevertheless, we analyze different cases by allowing for the borrower's continuation rent to be higher or lower under SDI entry, relative to the case when the initial lender controls the company.

If there is no SDI entering the firm and the initial lender keeps the debt claim, then the lender receives a payoff of $u_l^n (= V^n - u_b^n)$. On the other hand, if an SDI enters the company, then the lender and the SDI share the surplus net of the borrower's continuation rent. In this case, we denote the lender's and the SDI's payoffs as u_l^e and u_s^e, respectively. The next section details the bargaining procedure we use to pin down these payoffs.

This concludes the description of the setup for the two phases; Figure 1.A.1 summarizes the timeline and possible outcomes for the entrepreneur/borrower, the initial lender, and the distress investor.

A later-stage distress investor taking over the control of the firm upon failure can affect the project in two different ways: (i) by changing the continuation value and/or (ii) by changing the borrower's continuation rent. For instance, an SDI that has experience with distressed firms as well as the ability to run them efficiently might increase the (total) continuation value of the firm. Alternatively, an SDI who has his own management team might depend less on the human capital of the entrepreneur, reducing her bargaining power upon continuation. Let us characterize the advantage that the SDI has relative to the initial lender using two parameters: the SDI's advantage in terms of increasing total firm value is denoted by v (possibly negative, which means a disadvantage); and the SDI's advantage in reducing the borrower's continuation rent is denoted by d (also possibly negative). We can thus re-write the value of the firm under SDI management as

$$V^e = V^n + v, \quad v \geq -V^n, \tag{1.1}$$

where V^n, recall, is the value of the firm under initial-lender management. Similarly, the borrower's continuation rent in case of SDI participation can be re-written as

$$u_b^e = u_b^n - d, \quad d \leq u_b^n, \tag{1.2}$$

where u_b^n, recall, is the borrower's continuation rent without SDI entry.

Whenever $v > 0$ we will refer to the SDI as *value-enhancing* and whenever $d > 0$ we will refer to the SDI as *disciplining*. The rationale for the term "disciplining" is that with $d > 0$ the borrower payoff associated with failure is reduced upon SDI entry, which at the margin softens the moral hazard problem in phase 1. In our model, the pair (v, d) characterizes the SDI's "type" (or "style"). As we show later, the SDI's type importantly drives our results.

1.2.2 Equilibrium: some intermediate derivations

In this section we characterize several equilibrium outcomes that hold in general and are useful for later results. We start by formalizing our assumption stated previously that projects are not feasible under shirking:

Assumption 1. *Under shirking, the parameter configuration is such that the project's NPV is negative regardless of SDI intervention. In particular, we assume*

$$(p-\Delta)(R+V)+(1-p+\Delta)\max(V^e,V^n)+B\leq I. \tag{1.3}$$

This assumption ensures that when the entrepreneur shirks, even if in the extreme case where the SDI's payoff is zero, either the entrepreneur's or the initial lender's expected payoff is negative, and hence the project is not feasible. This assumption simplifies the analysis, while maintaining the centrality of the moral hazard problem.

Next we provide some intermediate results regarding SDI entry (Lemma 1) and financing feasibility (Lemmas 2 and 3).

Lemma 1. *The ex ante likelihood of SDI involvement is given by*

$$q=\begin{cases}\min\left(1,\frac{u_s^e}{C_s}\right), & \text{if } u_s^e>0\\ 0, & \text{otherwise.}\end{cases} \tag{1.4}$$

A necessary condition for a strictly positive probability of SDI entry is

$$u_s^e>0\Leftrightarrow V^e-u_l^e-u_b^e>0\Leftrightarrow v+d>0. \tag{1.5}$$

Lemma 2. *Let $\mathcal{P}$ denote the maximum (expected) pledgeable payoff to the initial lender. Then a necessary condition for financing is*

$$\mathcal{P}\geq I-W, \tag{1.6}$$

where

$$\mathcal{P}\equiv p\left\{R-\frac{B}{\Delta}+V-[qu_b^e+(1-q)u_b^n]\right\}+(1-p)\left[q(V^e-u_b^e-u_s^e)+(1-q)(V^n-u_b^n)\right]. \tag{1.7}$$

Condition (1.6) corresponds then to a regular participation constraint for the initial lender, considering that the loan contract provides incentives to the borrower to exert effort such that the borrower's incentive-compatibility constraint is satisfied. We can therefore rewrite condition (1.6) as

$$\begin{aligned} W \geq\ & \underbrace{p\frac{B}{\Delta} + qu_b^e + (1-q)u_b^n}_{\text{Agency Rent}} + \underbrace{(1-p)q(u_s^e - \mathbb{E}\left[C_s | C_s \leq u_s^e\right])}_{\text{SDI's Rent}} \\ & - \underbrace{\left\{p(R+V) + (1-p)\left[q(V^e - \mathbb{E}\left[C_s | C_s \leq u_s^e\right]) + (1-q)V^n\right] - I\right\}}_{\text{Project's NPV}} \\ \equiv\ & \underline{W}^*, \end{aligned} \tag{1.8}$$

which can be interpreted as a net worth requirement such that financing is not viable if $W < \underline{W}^*$. The negative sign of the last term indicates that projects with higher NPV are more likely to be financed. Conversely, if the entrepreneur's agency rent is high and/or the SDI captures a large net (expected) surplus, then financing may be unfeasible, even if the project generates a positive NPV. We note that the entrepreneur's agency rent is a combination of the canonical one-period agency rent (pB/Δ) and the borrower's continuation rent. As explained before, the borrower's continuation rent feeds back into the moral hazard problem in phase 1 and therefore leads to a higher agency rent.

Lemma 3. *In an interior solution, where $q \in (0, 1)$, the minimum amount of capital an entrepreneur must provide to secure funding, $\underline{W}^*$, becomes*

$$p\frac{B}{\Delta} + u_b^n - \left[p(R+V) + (1-p)V^n - I\right] + \underbrace{\frac{u_s^e\left[(1-p)(u_s^e - v) - d\right]}{\overline{C}_s}}_{\textit{SDI Effect}}. \tag{1.9}$$

If $v > 0 \wedge d > 0$, SDI entry unambiguously reduces the possibility of credit rationing (i.e., decreases $\underline{W}^*$).

The result at the end of Lemma 3 shows how SDI presence can impact the availability of financing ex ante. At this stage we are only able to characterize the most benign of cases. In the next section, after endogenizing the continuation payoffs for the SDI and the initial lender, we will also show how SDIs can easily generate negative spillovers on initial finance.

Finally, Lemma 4 characterizes the project's NPV and how it is affected by the presence of SDIs.

Lemma 4. *In an interior equilibrium, where $q \in (0,1)$, the overall NPV of the project is given by*

$$NPV^* = p(R+V) + (1-p)V^n - I + \underbrace{\frac{(1-p)u_s^e \left(v - \mathbb{E}\left[C_s | C_s \leq u_s^e\right]\right)}{\overline{C}_s}}_{\text{SDI Effect}}. \tag{1.10}$$

Equation (1.10) shows that a value-destroying investor ($v < 0$) unambiguously reduces the NPV of a funded project. Nonetheless, even value-destroying SDIs may relax credit rationing, as long as the disciplining effect is strong enough; in particular, if $d > (1-p)(u_s^e - v)$ (see Lemma 3).

1.3 The case of high-leverage firms

In this section we further formalize how surplus is shared between different agents and conduct a more detailed analysis of the model. Throughout this section, we assume that the endogenous face value of debt is high and in case of failure, regardless of whether an SDI enters or not, the firm has negative net worth.[8]

Assumption 2. *In equilibrium, the face value of the loan is high. Specifically, the continuation value of the firm net of the borrower's continuation rent is not sufficient to cover the debt payment:*

$$R_l^* > \max\left(V^n - u_b^n, V^e - u_b^e\right). \tag{1.11}$$

If there is no SDI entering the firm and the company is controlled by the initial lender, then after paying the entrepreneur, the lender receives a payoff of

$$u_l^n = V^n - u_b^n.$$

[8] In section 1.4 we will adapt the model to the complementary case where the face value of the loan is lower than the firm's net worth. Though both versions fit within the structure of the model presented in section 1.2, they require different institutional concerns to be addressed.

Furthermore, upon SDI entry we assume the initial lender and the SDI share the surplus according to an efficient bargaining procedure. The initial lender and the SDI have equal chances of being the one making a take-it-or-leave-it offer. The initial lender's expected payoff under the assumed bargaining rule is then

$$u_l^e = \frac{1}{2}\left[\underbrace{V^n - u_b^n}_{\text{SDI's offer}} + \underbrace{V^e - u_b^e}_{\text{Lender's offer}}\right] \tag{1.12}$$

$$= V^n - u_b^n + \frac{v+d}{2}, \tag{1.13}$$

with the SDI retaining the remaining, given by

$$u_s^e = V^e - u_b^e - u_l^e.$$

Our non-cooperative bargaining approach is therefore equivalent to the (cooperative) Nash bargaining solution, where each player obtains the same payoff in excess of her threat point. After simplifying, the SDI's payoff is given by

$$u_s^e = \frac{v+d}{2}. \tag{1.14}$$

Finally, it is perhaps worthwhile to clarify that in subsequent analyses throughout this section we always treat u_b^n, the borrower's continuation rent in case the initial lender controls the firm, as exogenous.[9]

1.3.1 Credit rationing

Proposition 1 below formally summarizes the impact of SDI entry on financing feasibility.

Proposition 1. *In an interior equilibrium, where $q \in (0,1)$, (expected) pledgeable income is given by*

$$\mathcal{P}^* = p\left(R - \frac{B}{\Delta} + V - u_b^n\right) + (1-p)(V^n - u_b^n) + \underbrace{\frac{v+d}{2\overline{C}_s}\left[pd + (1-p)\frac{v+d}{2}\right]}_{\textit{SDI Effect}}. \tag{1.15}$$

[9] This is no longer the case in section 1.4, where it is more natural, due to institutional details, that u_b^n is endogenous.

SDI intervention therefore relaxes the credit rationing problem, increasing the funding probability of new projects, as long as

$$d > -\frac{1-p}{1+p}v. \tag{1.16}$$

It follows that the set of financing-improving SDIs is larger for long-shot projects, i.e., for lower probability of success p.

Endogenous SDI entry has two separate effects on capital rationing. First, since the initial lender only allows SDIs that increase its payoff to enter (i.e., $u_l^e \geq u_l^n$, or $v+d \geq 0$), there is a direct positive effect of SDI entry on the initial lender's continuation payoff. The last term in equation (1.15) captures this effect where $v + d \geq 0$ and SDI entry relaxes credit rationing. Second, by affecting the borrower's payoff under failure through d, SDI entry changes the need to use high-powered incentives for the entrepreneur to behave. More specifically, whenever $d > 0$, the entry of an SDI makes failure less appealing to the entrepreneur, reducing the agency rent and increasing credit availability. Conversely, through the same channel, an SDI that worsens the moral hazard problem (i.e., $d < 0$) reduces the credit available in the first stage. For sufficiently negative values of d, SDI entry can tighten initial financing even if the SDI increases the continuation value.

Finally, as the probability of failure increases, credit rationing becomes less of a problem with an SDI that worsens moral hazard. Intuitively, as p decreases in equation (1.15), the impact of SDI on the supply of credit through the first channel, namely by directly increasing the initial lender's payoff, becomes more important. Hence, in relative terms, the negative impact on credit supply of an SDI that worsens the agent's moral hazard is attenuated.

1.3.2 NPV: level and allocation

The initial lender provides ex ante funding competitively, which implies the project's NPV is shared between the entrepreneur and the SDI. Perhaps surprisingly, SDI (equilibrium) entry has ambiguous implications in terms of NPV and the entrepreneur's ex ante profit. These results are formalized in Proposition 2 below.

Proposition 2. *Consider an interior equilibrium with $q \in (0, 1)$. The ex ante equilibrium profit of the entrepreneur, denoted by π_b^*, is given by:*

$$\pi_b^* = p\,(R + V) + (1 - p)V^n - I + \underbrace{(1 - p)\frac{(v + d)(v - d)}{4\overline{C}_s}}_{\text{SDI Effect}}, \tag{1.17}$$

which implies that SDI intervention increases the expected profit for the entrepreneur if and only if $d < v$. The project's NPV is given by

$$NPV^* = p(R + V) + (1 - p)V^n - I + \underbrace{(1 - p)\frac{(v + d)(3v - d)}{8\overline{C}_s}}_{\text{SDI Effect}}, \tag{1.18}$$

which implies that SDI intervention increases NPV if and only if $d < 3v$.

Note that the conditions listed in the proposition for negative value effects (total NPV and/or the entrepreneur's ex ante profit) are compatible with equilibrium SDI entry, which requires only that $v + d > 0$, i.e., that the offer is attractive for the lender. In particular, under some conditions, the initial lender will accept value-destroying SDI offers that "squeeze" the entrepreneur but make the lender better off. Since there is no way to avoid this ex post value destruction ex ante, the NPV is reduced when such value-destroying SDIs are more pervasive.

1.3.3 Main impacts of SDI entry: summary and discussion

In this section we summarize the main regions of the parameter space and provide some economic intuition and discussion for each of these regions. Figure 1.A.2 illustrates these regions, building on the results implied by Propositions 1 and 2. Throughout the discussion we refer to each region as characterizing an SDI "type".[10]

Region 1. In this region, SDI entry improves pledgeable income but decreases NPV. These SDIs are characterized by relatively low v, possibly negative (value-destroying),

[10] We do not discuss how contextual variables such as technology or regulation impact the prevalence of particular SDI types in a given industry. This would be relevant to empirically test the predictions of the model in the cross section of industries for example; but that is outside the scope of the paper.

and a relatively high d (disciplining). The only social value that these SDIs may provide is in alleviating credit rationing. If, however, credit rationing is not a concern, then these SDIs are socially undesirable. Essentially they are rent-seeking institutions which are able to extract surplus from the entrepreneur ex post by "bribing" the initial lender, who is unable to commit ex ante not to accept said "bribe". Interestingly this type of equilibrium can occur even with a positive v, which is perhaps not obvious. The reason why NPV goes down even though $v > 0$ is that there is an inefficiently high level of entry (with concomitantly high average entry costs), motivated precisely by the payoff associated with expropriating the entrepreneur. Mapping this region to the world of distress investors, the type of SDI from region 1 is an organization that focuses on monitoring technologies and/or has power over the entrepreneur in some form.

Region 2. In this region SDIs are of a relatively nicer sort as compared to region 1, in that they create enough continuation value such that the NPV increases; one could say they have some understanding of the firm's core business. Nevertheless, for these SDIs the disciplining dimension is still relatively strong and therefore their presence hurts the entrepreneur ex post. These SDIs are socially useful in two dimensions: alleviating credit rationing if this is a concern and improving the social contribution of the project. This notwithstanding, the reduction in the entrepreneur's ex ante profit could have negative incentive effects that we do not model, for example in terms of the effort that goes into identifying project opportunities.

Region 3. Here SDIs display a bias towards v and away from d, as compared to regions 1 and 2. These SDIs are organizations with very strong business skills in the distressed firm's sector. Even if $d > 0$, the discipline dimension is not so strong that the entrepreneur is hurt ex ante. Whenever $d > 0$, meaning that the entrepreneur has a lower payoff ex post, it is still the case that her ex ante profit benefits from SDI entry. This occurs because with a high v the initial lender is better off ex post and passes these gains to the entrepreneur via the initial financing conditions (recall the initial lender provides funding competitively). In a way this region is the best of all worlds in our model, where everyone benefits from SDI presence. Interestingly, this ideal type of SDI achieves a kind of balance between value enhancement and discipline.

Region 4. Last but not least, this region represents a potentially unfortunate type of SDI, namely organizations who on average have strong business skills within the distressed firm's sector ($v > 0$) but still rely importantly on the entrepreneur ($d < 0$). Since upon entry they increase the entrepreneur's payoff significantly, this worsens the moral hazard problem and could trigger credit rationing ex ante. We believe this region is empirically plausible, as we explain next. In many cases, the initial lender, for example a traditional bank, will have very low ability in managing a distressed firm, including retaining key employees. Without skilled SDIs around, the firm may therefore end up being liquidated. Although this is not necessarily positive in itself, it has the benefit of providing the entrepreneur with strong incentives, since upon liquidation her payoff will be low. Once skilled SDIs are around and willing to rescue the company, the entrepreneur suddenly becomes more valuable following failure (negative d). And since ex post lenders will like the SDI's offer, they cannot commit ex ante not to accept it (even when doing so ex ante be beneficial). Ultimately this type of SDI might therefore *inadvertently* worsen credit rationing.

A final comment is in order. An important feature of the model is that bargaining between the SDI and the initial lender takes place after the cost of entry has been incurred. This implies that from the perspective of the SDI, entry is inefficiently infrequent (bargaining friction), because the (sunk) entry cost is not internalized. From the social perspective, this means that when SDIs are desirable, there will unfortunately be too few around. On the flip side, if SDIs are socially undesirable, fortunately not too many will enter the market.

1.3.4 Extension: SDI entry and ex ante project choice

In the previous section we took project characteristics as given and asked whether and how SDI presence affects financing ex ante. In this section we go one step further and ask if SDI presence can impact which types of projects entrepreneurs look for. The motivation for the analysis is as follows. In some instances, SDI presence is bad news for the entrepreneur, for example because of a reduction in pledgeable income. Given an undesirable effect of SDIs, the entrepreneur can try to reduce SDI entry by picking projects that are less attractive to later-stage investors, for example projects with lower continuation value.[11] In order to conduct the analysis we make some additional choices regarding functional forms, described below.

We now refer to V—so far just the continuation value following success—as the *baseline continuation value* and assume the following:

$$V^n = \lambda V \tag{1.19}$$

$$v = \gamma V, \tag{1.20}$$

which implies that firm value upon entry, V^e, is equal to $V(\lambda + \gamma)$. We assume $\lambda \in [0, 1]$ and $\gamma > -\lambda$ (otherwise V^e could become negative). In the coming sections, we assume that V is one of the project characteristics that the entrepreneur can choose, even if only partially/locally. One can intuitively think of projects with higher V as having higher duration.

Next, we assume that the SDI's disciplining capacity is proportional to u_b^n:

$$d = \delta u_b^n, \tag{1.21}$$

with $\delta < 1$ (otherwise u_b^e, the borrower's continuation rent upon SDI entry, could become negative) but possibly negative. In the coming sections, we assume that u_b^n is also one of the project characteristics that the entrepreneur can choose, even if only partially/locally. One can think about projects with higher u_b^n as being more reliant on entrepreneurial human capital and/or effort during continuation.

Finally, it is useful to note that the earlier condition for the lender to (strictly) benefit from SDI entry, $v + d > 0$, can now be written as

$$\gamma V + \delta u_b^n > 0. \tag{1.22}$$

[11] Conversely, if SDI entry is desirable by the entrepreneur, she might choose projects that attract more SDIs.

1.3.4.1 Continuation value (V)

In this section we consider if an entrepreneur would always prefer projects with higher V, as would be intuitive. The main results are presented in Proposition 3.

Proposition 3. *Comparative statics on baseline continuation value V are characterized by the following:*

1. *It is always the case that $\frac{\partial \pi_b^*}{\partial V} \geq 0$ and $\frac{\partial NPV^*}{\partial V} \geq 0$.*
2. *Consider parameter configurations where in equilibrium $q = 0$ or $q = 1$. Then $\frac{\partial \mathcal{P}^*}{\partial V} \geq 0$.*
3. *Suppose that $\gamma > 0$. Then there exist interior equilibria with $q \in (0, 1)$ where $\frac{\partial \mathcal{P}^*}{\partial V} < 0$. A necessary—but not sufficient—condition for this result to hold is that*

$$\delta < -\frac{\gamma V(1-p)}{u_b^n(1+p)}. \tag{1.23}$$

The first point in the proposition is consistent with our a priori intuitions. Everything else constant, a project with higher continuation value V is socially desirable and also makes the entrepreneur better off ex ante. The second point shows that in the extreme cases where SDIs either never enter or always enter, then pledgeable income also improves with a higher continuation value. The interesting result is in the third point, which shows that under certain conditions, pledgeable income can *decrease* in continuation value.

The counter-intuitive result described in the third point is illustrated in Figure 1.A.3. In this case, SDI entry creates value ($\gamma > 0$) but makes failure softer for the entrepreneur ($\delta < 0$, with δ sufficiently negative), which feeds back into the agency rent and thereby lowers pledgeable income. Notice that in Figure 1.A.3, when the project's continuation value is sufficiently low, no SDI entry is allowed, since it would not increase the initial lender's payoff ($v + d < 0$). As such, in this region (in this example, $V < 59.4$) increases in V improve pledgeable income, as intuitively one would expect. Similarly, for sufficiently high values of V (in particular, $V > 67.4$), SDI entry becomes certain and pledgeable income once again increases with the project's continuation value. However, when SDI entry is uncertain, an entrepreneur who is concerned about pledgeable income (low net worth) would at least locally prefer projects with lower continuation value in order to attract fewer SDIs. Unfortunately, an improvement in pledgeable income comes at the expense of a lower NPV.[12] Note that this is an asymmetric result, in the sense that SDI presence will never per se cause entrepreneurs to look for projects with higher V.[13] This follows from point 1 in the proposition: entrepreneurs already naturally prefer the highest possible V. To be clear, suppose that SDIs improve pledgeable income and suddenly they become more pervasive (lower entry cost). The good news for financially-constrained entrepreneurs notwithstanding, the higher frequency of SDI entry would not affect the entrepreneur's project ranking along the V dimension.

1.3.4.2 Borrower continuation rent (u_b^n)

In this section we consider how entrepreneurs rank projects with regards to their borrower continuation rent u_b^n, which can be understood as the level of ex post reliance on entrepreneurial human capital and/or effort. Without SDIs one knows that entrepreneurs would be (weakly) better off with lower u_b^n, for two reasons: first, since this payoff feeds back into the agency rent, a higher u_b^n worsens credit rationing; second, changes in u_b^n do not impact the project's NPV and the ex ante payoff of the entrepreneur, since the initial lender provides financing competitively. What is less obvious is how SDI presence changes these economics, namely in terms of pledgeable income; a counter-intuitive result is presented in Proposition 4.

Proposition 4. *Suppose that $\delta > 0$. Then there exist interior equilibria with $q \in (0,1)$ where $\frac{\partial \mathcal{P}^*}{\partial u_b^n} > 0$. A necessary—but not sufficient—condition for this to hold is that*

$$\delta > \frac{-1 + \sqrt{1 + 2\frac{pu_b^n}{\overline{C}_s}}}{\frac{pu_b^n}{\overline{C}_s}}. \tag{1.24}$$

[12] Unless the entrepreneur can also be strategic about other features simultaneously (e.g., higher R or p).

[13] A caveat to this argument is that it applies fully if one thinks about *costless* project selection. The analysis would be more complex if we introduced costly project search.

The proposition shows that in some cases, pledgeable income is actually higher for projects with higher borrower continuation rent u_b^n. This is illustrated in Figure 1.A.4 (solid blue line). This result follows from the combination of two effects: (i) a higher u_b^n encourages SDI entry, via a better bargaining position *vis-à-vis* the initial lender; (ii) SDI entry can be beneficial for pledgeable income (namely for a strongly disciplining SDI).

Figure 1.A.4 also shows two other outcomes that are not obvious. First, project NPV goes up with borrower continuation rent u_b^n. Second, the entrepreneur's ex ante profit π_b^* decreases with borrower continuation rent u_b^n. These effects are connected with the bargaining processs between the SDI and the initial lender. With higher u_b^n the SDI is able to extract a larger fraction of the surplus when negotiating with the initial lender. And while this is socially efficient (higher NPV), due to the fact that the SDI's entry cost is not internalized during bargaining, it also implies that the entrepreneur has a lower ex ante payoff. Therefore, whenever pledgeable income is not a concern, the following counter-intuitive result holds: entrepreneurs choose projects that are somehow less problematic ex post (low u_b^n), yet this is socially inefficient.

1.4 The case of low-leverage firms

In this section we analyze the case where in the failure state the company is still viable such that its assets are worth more than the face value of the loan (i.e., positive net worth). If the project fails, then the entrepreneur lacks the liquidity needed to meet the debt payment but since distress is associated with a short-term liquidity problem, as opposed to the high-leverage case, it does not result in control rights being transferred to the initial lender. Instead, the entrepreneur and the lender renegotiate the terms of the existing loan. We extend the model in order to analyze the impact of a potential SDI entry on the outcome of such a private workout.

As in the case of high leverage, if the project is successful, then the entrepreneur maintains full control over the company in phase 2 where she receives V. We continue to assume that an SDI may enter only conditional on failure. The continuation value of the project upon failure is still denoted by V^e if an SDI enters and V^n if there is no SDI entry.

Consistent with the high-leverage case, the difference between the continuation values of the project with and without SDI entry is denoted by v:

$$v = V^e - V^n, \quad v \geq -V^n.$$

Furthermore, Assumption 1 continues to hold such that whenever the entrepreneur shirks, the project's NPV is negative regardless of SDI intervention.

First, consider the case where there is no SDI entry upon failure and the existing loan is exchanged with a new one that has a longer maturity. The new debt is due at a later stage which we do not explicitly model.[14] Restructuring the loan is costly for the initial lender and we assume that the lender imposes these costs fully on the entrepreneur in exchange for extending the maturity. More specifically, the modified claim of the initial lender generates a payoff of

$$u_l^n = R_l + C_l, \tag{1.25}$$

where C_l denotes the initial lender's cost of restructuring the existing loan.[15] For now, we assume that C_l is fixed and exogenous but later on we will allow C_l to vary with loan size.

In case of default, if there is no SDI entry, then the entrepreneur no longer receives a fixed payment, but becomes the residual claimant. More specifically, after the initial lender is paid u_l^n, the entrepreneur receives the remaining amount given by $V^n - u_l^n > 0$. The entrepreneur is still in control of the firm and hence keeps the firm alive as long as her payoff is positive.

Now consider the scenario where SDI entry is possible. As opposed to the high-leverage case, ex post bargaining is no longer between the SDI and the initial lender, but between the SDI and the entrepreneur. The entrepreneur allows for SDI entry only if she is not worse off with an SDI than renegotiating the loan with the initial lender. We assume

[14] In a distressed debt exchange where the firm is typically insolvent, the initial lender might be forced to make some concessions in the form of reduced face value and lower interest payments, especially if legal bankruptcy would reduce the lender's recovery. Conversely, if under legal bankruptcy, the loan is expected to recover its full face value, then the lender's bargaining power might be higher in a private workout.

[15] We assume that the bank does not realize any losses or profits from this exchange such that the present value of the cash flows from the new contract is the same as in the original loan contract. Furthermore, C_l is contracted ex ante which eliminates the possibility of the bank ex post extracting rents from the firm by holding out from negotiations.

that upon entry, the SDI pays down the full face value of the loan to the initial lender. One can consider this payment as short-term liquidity provided to the entrepreneur by the SDI in the form of a zero-interest loan with an extended maturity. Below we formalize the assumption that ensures in equilibrium the initial lender recovers the full face value.

Assumption 3. *In equilibrium, the face value of the loan is low such that if there is no entry, the continuation value of the firm (net of restructuring costs) is always above the face value of debt. In case of SDI entry, the continuation value is large enough to pay the entrepreneur her outside option and at the same time cover the full face value of the loan. Formally,*

$$R_l^* < \min\left(V^n - C_l, V^e - u_b^n\right). \tag{1.26}$$

Under Assumption 3 if an SDI enters, upon which the entrepreneur receives at least her outside option, u_b^n, then the initial lender recovers the full face value of the original loan without any postponement or haircuts such that in net terms

$$u_l^e = R_l.$$

In equilibrium, the lender breaks even and the first stage payoff to the lender is still just

$$R_l^* = I - W.$$

This result follows from the fact that in every state the initial lender recovers R_l and whenever there is no SDI entry renegotiation costs are fully covered by the entrepreneur.

In case of SDI entry, the firm's existing debt to the initial lender is paid down and in exchange, the SDI receives newly issued securities.[16] The entrepreneur and the SDI share endogenous fractions of the firm's continuation value, net of the payment to the initial

[16] For simplicity, we assume that the existing bank loan is replaced with a new loan by the SDI with the same face value and perhaps an extended maturity. In reality, the face value of this loan might vary with the SDI's investment strategy. For instance, while an active SDI that seeks to control the firm might prefer receiving more equity in the reorganized company, a passive SDI that does not intend to do so might enter by simply taking over the existing debt as well as some of the company's equity. In the context of Chapter 11, a distress investor might also enter the firm by providing DIP financing that is to be converted into equity upon reorganization (Miller, 2023), the so-called "loan-to-own" strategy.

lender, $V^e - R_l$, denoted by m and $1-m$, respectively. One plausible way to think about this arrangement is that the SDI receives a debt security with a face value of R_l that is due at a later stage and at the same time some equity with an ownership share of $1-m$. Applying the bargaining rule analogous to the high-leverage case yields the following payoff to the entrepreneur:

$$
\begin{aligned}
u_b^e = m(V^e - R_l) &= \frac{1}{2}\left[\underbrace{V^n - u_l^n}_{\text{SDI's offer}} + \underbrace{V^e - u_l^e}_{\text{entrepreneur's offer}}\right] \\
&= u_b^n + \frac{v + C_l}{2}. \qquad (1.27)
\end{aligned}
$$

Recall that in case of high-leverage projects, upon failure, the borrower loses her equity stake in the company and receives a fixed payment in the second stage. Conversely, when the firm has positive net worth, the entrepreneur becomes the residual claim holder and hence, her payoff depends strictly on the continuation value of the project. The wedge between the entrepreneur's payoffs with and without an SDI is

$$
u_b^e - u_b^n = \frac{v + C_l}{2},
$$

which implies that the entrepreneur is better off with SDI entry provided that $v + C_l > 0$. Interestingly, an SDI that reduces the continuation value (i.e., $v < 0$) might still be allowed to enter as long as the cost of renegotiating with the bank is high. On the other hand, the entry of a value-neutral or value-enhancing SDI is always preferred over renegotiating with the bank.

The following lemma characterizes the borrower's equilibrium ownership share.

Lemma 5. *In an interior equilibrium with $q \in (0,1)$, the entrepreneur's ownership share is given by*

$$
m^* = \frac{2u_b^n + v + C_l}{2(u_b^n + v + C_l)}. \qquad (1.28)
$$

Furthermore, the entrepreneur never loses the control of the firm such that $m^* > 1/2$ always holds.

Lemma 5 shows that whenever the entrepreneur relies less on debt financing upfront, she never loses the control of the firm to the SDI. This result follows from the entrepreneur's offer being accepted half of the time and the fact that such offer allocates the full continuation value ($V^e - R_l$) to the entrepreneur after the existing loan is paid down. As shown in the previous sections, financing the project with high leverage results in control rights being transferred to the debtholder in case of distress and the entrepreneur's second stage payoff depends solely on how important her human capital is for the continuation of the venture. On the other hand, with a more conservative capital structure, the entrepreneur never loses the control of the firm and her payoff strictly depends on the continuation value of the project.

As it is the case with a highly leveraged project, SDI entry is still costly and the SDI enters only if her payoff exceeds these costs. More specifically,

$$u_s^e = (1-m)(V^e - R_l) = \frac{v + C_l}{2} \geq C_s, \quad C_s \sim U[0, \overline{C}_s]$$

must hold for the SDI to participate in the firm which implies $v + C_l > 0$, a condition that is analogous to condition (1.5) in Lemma 1 of the high-leverage case.

The following proposition summarizes the effect of SDI entry on the entrepreneur's ex ante payoff as well as the NPV of the project.

Proposition 5. *Consider an interior equilibrium with $q \in (0,1)$. The entrepreneur exerts effort, provided that*

$$R + V \geq \lambda V - C_l + \frac{B}{\Delta} + \underbrace{q\left(\frac{v + C_l}{2}\right)}_{\text{SDI effect}}. \tag{1.29}$$

The ex ante profit of the entrepreneur is given by

$$\pi_b^* = p(R+V) + (1-p)(\lambda V - C_l) - I + \underbrace{(1-p)q\left(\frac{v + C_l}{2}\right)}_{\text{SDI effect}}, \tag{1.30}$$

which implies that the effect of SDI entry on the entrepreneur's expected payoff is *always positive. The project's NPV is given by*

$$NPV^* = p(R+V) + (1-p)(\lambda V - C_l) - I + \underbrace{3(1-p)q\left(\frac{v+C_l}{4}\right)}_{\text{SDI Effect}}, \tag{1.31}$$

where the SDI effect is always positive.

Different than in the high-leverage case, the borrower's incentive compatibility condition is independent of R_b whenever C_l is exogenous. There are two conditions that lead to this result. First, as opposed to the case with high leverage, where the borrower receives a fixed payment in case of failure, in the low-leverage case she becomes the residual claim holder. Second, the initial lender receives R_l regardless of whether the project succeeds or fails, making R_l irrelevant for the borrower's effort decision.

The last term in inequality (1.29) is always positive which implies that SDI involvement encourages the entrepreneur not to exert effort by reducing ex ante expected costs of renegotiating the loan. Considering that renegotiation costs are fully (partially) paid by the entrepreneur without (with) SDI entry, increasing C_l always relaxes credit rationing by making failure less appealing to the entrepreneur. Specifically, the derivative of the right-hand-side in inequality (1.29) with respect to C_l is

$$-1 + \frac{v + C_l}{2\overline{C}_s} \leq 0,$$

which is always negative in an interior equilibrium.

The impact of SDI entry on the entrepreneur's expected payoff is straightforward to see: Since the entrepreneur is the one who decides on whether the SDI enters or not, SDI entry is allowed only if it increases the entrepreneur's expected payoff relative to restructuring the loan (i.e., $v + C_l \geq 0$). Also note that the SDI effect increases with the cost of restructuring the loan which provides higher direct savings to the entrepreneur and at the same time increases the ex ante likelihood of SDI entry.

The entry of an SDI that reduces the NPV of the project is always blocked by the entrepreneur. This result is different than in the highly leveraged project case where SDI entry is determined by the initial lender who breaks even in equilibrium. In the high-leverage case, even if SDI entry is costly and hence reduces the NPV of the project, SDI entry is still possible as long as it increases the second stage payoff to the initial lender. Conversely, in the low-leverage case the entrepreneur is the residual claim holder and whenever she allows for SDI entry, it is always the case that the NPV of the project also benefits from it.

1.4.1 The impact of C_l and W

In this subsection, we analyze the impact of restructuring costs and cash on hand on the borrower's payoff and the NPV of the project.

Proposition 6. *In an interior solution where $q \in (0, 1)$, comparative statics on the cost of restructuring the loan, C_l, are characterized by the following:*

1. *It is always the case that $\frac{\partial \pi_b^*}{\partial C_l} < 0$, but the derivative becomes less negative as the likelihood of SDI entry increases.*
2. *Whenever SDI entry is highly likely such that $q \in \left[\frac{2}{3}, 1\right)$, then $\frac{\partial NPV^*}{\partial C_l} \geq 0$.*
3. *If $q \in \left(0, \frac{2}{3}\right)$ such that SDI entry is less likely, then $\frac{\partial NPV^*}{\partial C_l} < 0$ holds.*

The cost of restructuring the loan, C_l, has an unambiguous negative effect on the borrower's ex ante payoff. Consider the extreme case where SDI entry is not possible. Then, by inspecting equation (1.30) it is straightforward to see that a one-dollar increase in C_l reduces the entrepreneur's ex ante payoff by $\$(1 - p)$. Now consider the case where upon failure an SDI may enter the firm with a likelihood of q. With SDI involvement being possible, increasing C_l by one dollar decreases u_b^n by exactly one dollar. Although SDI entry allows for saving on costs of restructuring the loan, since the SDI and the entrepreneur equally share the resulting surplus, an increase in C_l reduces the entrepreneur's payoff in the entry scenario as well.

Increasing restructuring costs can have opposing effects on the NPV of the project which makes the overall effect ambiguous. On the one hand, if the project fails and there is no SDI involvement, then the continuation payoff is reduced by the costs of renegotiating the loan, leaving less surplus in net terms. On the other hand, while increasing

C_l reduces the probability of costly renegotiation, it also increases the expected costs of entry because high-cost SDIs who could not enter before are now able to participate in the firm. Furthermore, for $v \neq 0$ the increase in the likelihood of SDI entry has a direct impact on the expected continuation value of the firm. Ultimately, the overall effect of a change in C_l on the NPV of the project is given by the difference between the following terms: the change in expected continuation value net of change in expected entry costs,

$$(1-p)q\left(v - \frac{v + C_l}{4}\right) = (1-p)q\left(\frac{3v - C_l}{4}\right), \tag{1.32}$$

and the change in the expected costs of renegotiation,

$$(1-p)(1-q)C_l. \tag{1.33}$$

Notice that both of these terms are non-linear in C_l.[17] When SDI entry is not frequent (i.e., C_l is low), increasing C_l further does not increase SDI entry enough to justify the increase in expected renegotiation costs, and hence NPV decreases. On the other hand, if SDI entry is highly likely, then the reduction in $(1-q)$ generated by an increase in C_l overcomes the increase in the magnitude of renegotiation costs, reducing the expected value of such costs and increasing the NPV of the project.

Figure 1.A.5 illustrates an example in which the expected payoff to the entrepreneur, denoted by the blue curve on the left panel, decreases with C_l and the NPV of the project, denoted by the blue curve on the right panel, first decreases with C_l but then becomes an increasing function of it for most of the values on the x-axis. The particular SDI in this example is a value-enhancing type with $v = 12.5$ and the costs of entry are not high

[17] The partial derivative of $(1-p)q\left(\frac{3v-C_l}{4}\right)$ with respect to C_l is

$$(1-p)\left(\frac{v - C_l}{4\overline{C}_s}\right),$$

which is definitely negative if the SDI destroys value and is positive only if $v > C_l$. The partial derivative of $-(1-p)(1-q)C_l$ is

$$-(1-p)\left(1 - \frac{v + 2C_l}{2\overline{C}_s}\right),$$

which is positive for higher values of C_l implying that if C_l is large, increasing it further can reduce the expected costs of renegotiating the loan.

($\overline{C}_s = 10$). Therefore, even for lower values of C_l, SDI entry is still likely such that $q > 2/3$. Consider a 2-unit increase in C_l from 4 to 6. The probability of SDI entry increases by 0.1 from 0.825 to 0.925 and even though C_l is now higher, the expected costs of renegotiation given in (1.33) decreases from 0.14 to 0.09. Similarly, the change in expected continuation value net of change in expected entry costs given in (1.32) increases from 1.382 to 1.456. The latter result follows from the SDI being a value-enhancing type and thus, even if entry costs increase with C_l, SDI entry becomes frequent enough to justify the increase in such costs.

1.4.2 Extension: optimal capital structure

When we presented the high-leverage case, we also studied an extension in section 1.3.4 where we asked whether entrepreneurs could adjust to SDI presence by choosing projects with certain characteristics. This section presents an analogous analysis of whether entrepreneurs can do the same, this time by altering their debt-vs-equity choices. More specifically, by varying the amount of cash on hand invested into the project, and hence the resulting share of debt in the capital structure, we study whether entrepreneurs can increase their expected payoff.

Let us first consider the case where the entrepreneur's savings, denoted by W_l, are high enough to finance the project with low leverage but also low enough to require external financing (i.e., $W_l < I$). More specifically, Assumption 3 holds:

$$I - \min\left(V^n - C_l, V^e - u_b^n\right) < W_l < I,$$

which implies that in equilibrium the initial lender is paid the full face value of the loan upon failure regardless of an SDI enters or not (i.e., overcollateralized loan). Let the entrepreneur's ex ante payoff with a less leveraged capital structure be denoted by π_b^l.

Alternatively, consider the case where the entrepreneur invests less of her savings, $W_h < W_l$, such that Assumption 2 holds and the project is financed with high leverage. We denote the entrepreneur's ex ante payoff with high leverage by π_b^h which is independent of W_h. Proposition 7 compares the expected payoff to the entrepreneur as well as the NPV of the project if she invests W_l versus W_h.

Proposition 7. *In an interior solution where the entrepreneur can undertake the project with high or low leverage and $C_l > 0$, the optimal and efficient amounts of borrowing are characterized by the following:*

1. *The entrepreneur prefers borrowing more (i.e., $\pi_b^h > \pi_b^l$) provided that*

$$\frac{2v + C_l + d^2/C_l}{4\overline{C}_s} < 1. \tag{1.34}$$

2. *High leverage yields a higher NPV (i.e., $NPV_h^* > NPV_l^*$) provided that*

$$\frac{3(2v + C_l) + d^2/C_l - 2dv/C_l}{8\overline{C}_s} < 1. \tag{1.35}$$

The entrepreneur's decision between the two capital structures is determined by the relative magnitude of $|d|$, the disciplining impact of the SDI, and C_l, the costs of renegotiating the loan. Specifically, if $|d| < C_l$, then the inequality in (1.34) is satisfied unambiguously[18], and hence high leverage is preferred over an overcollateralized loan. In other words, to the extent that SDI involvement does not change the entrepreneur's agency rent significantly in either direction, the entrepreneur prefers using less of her savings and borrows more.

The economic intuition behind this result links back to the discussion in section 1.3.3. Consider first regions 1 and 2 in Figure 1.A.2 where the SDI has a significant disciplining impact on the entrepreneur (i.e., d is large and positive). Recall that this is either the type of SDI that does not have much value impact and expropriates the entrepreneur by making an attractive ex post offer to the bank, or the type that is value-enhancing but at the same time disciplines the entrepreneur. In either case, such SDIs hurt the entrepreneur by reducing her ex ante payoff. Although low leverage comes with restructuring costs that are fully paid by the borrower, as long as SDI entry is likely (i.e., $v + C_l$ is high) and the cost of restructuring is low relative to the disciplining effect of an SDI entering the highly leveraged firm (i.e., $C_l < d$), the entrepreneur prefers a less levered capital structure. In other words, the entrepreneur avoids an SDI that is strict in disciplining her by using more cash on hand and borrowing less, provided that renegotiating the loan is not too costly.

[18] Note that $q < 1$ requires $\overline{C}_s > (v + C_l)/2$.

Now consider region 3 in Figure 1.A.2 where SDIs have strong business skills that allow them to improve continuation value without relying much on the entrepreneur's skills. With such SDIs, the entrepreneur can benefit from the increase in the continuation value without being disciplined by the SDI. Provided that renegotiation costs are relatively large (i.e., $C_l > |d|$), the entrepreneur avoids the risk of costly renegotiation by using less cash on hand and borrowing more. Finally in region 4, although SDI entry increases the entrepreneur's second stage payoff (i.e., $d < 0$), it also worsens moral hazard, and for large values of $|d|$ SDI entry becomes less likely. In this case by choosing a less levered capital structure, the entrepreneur can increase the likelihood of SDI intervention.

Figure 1.A.5 also illustrates an example of the entrepreneur's capital structure choice. The dashed horizontal line on the left panel shows the entrepreneur's expected payoff with high leverage. When renegotiation costs are low, the blue curve lies above the horizontal line (i.e., $\pi_b^l > \pi_b^h$) and the entrepreneur prefers using more of her savings and borrows less. With a more levered capital structure the entrepreneur is subject to the disciplining effect of the SDI which reduces her payoff. In this particular example the SDI is value-enhancing with a high v, thus even if C_l is low, SDI entry is frequent enough to make low leverage preferred by the entrepreneur.

Interestingly, the values of C_l that attract the entrepreneur to a less levered capital structure do not necessarily maximize the NPV of the project. When renegotiation costs are low, SDIs participate more frequently in a firm with more debt in its capital structure than a less levered firm because they can reduce the entrepreneur's second stage payoff ($d = 6 > 0$) which in turn increases the NPV of the project. To summarize, when renegotiation costs are low, the entrepreneur prefers avoiding a disciplining SDI by borrowing less and renegotiating the loan even though it may not be the most efficient alternative. For intermediate levels of C_l, high leverage is both the optimal and the most efficient capital structure. Finally, when C_l is high enough such that SDI entry is almost certain, even if the entrepreneur prefers borrowing more, less leverage yields a higher NPV.

1.4.3 Extension: C_l as a function of R_l

So far we have assumed that renegotiation costs were exogenously given and did not depend on the parameters of the model. Next, we will relax this assumption by allowing for renegotiation costs to vary with loan size. While some of these costs might be independent of the loan size (e.g., transaction costs), restructuring large loans can also be more costly due to their more prominent impact on the bank's balance sheet. Therefore, we assume that the costs associated with extending the loan both have a fixed component as well as a part that is proportional to the size of the loan. More specifically,

$$C_l = \mu + \beta R_l, \quad \mu \geq 0 \text{ and } \beta \geq 0. \tag{1.36}$$

Given this functional form of restructuring costs, in an interior equilibrium, where $q \in (0, 1)$, the following condition must hold

$$v + \mu + \beta(I - W) < 2\overline{C}_s \Rightarrow v + \mu \leq 2\overline{C}_s,$$

provided that $W < I$.

When renegotiation costs are exogenous, given that the lender is competitive, neither the ex ante payoff of the entrepreneur nor the NPV of the project depends on how much cash on hand the entrepreneur invested into the project initially. Conversely, whenever C_l is an increasing function of loan size, given $R_l^* = I - W$, there is a direct relationship between cash on hand and the cost of renegotiating with the lender. Given the linear form of renegotiation costs, the borrower's incentive compatibility constraint becomes

$$R + V \geq V^n - \mu - \beta(I - W) + \frac{B}{\Delta} + \frac{(v + \mu + \beta(I - W))^2}{4\overline{C}_s}.$$

In an interior solution, the right-hand-side of the inequality is an increasing function of W indicating that if the entrepreneur invests more of her savings, then renegotiation becomes less costly, making failure more appealing to the entrepreneur.

Proposition 8 summarizes the impact of cash on hand on the equilibrium outcomes.

Proposition 8. *In an interior solution, comparative statics on cash on hand, W, are characterized by the following:*

1. *It is always the case that* $\frac{\partial \pi_b^*}{\partial W} \geq 0$*, but the derivative is reduced as the likelihood of SDI entry increases.*
2. *Whenever SDI entry is highly likely such that* $q \in \left[\frac{2}{3}, 1\right)$*, then* $\frac{\partial NPV^*}{\partial W} < 0$.
3. *If* $q \in \left(0, \frac{2}{3}\right)$ *such that SDI entry is less likely, then* $\frac{\partial NPV^*}{\partial W} \geq 0$.

The first point shows that external financing is costly and an entrepreneur that has enough savings to cover the initial outlay would not raise any debt if low leverage is the only feasible source of financing. However, the possibility of SDI entry reduces the expected cost of external financing as well as the benefit to financing the project internally. The second and third points are perhaps the most interesting results. When there is no SDI involvement or when there is under-provision of distress lenders, having more cash on hand reduces the restructuring costs and increases the NPV. Therefore, in a market where there is inefficiently low SDI entry, it is both optimal and efficient to have financially less constrained entrepreneurs. On the contrary, if SDI involvement is highly likely, then increasing cash on hand discourages SDI entry and reduces the NPV. Consequently, in a market where SDI entry is not costly, financially constrained entrepreneurs can increase welfare even if they personally benefit from having more cash on hand.

1.5 Conclusion

Over the last decades distress investors have become more visible in credit markets but yet research about them is scarce, in particular when it comes to ex ante effects. In this paper, we aim to partly fill this gap by extending the canonical moral hazard model in corporate finance to incorporate the possibility of specialized investors appearing in case of distress. We study the spillover effects of distress investors on the firm's access to credit, entrepreneur's surplus and NPV of the project.

We begin our analysis with a severe distress case where the firm becomes insolvent if the project fails and the control of the firm is transferred from the entrepreneur to the lender. We show that SDIs might worsen borrower moral hazard and reduce the availability of initial financing. Furthermore, some SDIs can reduce project NPV. We also study a less severe distress case where the entrepreneur is still the owner of the firm even if the project fails but she renegotiates with the bank to extend the duration of the loan. Since the entrepreneur controls the firm, the negative NPV effect is absent if an SDI enters the firm.

Finally, we show that SDI presence can shape the entrepreneur's choice of project characteristics and capital structure.

Appendix of Chapter 1

1.A.1 Proofs

Proof of Lemma 1. Suppose that the initial lender has full control over the acceptance of SDI offers. Then, it must be the case that $u_l^e \in [u_l^n, V^e - u_b^e)$. If the SDI pays the minimum possible amount to the initial lender, then the SDI payoff is given by:

$$\begin{aligned} u_s^e &= V^e - u_l^n - u_b^e \\ &= V^e - V^n - (u_b^e - u_b^n) \\ &= v + d. \end{aligned}$$

For a strictly positive probability of SDI intervention, it must be then the case that $v+d > 0$. Therefore, for $v < 0 \wedge d < 0$, SDI intervention is not possible.

Alternatively,

$$\begin{aligned} u_s^e &= V^e - u_l^e - u_b^e \\ &= V^n + v - u_l^e - u_b^e \\ &= V^n + v - u_l^e - (u_b^n - d) \\ &= u_l^n - u_l^e + v + d. \end{aligned}$$

Since the initial lender only allows SDIs that increase its payoff, in equilibrium $u_l^n - u_l^e < 0$ holds. Therefore, $u_s^e > 0$ is true if and only if $v + d > 0$. This concludes the proof.■

Proof of Lemma 2. The entrepreneur's IC constraint is given by

$$p(R_b+V)+(1-p)[qu_b^e+(1-q)u_b^n] \geq (p-\Delta)(R_b+V)+(1-p+\Delta)[qu_b^e+(1-q)u_b^n]+B,$$

which implies the following lower bound for the entrepreneur's first stage payoff

$$R_b \geq \frac{B}{\Delta} - V + qu_b^e + (1-q)u_b^n \equiv \underline{R_b}.$$

The lender's participation constraint is

$$pR_l + (1-p)[qu_l^e + (1-q)u_l^n] \geq I - W.$$

Substituting R_l with $R - \underline{R_b}$ yields

$$\mathcal{P} = p\left[R - \frac{B}{\Delta} + V - qu_b^e - (1-q)u_b^n\right] + (1-p)[qu_l^e + (1-q)u_l^n] \geq I - W.$$

This concludes the proof.■

Proof of Lemma 3. In an interior solution, where $q \in (0,1)$, the minimum amount of capital provided by the entrepreneur for financing to be feasible is given by

$$\underline{W}^* = I - \Bigg(p\left\{R - \frac{B}{\Delta} + V - [qu_b^e + (1-q)u_b^n]\right\}$$
$$+ (1-p)\left[q(V^e - u_b^e - u_s^e) + (1-q)(V^n - u_b^n)\right]\Bigg),$$

which can be re-written as

$$\underline{W}^* = I - p\left(R - \frac{B}{\Delta} + V\right) + qu_b^e + (1-q)u_b^n + (1-p)[qu_s^e - qV^e - (1-q)V^n]$$
$$= I - p\left(R - \frac{B}{\Delta} + V - u_b^n\right) - (1-p)(V^n - u_b^n) + q(u_b^e - u_b^n) + (1-p)q(u_s^e - v)$$
$$= I - p\left(R - \frac{B}{\Delta} + V - u_b^n\right) - (1-p)(V^n - u_b^n) + \frac{u_s^e}{\overline{C}_s}\left[(1-p)(u_s^e - v) - d\right].$$

Finally, it is clear that the contribution of an SDI is given by

$$\underline{W}^* - \lim_{\overline{C}_s \to \infty} \underline{W}^* = \frac{u_s^e}{\overline{C}_s}\left[(1-p)u_s^e - (1-p)(v+d) - pd\right]. \tag{A.37}$$

Suppose now that $v > 0 \wedge d > 0$. Since we are assuming that $u_l^e \in [u_l^n, V^e - u_b^e)$, u_s^e must be bounded between 0 and $V^e - u_b^e - u_l^n$, as the initial lender has full control over the acceptance of offers and thus demands at least u_l^n. Therefore, $u_s^e \in (0, V^e - u_b^e - u_l^n]$ and

$$u_s^e \leq V^e - u_b^e - u_l^n = V^n + v - u_b^e - u_l^n = v + d$$
$$\Leftrightarrow (1-p)u_s^e \leq (1-p)(v+d) \leq (1-p)(v+d) + pd.$$

Consequently, for $v > 0 \wedge d > 0$ and if the initial lender has full control over the acceptance of the SDI offer, SDI intervention unambiguously ameliorates credit rationing. This concludes the proof.■

Proof of Lemma 4. Firstly, consider the formula for the overall NPV of the project:

$$NPV^* = p(R+V) + (1-p)\left[q(V^e - \mathbb{E}\left[C_s | C_s \leq u_s^e\right]) + (1-q)V^n\right] - I$$
$$= p(R+V) + (1-p)V^n + (1-p)q\left(v - \mathbb{E}\left[C_s | C_s \leq u_s^e\right]\right) - I. \tag{A.38}$$

Thus, in an interior solution the SDI contribution is given by

$$\frac{(1-p)u_s^e\left(v-\mathbb{E}\left[C_s|C_s\leq u_s^e\right]\right)}{\overline{C}_s},$$

which is necessarily negative if $v<0$. However, the overall impact of SDI participation may nonetheless be ambiguous, as long as the value-destroying distress investor relaxes credit rationing, i.e.,

$$\frac{u_s^e\left[(1-p)(u_s^e-v)-d\right]}{\overline{C}_s}<0\;\Leftrightarrow d>(1-p)(u_s^e-v).$$

This concludes the proof.■

Proof of Proposition 1. One can re-write the definition of pledgeable income given in equation (1.7) as

$$\mathcal{P}=p\left(R-\frac{B}{\Delta}+V-u_b^n\right)+(1-p)(V^n-u_b^n)+q\left[pd+(1-p)(v+d-u_s^e)\right].$$

Furthermore, substituting for q and u_s^e yields that pledgeable income in an interior solution where $q\in(0,1)$ is given by the following relationship

$$\mathcal{P}=p\left(R-\frac{B}{\Delta}+V-u_b^n\right)+(1-p)(V^n-u_b^n)+\frac{v+d}{2\overline{C}_s}\left[pd+(1-p)\frac{v+d}{2}\right].\quad\text{(A.39)}$$

Finally, the impact of SDI intervention is positive if and only if

$$pd+(1-p)\frac{v+d}{2}>0$$

$$d>-\frac{1-p}{1+p}v.$$

This concludes the proof.■

Proof of Proposition 2. In the general version of the model, the expected profit of the entrepreneur is

$$\pi_b^*=p(R_b^*+V)+(1-p)\left[qu_b^e+(1-q)u_b^n\right]-W.$$

Since in equilibrium the initial lender breaks even it must be the case that

$$pR_l^* + (1-p)\left[qu_l^e + (1-q)u_l^n\right] - (I - W) = 0 \Leftrightarrow$$
$$R_l^* = \frac{I - W - (1-p)\left[qu_l^e + (1-q)u_l^n\right]}{p}.$$

Considering that $R_b^* = R - R_l^*$, we may re-write the ex ante profit of the entrepreneur in an interior solution where $q \in (0,1)$ as

$$\pi_b^* = p(R+V) - I + (1-p)\left[qu_l^e + (1-q)u_l^n\right] + (1-p)\left[qu_b^e + (1-q)u_b^n\right]$$
$$= p(R+V) + (1-p)V^n - I + (1-p)\frac{(v+d)(v-d)}{4\overline{C}_s}. \tag{A.40}$$

Given this result, it is clear that the SDI's contribution to the profit of the entrepreneur is positive as long as

$$v > d.$$

The NPV of the project given in equation (A.38) can be re-written as

$$NPV^* = p(R+V) + (1-p)V^n - I + (1-p)\frac{u_s^e}{\overline{C}_s}\left(v - \frac{v+d}{4}\right)$$
$$= p(R+V) + (1-p)V^n - I + (1-p)\frac{(v+d)(3v-d)}{8\overline{C}_s}.$$

Clearly the last term is positive as long as $3v > d$. This concludes the proof.■

Proof of Proposition 3. Incorporating the assumptions $V^n = \lambda V$, $v = \gamma V$, and $d = \delta u_b^n$ in equation (1.17), the partial derivative of π_b^* with respect to V can be written, for an interior solution with $q \in (0,1)$, as

$$\left.\frac{\partial \pi_b^*}{\partial V}\right|_{q\in(0,1)} = p + (1-p)\lambda + \frac{(1-p)\gamma^2 V}{2\overline{C}_s}. \tag{A.41}$$

It follows that this partial derivative is always positive, independently from the sign of γ. In fact, even in both corner solutions, for $q \in \{0,1\}$ this must be the case. Notice that, for $q = 0$,

$$\left.\frac{\partial \pi_b^*}{\partial V}\right|_{q=0} = p + (1-p)\lambda \geq 0, \tag{A.42}$$

and for $q = 1$,

$$\left.\frac{\partial \pi_b^*}{\partial V}\right|_{q=1} = p + (1-p)\lambda + (1-p)\frac{\gamma}{2} \geq 0, \tag{A.43}$$

which is necessarily positive, since by assumption $\lambda > -\gamma$.

Moreover, for $q \in (0,1)$ the partial derivative of the project's NPV with respect to the baseline continuation value is given by

$$\left.\frac{\partial NPV^*}{\partial V}\right|_{q\in(0,1)} = p + (1-p)\lambda + \frac{(1-p)\gamma\,[3\gamma V + \delta u_b^n]}{4\overline{C}_s}. \tag{A.44}$$

This partial derivative must necessarily be positive as well. Suppose first that $\gamma > 0$. Then all terms are positive, since $2\gamma V + (\gamma V + \delta u_b^n) > 0$.[19]

Consider now that $\gamma < 0$: for the last term to be negative it must be the case that

$$\frac{(\gamma V + \delta u_b^n) - (-2\gamma V)}{4\overline{C}_s} > 0.$$

However, since the probability of SDI entry is bounded, this term is also majorized at 0.5. Given that by assumption $\lambda > -\gamma$, this partial derivative is necessarily positive.

Consider now this partial derivative in corner solutions. If $q = 0$, then

$$\left.\frac{\partial NPV^*}{\partial V}\right|_{q=0} = p + (1-p)\lambda \geq 0, \tag{A.45}$$

and if $q = 1$, by the same reasoning applied above,

$$\left.\frac{\partial NPV^*}{\partial V}\right|_{q=1} = p + (1-p)\lambda + (1-p)\frac{3}{4}\gamma \geq 0. \tag{A.46}$$

Now, consider the partial derivative of the project's pledgeable income with respect to V. Starting with a corner solution, if $q = 0$, this partial derivative is

$$\left.\frac{\partial \mathcal{P}^*}{\partial V}\right|_{q=0} = p + (1-p)\lambda \geq 0. \tag{A.47}$$

[19] Recall that in an interior solution, with $q \in (0,1)$, $v + d = \gamma V + \delta u_b^n > 0$.

On the other hand, if $q = 1$:

$$\left.\frac{\partial \mathcal{P}^*}{\partial V}\right|_{q=1} = p + (1-p)\lambda + (1-p)\frac{\gamma}{2} \geq 0, \tag{A.48}$$

since again by assumption $\lambda > -\gamma$.

Finally, in an interior solution, this partial derivative is given by

$$\left.\frac{\partial \mathcal{P}^*}{\partial V}\right|_{q\in(0,1)} = p + (1-p)\lambda + \frac{\gamma\left[(1-p)\gamma V + \delta u_b^n\right]}{2\overline{C}_s}. \tag{A.49}$$

It is clear that for this partial derivative to be negative, then $\gamma < 0 \vee \delta < 0$. Consider the case where $\gamma > 0 \wedge \delta < 0$. For this partial derivative to be negative δ must be sufficiently negative and a necessary condition is that

$$\delta < -\frac{\gamma V(1-p)}{u_b^n} \Rightarrow \delta < -\frac{\gamma V(1-p)}{u_b^n(1+p)}. \tag{A.50}$$

This concludes the proof.■

Proof of Proposition 4. In an interior solution, where $q \in (0,1)$, the partial derivative of pledgeable income with respect to the entrepreneur's second stage payoff without SDI entry, u_b^n, is

$$\left.\frac{\partial \mathcal{P}^*}{\partial u_b^n}\right|_{q\in(0,1)} = -1 + \frac{(\gamma V + \delta u_b^n)}{2\overline{C}_s}\delta + \frac{p u_b^n}{2\overline{C}_s}\delta^2. \tag{A.51}$$

Suppose that $\delta > 0$. Since it must be the case that

$$\frac{\gamma V + \delta u_b^n}{2\overline{C}_s}\delta < \delta,$$

then for this partial derivative to be positive, a necessary condition when $\delta > 0$ is

$$\frac{p u_b^n}{2\overline{C}_s}\delta^2 > 1 - \delta.$$

Finally, this inequality implies that

$$\delta > \frac{-1 + \sqrt{1 + 2\frac{p u_b^n}{\overline{C}_s}}}{\frac{p u_b^n}{\overline{C}_s}}. \tag{A.52}$$

This concludes the proof.■

Proof of Lemma 5. Substituting for $V^e = V^n + v$ and $V^n = u_b^n + R_l + C_l$ in equation (1.27) yields

$$m^* = \frac{2u_b^n + v + C_l}{2(V^e - R_l)} = \frac{2u_b^n + v + C_l}{2(V^n + v - R_l)} = \frac{2u_b^n + v + C_l}{2(u_b^n + v + C_l)}.$$

It is straightforward to see that the numerator is more than half of the denominator such that

$$2u_b^n + v + C_l > u_b^n + v + C_l \Rightarrow \frac{2u_b^n + v + C_l}{2(u_b^n + v + C_l)} > \frac{u_b^n + v + C_l}{2(u_b^n + v + C_l)} = \frac{1}{2}.$$

This concludes the proof.■

Proof of Proposition 5. First, consider the case where there is no SDI entry. The entrepreneur's IC constraint is given by

$$\Delta(R_b + V) \geq \Delta(V^n - R_l - C_l) + B.$$

$R - R_l = R_b$ still holds and substituting it in the IC constraint yields

$$R + V \geq V^n - C_l + \frac{B}{\Delta}.$$

The borrower's IC constraint is independent of R_b. Now consider the IC constraint when SDI entry is possible:

$$\Delta(R_b + V) \geq \Delta[qu_b^e + (1-q)u_b^n] + B.$$

Substituting for $R_l = R - R_b$, $u_b^n = V^n - R_l - C_l$ and $u_b^e = u_b^n + \frac{v+C_l}{2}$ yield

$$R + V \geq \lambda V - C_l + \frac{B}{\Delta} + q\frac{v + C_l}{2}.$$

Considering that $R_b^* = R - R_l^*$, we may re-write the ex ante profit of the entrepreneur in an interior solution, where $q \in (0, 1)$, as

$$\begin{aligned}
\pi_b^* &= p(R_b + V) - W + (1-p)\left[qu_b^e + (1-q)u_b^n\right] \\
&= p(R - I + W + V) - W + (1-p)\left[V^n - I + W - C_l + q\frac{v + C_l}{2}\right] \\
&= p(R + V) + (1-p)(V^n - C_l) - I + (1-p)q\left(\frac{v + C_l}{2}\right). \qquad \text{(A.53)}
\end{aligned}$$

Finally, the NPV of the project is given by

$$\begin{aligned}
NPV^* &= p(R + V) - I + (1-p)q(V^e - \mathbb{E}\left[C_s | C_s \leq u_s^e\right]) + (1-p)(1-q)(V^n - C_l) \\
&= p(R + V) + (1-p)(V^n - C_l) - I + (1-p)q(v + C_l - \mathbb{E}\left[C_s | C_s \leq u_s^e\right]) \\
&= p(R + V) + (1-p)(\lambda V - C_l) - I + 3(1-p)q\left(\frac{v + C_l}{4}\right). \qquad \text{(A.54)}
\end{aligned}$$

This concludes the proof.■

Proof of Proposition 6. The partial derivative of equation (1.30) with respective to C_l is

$$\frac{\partial \pi_b^*}{\partial C_l} = -(1-p) + (1-p)\frac{v + C_l}{2\overline{C}_s} = -(1-p) + (1-p)q.$$

In an interior equilibrium, where $q \in (0, 1)$, the derivative is always negative implying that the borrower's ex ante payoff is reduced by the cost of renegotiating the loan.

Similarly, taking the derivative of equation (1.31) with respect to C_l yields

$$\frac{\partial NPV^*}{\partial C_l} = -(1-p) + 3(1-p)\frac{v + C_l}{4\overline{C}_s} = -(1-p) + \frac{3}{2}(1-p)q.$$

Furthermore, for the values of the probability of SDI entry that satisfy $q \in \left(\frac{2}{3}, 1\right)$, $\frac{\partial NPV^*}{\partial C_l} > 0$ holds. This concludes the proof.■

Proof of Proposition 7. The entrepreneur's expected payoff using more cash on hand is

$$\pi_b^l = p(R + V) + (1-p)(\lambda V - C_l) - I + (1-p)\frac{(v + C_l)^2}{4\overline{C}_s}. \qquad \text{(A.55)}$$

Recall the borrower's ex ante payoff in a highly levered capital structure given in equation (1.17):

$$\pi_b^h = p\,(R+V) + (1-p)\lambda V - I + (1-p)\frac{(v+d)(v-d)}{4\overline{C}_s}. \tag{A.56}$$

It follows from equation (A.55) and (A.56) that

$$\pi_b^h > \pi_b^l \;\Rightarrow\; 4\overline{C}_s > d^2/C_l + C_l + 2v.$$

Similarly, the NPV of the project with low leverage is

$$NPV^l = p(R+V) + (1-p)(\lambda V - C_l) - I + 3(1-p)\frac{(v+C_l)^2}{8\overline{C}_s}, \tag{A.57}$$

and high leverage it is

$$NPV^h = p(R+V) + (1-p)\lambda V - I + (1-p)\frac{(v+d)(3v-d)}{8\overline{C}_s}. \tag{A.58}$$

Equation (A.57) and (A.58) together imply that

$$NPV^h > NPV^l \;\Rightarrow\; 8\overline{C}_s > d^2/C_l + 3C_l + 6v - 2dv/C_l.$$

This concludes the proof.■

Proof of Proposition 8. Substituting for $C_l = \mu + \beta(I-W)$ in equation (1.30) and taking the partial derivative with respective to W yields

$$\frac{\partial \pi_b^*}{\partial W} = (1-p) - \beta(1-p)\frac{v+\mu+\beta(I-W)}{2\overline{C}_s} = (1-p) - (1-p)q \geq 0.$$

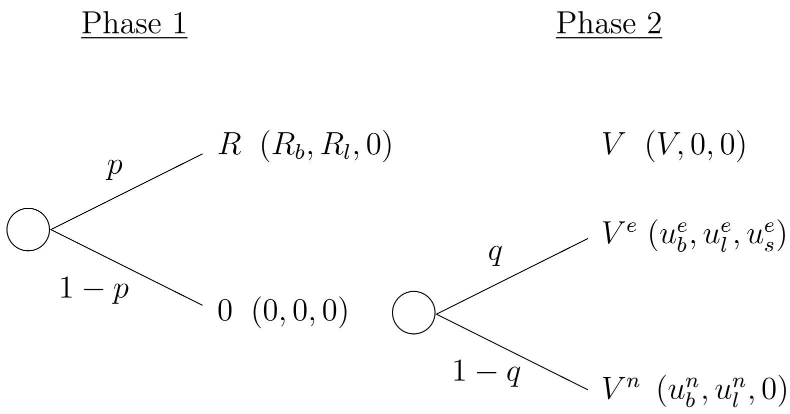
Note that the derivative decreases as the likelihood of SDI entry increases.

Similarly, substituting for $C_l = \mu + \beta(I-W)$ in equation (1.31) and taking the partial derivative with respective to W yields

$$\frac{\partial NPV^*}{\partial W} = (1-p) - 3\beta(1-p)\frac{v+\mu+\beta(I-W)}{4\overline{C}_s} = (1-p) - (1-p)\frac{3}{2}q.$$

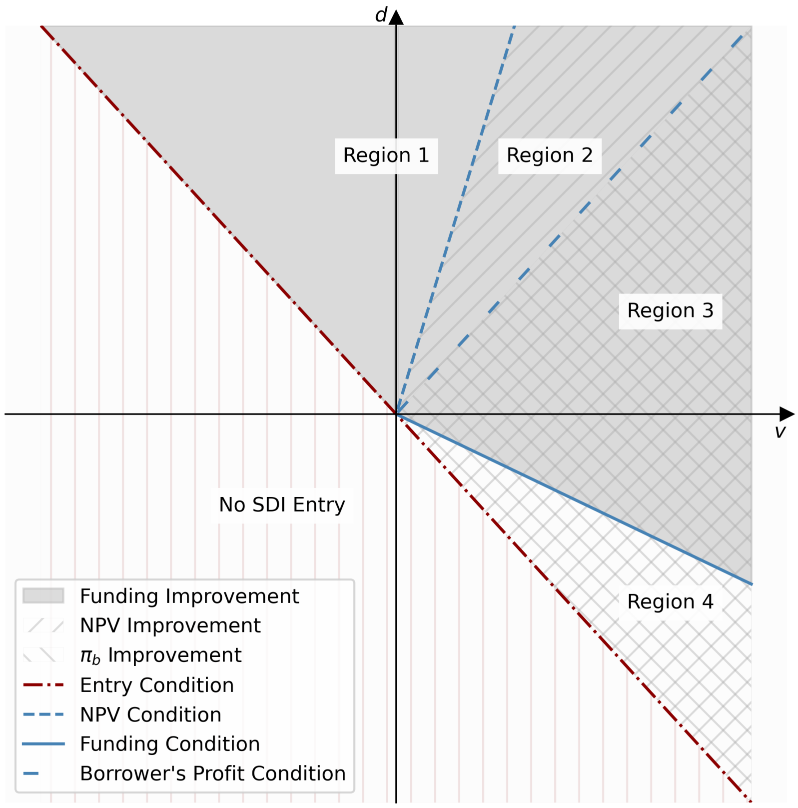
Furthermore, for the values of the probability of SDI entry that satisfy $q \in \left(\frac{2}{3}, 1\right]$, $\frac{\partial NPV^*}{\partial W} < 0$ holds. This concludes the proof.■

FIGURE 1.A.1: Timeline and Payoffs



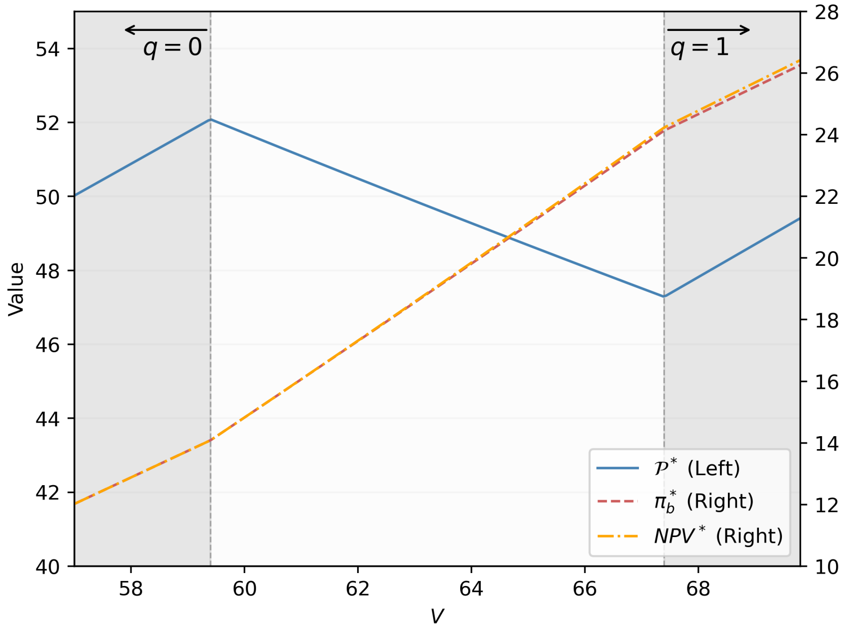
The figure depicts the two phases of the project under no-shirking. The outcomes in parenthesis represent the payoffs for the entrepreneur (first entry), the initial lender (second entry) and the SDI (third entry). The (endogenous) likelihood of SDI involvement is denoted by q. If the SDI enters the company, then the continuation value of the project is given by V^e, and the entrepreneur, the initial lender and the SDI receive u_b^e, u_l^e and u_s^e, respectively. If SDI entry does not materialize, then the continuation value of the project is given by V^n, and the entrepreneur, the initial lender and the SDI receive u_b^n, u_l^n and 0, respectively.

FIGURE 1.A.2: Feasible Regions for a Highly Leveraged Project



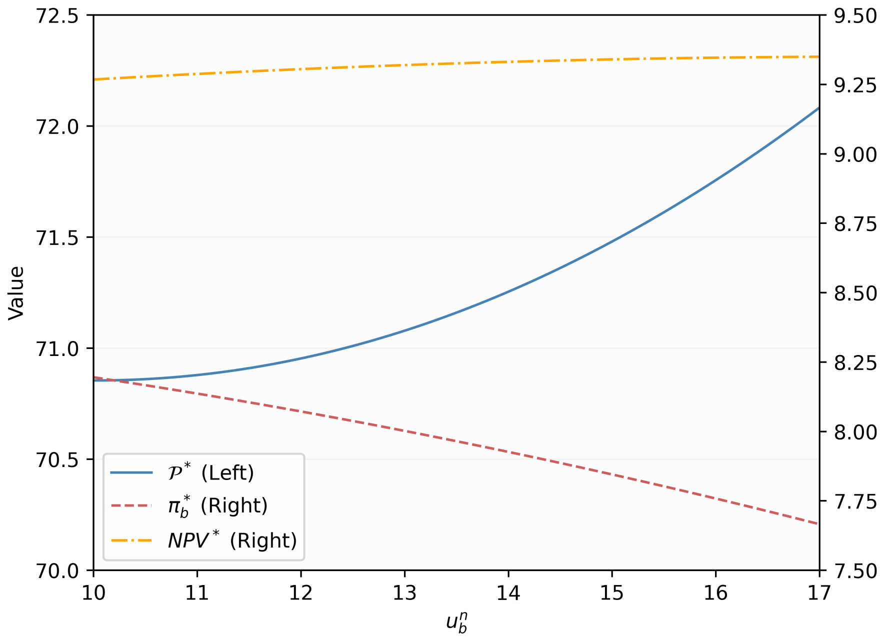
This figure shows the set of feasible regions, for a highly leveraged project, as a function of the advantage of the SDI relative to the initial lender in (i) running the firm efficiently, denoted by v and (ii) the second stage payoff to be paid to the entrepreneur, denoted by d.

FIGURE 1.A.3: High Leverage, Continuation Value, and Project Choice



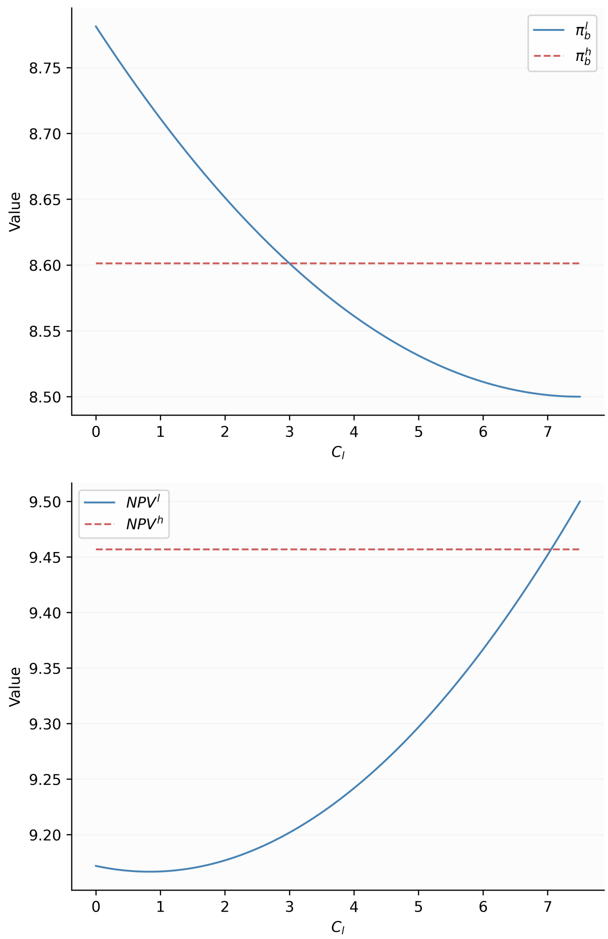
This figure shows several equilibrium outcomes as a function of V, the continuation value following success. These outcomes were generated for $V \in [57.5, 69.8]$ and considering the following parameter values: $R = 60$; $\lambda = 0.3$; $\gamma = 0.25$; $p = 0.8$; $\Delta = 0.75$; $u_b^n = 15$; $\delta = -0.99$; $B = 30$; $I = 85$; $W = 45$; and $\overline{C}_s = 1$. The (expected) pledgeable income, $\mathcal{P}^*$, is represented in blue (solid line; left y-axis); the ex ante profit of the entrepreneur, π_b^*, in red (dashed line; right y-axis); and the project's NPV^* in orange (dash-dotted line; right y-axis).

FIGURE 1.A.4: High Leverage, Continuation Rent and Project Choice



This figure shows several equilibrium outcomes as a function of u_b^n, the borrower's continuation rent without SDI entry. These outcomes were generated for $u_b^n \in [10, 17]$ and considering the following parameter values: $R = 50$; $V = 70$; $\lambda = 0.4$; $\gamma = 0.25$; $p = 0.8$; $\Delta = 0.55$; $\delta = 0.99$; $B = 20$; $I = 94$; $W = 50$; and $\overline{C}_s = 17.5$. The (expected) pledgeable income, $\mathcal{P}^*$, is represented in blue (solid line; left y-axis); the ex ante profit of the entrepreneur, π_b^*, in red (dashed line; right y-axis); and the project's NPV^* in orange (dash-dotted line; right axis).

Figure 1.A.5: Low Leverage, Entrepreneur Profit, and Project NPV



This figure shows the expected payoff to the entrepreneur (left panel) and the NPV of the project (right panel) as a function of C_l, the costs of renegotiating the loan, for the two different capital structures. These outcomes were generated based on the following parameter values: $R = 60$; $V = 50$; $\lambda = 0.5$; $p = 0.8$; $\Delta = 0.75$; $B = 30$; $I = 85$; $W = 70$; $v = 12.5$; $d = 6$; and $\overline{C}_s = 10$. The blue solid line on the left (right) panel represents the entrepreneur's expected payoff (the NPV of the project) with low leverage and dashed red line represents her expected payoff (the NPV of the project) in case of high leverage.

2

The Heterogeneous Effects of Household Debt Relief

2.1 Introduction

Large-scale debt relief for distressed borrowers is often hampered by information frictions between lenders and borrowers (Adelino, Gerardi and Willen (2013), Eberly and Krishnamurthy (2014)), institutional frictions such as securitization (Piskorski, Seru and Vig (2010), Agarwal et al. (2011), Kruger (2018)) and financial and organizational constraints faced by intermediaries (Aiello (2022)). Thus, designing debt relief programs requires making trade-offs between a slower and document-intensive approach that targets only "truly" distressed households (that minimizes type I error) versus a quick-to-implement and catch-all approach that reaches most households (that minimizes type II error). During the Great Recession, the U.S. government chose the former approach. Despite the implementation of the Home Affordable Modification Program (HAMP), which incentivized financial intermediaries to modify delinquent mortgages, up to two-thirds of heavily indebted households received no debt relief (Noel (2021)). The failure to assist more households contributed to employment losses and the slow economic recovery after the crisis (Dynan, Mian and Pence (2012), Mian and Sufi (2014), Piskorski and Seru (2021)). Two key questions emerge from this literature: first, to what extent the information accessible to lenders effectively characterizes the households that opt into assistance measures, and second, how these households use the additional liquidity they receive.

During the initial months of the COVID-19 pandemic, unlike the 2007-2009 foreclosure crisis, governments worldwide swiftly implemented debt forbearance programs, temporarily suspending debt payments to prevent widespread financial distress and defaults. In Portugal, eligibility for mortgage payment suspensions required households to be employed in sectors directly affected by lockdowns or to have experienced an income reduction of at least 20% compared to pre-pandemic levels. However, the enforcement of these eligibility criteria was typically lax, with limited verification of households' compliance. The focus on households facing pandemic-related financial hardship and the practice of allowing easy access to the program was also adopted by other European countries and the United States.[1]

This paper uses a transaction-level panel from a leading Portuguese bank to examine the determinants of selection into forbearance and the effects of debt payment suspension implemented between March 2020 and September 2021. The analysis focuses on the impact of forbearance on household consumption, savings, and unsecured debt. We measure the effect of the additional liquidity provided by forbearance by relying on: (1) the high frequency of the data on checking and savings accounts, as well as credit and debit card activity, which allows us to identify sharp changes in behavior around the start of forbearance; (2) the ability to control for both levels and changes in income, the main unobserved variables in similar studies, and performing the comparisons within time-varying income-by-wealth household groups; and (3) the validation that household consumption, saving, and unsecured debt were following parallel trends before the forbearance.

In our analysis, we are interested not only in the changes in household behavior due to the program but also in the selection of households into forbearance (whether they met the formal criteria or not) and potential heterogeneous treatment effects. Thus, our estimated average effects should be interpreted as the effect of forbearance on the set of households who choose to suspend debt payments relative to otherwise similar households

[1] The U.S. CARES Act was targeted at borrowers experiencing "financial hardship," but the program did not require any proof or documentation of hardship (National Credit Union Administration (2020)). The programs were similar across countries in the European Union (see, e.g., European Banking Authority (2020)).

who choose not to suspend payments. To the best of our knowledge, this is the first study to use household-level data on income, consumption, and balance sheet to explore who accesses large-scale forbearance programs and to measure the marginal propensity to consume (MPC) and save out of liquidity, two key inputs into the design of such programs.

We show that, on average, households who entered forbearance were more financially fragile than those who did not, as they had lower income, lower wealth, and higher debt burden even before the pandemic, consistent with the experience in the United States (Cherry et al. (2021), Gerardi, Lambie-Hanson and Willen (2022)). They also suffered a larger wage drop in March and April of 2020, although total income was less affected than wages as these households received larger government transfers.

Households in forbearance increased their consumption starting in the summer of 2020 compared to the pre-pandemic period by utilizing a significant fraction of their postponed debt payments. We estimate an MPC out of postponed debt payments of about 15 cents per euro during the first year after payment suspension, rising to about 22 cents in the long term (i.e., more than one year post-suspension). These estimates align closely with those reported in Johnson, Parker and Souleles (2006) and Parker et al. (2013) regarding the effects of temporary income shocks, such as federal income tax rebates and the 2008 economic stimulus payments, respectively. This similarity is notable given the distinct nature and duration of the shocks. Unlike the one-time nature of tax rebates, the forbearance program provides households with additional liquidity over an extended period of 18 months. Moreover, it does not constitute a net transfer, as no principal is forgiven, and missed interest payments are capitalized into the loan balance.

We include the change in income, relative to the 2019 average, as a control variable in our regression analyses. Our findings indicate that the MPC from liquidity provided via forbearance is of similar magnitude to the MPC observed in response to income changes for the households in our sample. Specifically, the sensitivity of consumption to income changes is approximately 0.08 euros per euro of income on average, increasing to around 0.13 euros per euro for households receiving forbearance.

Households in forbearance also increased their saving in deposits (checking and savings accounts) by about 35 cents per euro in forbearance shortly after the program's initiation, stabilizing at about 23 cents in the long term. Mortgage payment suspension also resulted in higher consumption and saving rates (relative to income) among households in forbearance compared to those outside forbearance. Specifically, forbearance is associated with a 6 percentage point increase in the consumption rate and a 5 percentage point increase in the saving rate.

The impact on unsecured debt was modest compared to consumption and saving. Households reduced their unsecured debt (i.e., overdrafts and credit card borrowing) by about 4 cents per euro in forbearance shortly after entering the program, while debt at other banks decreased by 4 cents only more than one year after the start of the program.

These average estimates overlook substantial heterogeneity based on liquid wealth (as proxied by total deposits), income, and indebtedness (as proxied by the debt payment-to-income ratio). Households with below-median wealth increased their consumption by about 30 cents per euro of postponed payment after entering forbearance. In contrast, households with above-median wealth at the bank had a much smaller increase in spending of about 7 cents per euro. While this may seem an intuitive result, previous work has not always found a strong cross-sectional spread in MPC estimates based on the level of assets (e.g., Parker et al. (2013)). Our finding of substantial heterogeneity in MPCs aligns with recent studies using high-quality data on liquid assets. Notably, Ganong et al. (2023), who examine consumption responses to income shocks using data from the JP-Morgan Chase Institute, and Fagereng, Holm and Natvik (2021), who use tax return data from the Norwegian Tax Administration. Although both studies focus on income shocks rather than changes in available liquidity, as is the case in our analysis, the observed heterogeneity in MPCs remains consistent across these different settings. A similar pattern emerges when households are categorized by median income or indebtedness.[2] Additionally, we find that public sector employees who face less income uncertainty exhibit a

[2] Although, once again, we focus on changes in liquidity rather than income, our finding of heterogeneous effects by income is consistent with Baker et al. (2020) for the effects of the COVID-19 stimulus package by income level, as well as previous work using temporary shocks to household income (e.g., Hall and Mishkin (1982), Johnson, Parker and Souleles (2006), and Di Maggio et al. (2017)).

higher MPC (25 cents) than private sector employees (11 cents).

Saving shows the reverse pattern from consumption in the cross-section of households. While the below-median wealth group only saved about 10 cents per dollar out of postponed repayment, the above-median wealth group saved as much as 40 cents after the start of the forbearance. We find qualitatively similar results when we split households by median income or DTI ratio. Overall, our heterogeneous consumption and saving responses raise questions about the need for a mortgage moratorium for less fragile groups that opted for forbearance.

The design of the forbearance program, with its specific eligibility criteria, combined with the richness of our data, allows us to measure the responses of both targeted households and non-targeted households that nevertheless gained access.[3] We construct individual proxies for eligibility based on wage change and sector of employment, the two primary criteria for the program. Our estimates indicate that around 10% of households in our sample were eligible; however, actual enrollment diverged significantly from these eligibility criteria. Notably, most eligible households opted not to participate in the program (90%), while 80% of households that did suspend payments do not appear to be formally eligible based on our proxies (we refer to this group as "ineligible" below). This confirms that banks employed loose screening criteria, favoring households proactively seeking forbearance. Consequently, the program missed many intended targets but reached a broader range of households not originally designated as recipients.

Interestingly, ineligible households that entered forbearance were, on average, the most financially fragile group before the pandemic, even though their income was not disproportionately affected by the pandemic. This indicates that, although the program was intended for households experiencing significant shocks during the pandemic, the actual participants were more likely to be those with pre-existing low income, low wealth,

[3] Previous studies have considered the characteristics of borrowers accessing forbearance during the COVID pandemic, including differences in credit scores, race, and income levels, as well as the effects on delinquencies and debt usage (see Yannelis and Amato (2023) for a survey). Ganong and Noel (2020) study the consumption response to mortgage modifications following HAMP using end-of-month credit card balances and payments to calculate monthly expenditures. Albuquerque and Varadi (2024) consider the consumption response around the U.K. mortgage moratoria during the pandemic using data from an online personal budgeting application.

or high debt burden. In fact, we show that the level of deposits at the bank is a stronger predictor of forbearance status than the wage drop due to the pandemic. These ineligible households also exhibit a higher likelihood of job loss one year into the pandemic, suggesting they may have sought forbearance as a precaution against anticipated future economic shocks.

When we break down the average consumption effect by eligibility status, we find that ineligible households who opt for forbearance exhibit significantly higher marginal propensities to consume, averaging about 18 cents per euro of postponed payment, compared to just 7 cents for eligible households in forbearance, even controlling for time-varying income-by-wealth fixed effects. This 11-cent difference between the two groups indicates that the ease of access and the inclusion of ineligible borrowers in the forbearance program substantially influenced the estimated average effect of forbearance. Additionally, eligible households that did not take up forbearance and continued to make their mortgage payments reduced consumption by about 14 cents compared to ineligible households that did not take up the program. This suggests that choosing not to enter the program required significant adjustments for these households. The pattern for saving in bank deposits is reversed. Eligible households in forbearance increased their saving by approximately 50 cents per euro of postponed payment, while ineligible households increased their saving by only 28 cents.

Finally, we examine the outcomes for households exiting the forbearance program and the potential effects of additional debt relief provided by banks in September 2021 at the direction of the regulator. Our findings indicate that households do not fully revert the increased consumption observed during forbearance. Specifically, consumption per euro of postponed payment declines from 23 cents to 13 cents once payments resume. This consumption response is accompanied by a reduction in saving of similar magnitude once payments resume. It is surprising that households do not immediately adjust to the resumption of payments, especially since much of the consumption response during forbearance occurs in categories that are typically considered "adjustable" (Chetty and Szeidl (2007)).

A small fraction of households that had entered forbearance in the first half of 2020 opted to take up additional relief measures offered by the bank in September 2021. This additional relief involved reduced or suspended payments, including loan maturity extensions, interest rate reductions, or further payment suspensions, targeting households that had been in forbearance over the previous 18 months and might still require support. Like the government moratoria, the bank was explicitly instructed to provide relief to any household that *might* need it, rather than limiting assistance to the most distressed borrowers. This approach involved proactively contacting all borrowers in forbearance to assess their need for further relief. During the initial program period, households that took up these additional measures exhibited a somewhat lower consumption sensitivity to forbearance and allocated more towards saving from postponed payments. This behavior persisted even after the implementation of the additional relief measures.

Overall, our findings provide new insights into the design of large-scale debt relief programs. Optimal program design should account for the behavior of ineligible households that strategically enter the program and how they allocate the additional resources between consumption and saving. Our results indicate that ineligible households substantially increase consumption and may face a heightened debt burden after exiting forbearance due to postponed principal and interest payments without a corresponding increase in savings. To the extent that debt relief policies are also aimed at stimulating demand during times of crisis, understanding the MPC of those who opt into forbearance is also important for policy design. We also show that consumption does not fully adjust downwards after exiting forbearance. This indicates that the program may inadvertently lead to more indebtedness among households that were not the intended targets. Our findings suggest that observable household characteristics, which are typically available to lenders (and not just unobservables, as earlier literature might have implied), can effectively identify households more likely to opt for forbearance when access criteria are less stringent, as well as predict how they are likely to use the additional liquidity.

Our paper adds to the literature on the effects of government and private debt relief programs. This literature focuses on information and institutional frictions, the impact of loan modifications on delinquency and consumption, and optimal policy design. In research that is directly relevant for understanding the optimality of short-term forbearance programs and the selection into these programs, Eberly and Krishnamurthy (2014) develop a framework for assessing and designing efficient mortgage modification programs. They show that a program with temporary payment reduction during a crisis is a cheaper alternative than principal forgiveness when borrowers are liquidity-constrained.[4] At the same time, lenders may find it optimal to perform principal reductions to reduce the incentive for borrowers to default. The most often cited concern about providing blanket debt relief to households is strategic behavior, i.e., that "too many" households will request help, even though most do not need assistance to remain current on their debts. Recent work shows that borrower default is generally not consistent with pure strategic behavior, i.e., borrowers do not default purely due to negative equity (Guiso, Sapienza and Zingales (2013), Gerardi et al. (2018) and Ganong and Noel (2023)).[5]

The consumption and delinquency effects of the policies during the Great Recession in the post-2008 period are already well documented (see, among many others, Agarwal et al. (2017), Ganong and Noel (2020), Abel and Fuster (2021), Agarwal et al. (2023)). For work on debt relief during the COVID-19 pandemic, Cherry et al. (2021) and Gerardi, Lambie-Hanson and Willen (2022) show that public and private forbearance programs contributed to low delinquencies in the United States. Hong and Lucas (2023) show that the credit policies implemented during the pandemic were an important source of incremental resources for households, in addition to governments' fiscal response, and Lee and Maghzian (2023) link forbearance to better macroeconomic outcomes. The reduction in delinquency rates was higher among low-income and minority individuals (Gerardi et al. (2021), An et al. (2022), Shi (2022)), but financial intermediary frictions may have

[4] Using a randomized trial that compares commonly employed debt relief measures, Aydin (2021) finds that forbearance is more effective when applied to constrained households or late-cycle delinquencies.

[5] A notable exception is Mayer et al. (2014) who find that borrower delinquency rates increase when Countrywide is forced by court decision to offer more generous modification terms. Recent experimental work looking at forbearance programs in India by Fiorin, Hall and Kanz (2023) suggests that the effect on moral hazard may be muted, and that borrowers are more likely to interact with the bank in the future if they are offered forbearance.

prevented some borrowers from receiving forbearance (Cherry et al. (2022), Kim et al. (2024)).

Our paper is also related to the literature on the consumption response to the COVID-19 pandemic. This literature focuses on the effects of (one-time or repeated) transfers rather than debt forbearance. Baker et al. (2020) studies the consumption response of households at different income levels and with different shocks to income around the onset of the pandemic and as a function of shelter-in-place orders. Ganong et al. (2024) show that unemployment benefits introduced at the height of the crisis had a large impact on spending but a small impact on employment, and Cox et al. (2020) investigate the heterogeneity across households and consumption categories in the initial phase of the pandemic.[6]

Our paper provides new insights into the dynamics of household consumption, saving, and unsecured debt around large-scale debt relief programs. Understanding the selection patterns for debt forbearance and the heterogeneous effects of policy tools on different household groups is crucial for effectively designing financial stability policies that operate through the household balance sheet channel.

2.2 Institutional Details

At the outbreak of the COVID-19 pandemic, governments and financial institutions worldwide issued legislative and non-legislative moratoria on loan payments, targeting households and non-financial corporations.[7] By the end of March 2020, just a week after the State of Emergency was declared and a national lockdown imposed, the Portuguese government mandated a debt forbearance program, suspending principal and interest pay-

[6] Intermediary frictions shaped the implementation of the CARES Act-driven debt relief during the pandemic. Cherry et al. (2021) and Kim et al. (2024) show that shadow banks provided mortgage forbearance at lower rates than banks, while Cherry et al. (2022) show higher forbearance provision among better-capitalized shadow banks. Research on other pandemic relief programs also finds variation in outcomes across financial intermediaries (e.g., Granja et al. (2022)).

[7] Figure 2.B.1 in the Internet Appendix provides an overview of the main events related to the Portuguese government's response to the pandemic, highlighting the debt forbearance program.

ments for certain types of loans upon eligible borrowers' applications.[8] By then, the measure's scope was restrictive, only including mortgage loans for acquiring owner-occupied properties. As the loan maturity date was deferred according to the duration of the forbearance, banks would bear the potential cost of the policy.

Access to the initial government program was limited to individuals: (1) infected with COVID-19 or providing assistance to a relative infected with COVID-19 (which represented a very small fraction of the individuals in the population during the early months of the pandemic);[9] (2) working in companies that reduced work hours due to the pandemic and requested paycheck assistance (the "layoff" regime); (3) unemployed; (4) eligible for financial support for self-employed; or (5) individuals working in industries more affected by the COVID-19 lockdowns as defined in the government legislation. If individuals satisfied one of these criteria, they could request a suspension of loan payments for six months until September 2020. Moreover, the eligibility criteria restricted forbearance to individuals who were not delinquent at the time (defined as those not having payments 90 days past due) nor had outstanding tax or social security liabilities. The program received widespread coverage across television and newspapers, reducing the likelihood that mortgage holders were unaware of the availability of assistance.

By April 2020, an interbank agreement led to a complementary and non-legislative moratorium, expanding the set of loans eligible for forbearance by including other mortgage loans, personal, and auto loans. The government also soon broadened the legislative moratoria, and by mid-June, the measure was extended to all individuals experiencing, or expecting, a 20% reduction in income due to the pandemic (the exact timing or definition of income was not clear in the legislation). At the same time, changes were made to the legislative program in order to include all types of mortgages for residential property and student loans. As a result of these measures, loans in forbearance as a percentage of the total number of loans increased from around 13% in April to 18% in June and then stabi-

[8] Borrowers would restart making higher payments at the end of moratoria due to unpaid interest. The number of payments would not change, so the loan maturity was effectively extended.

[9] About 42,000 cases in a population of about 10 million by the end of June of 2020, https://coronavirus.jhu.edu/region/portugal).

lized until 2021. In addition, the suspension of loan payments was extended until the end of March 2021, which would be extended until September 2021, or 18 months after the forbearance was first implemented.

Portugal was among the top three countries in Europe with the highest share of mortgages on repayment moratoria. According to the European Banking Authority (EBA), €365 billion in household loans (€268 billion of which were mortgages) entered moratoria in the Euro area by June 2020, about 7% of household loans (Nicolaou (2020)). In Portugal, €17 billion in mortgages, representing about 18% of all mortgages, were under repayment moratoria by June 2020. The U.S. Government Accountability Office reports that the use of forbearance peaked in the United States in May 2020 at about 7% of single-family mortgages (about 3.4 million) and gradually declined to about 5% percent by February 2021 (Pendleton (2021)).

During 2021, concerns over households' ability to resume payments led to new regulatory guidelines on the prevention and management of arrears, demanding a more proactive role for banks. In addition to closely monitoring borrowers, the local regulator asked banks to offer additional assistance measures after September 2021 to individuals at risk of defaulting. The exact nature of such measures was left at the banks' discretion and could include loan maturity extensions, interest rate reductions, or additional loan payment suspension. As we will show below, despite the bank's active effort to make the additional assistance measures known to borrowers, only a small fraction of them took advantage of this possibility.

2.3 Data

Our data comprises account-level transactions provided by a leading Portuguese bank. We restrict our analysis to clients who have an outstanding mortgage with the bank. We then group clients with a joint mortgage and who share checking accounts to define a household. In addition, in order to identify households using this particular bank as their primary bank, we focus on households who simultaneously satisfy the following criteria: (1) at least one member of the household has direct deposit of wages, pensions, or social security benefits (e.g., unemployment insurance);[10] and (2) at least one member of the household regularly uses debit and credit cards held at the bank for purchases and payments (an average of at least ten transactions per month).[11] The final sample includes about 137,363 households between January 2018 and June 2022.

Our data include purchases and payments with debit or credit cards, cash withdrawals, and electronic transactions from checking accounts at the transaction level. Given that our sample is composed of households with direct deposit of wages, pensions, and other social security benefits, we are able to estimate monthly household income using checking account transfers. Thus, we can track income even if individuals change jobs or become unemployed. We complement the data with third-party transfers, which include incoming transfers such as within-household transfers from other banks, tax refunds, or rental income. We can also identify the company where wage earners work.[12]

Our measure of consumption includes any purchases or payments using debit or credit cards using data from point-of-sale transactions and cash withdrawals.[13] We complement the data with automatic payments of utilities and other services. Our transaction-level data bypasses the concerns of using annual household wealth snapshots to calculate imputed consumption discussed in Baker et al. (2022). Although we have an almost complete picture of the activity at the bank, we do not observe outbound transfers to other banks or their intended recipients. This could represent additional saving (if a transfer goes to accounts at other banks owned by the household itself) or additional consumption (purchases of

[10] Households are offered a reduction in the mortgage spread if they choose to have wages and pensions deposited directly at the bank.

[11] On average, households in our sample made 39 monthly transactions, and the median is 35.

[12] Out of the 137,363 households, we find a valid employer match for about 100,000 of them. The remaining households include about 20,000 non-employed households (i.e., unemployed and retired), and about 17,000 employed individuals with an unmatched employer. To achieve this, we consider the name of the entity ordering the Single Euro Payments Area (SEPA) transfer and then use the Levenshtein Distance string metric to match the employer with the universe of firms operating in Portugal. Firm names and industry codes are drawn from SABI (Iberian Balance Sheet Analysis System).

[13] Including cash withdrawals is crucial for measuring consumption accurately, as a significant fraction of retail transactions in Portugal (and across Europe) are still done in cash during this period. According to the 2022 study on the payment attitudes of consumers in the euro area (SPACE) conducted by the European Central Bank, 64% of in-person retail transactions are done in cash in Portugal, as opposed to 31% by card and 5% by other means.

goods and services paid for by bank transfer rather than by card, cash, or automatic withdrawal). We are able to classify purchases by category starting in January 2020. We categorize transactions by relying on point-of-sale terminal information, namely the reported Merchant Category Code (MCC). This classifies merchants into categories based on the type of business and the reported industry code according to *Classificação das Actividades Económicas* (CAE) Revision 3.

The household balance sheet data include end-of-the-month balances for all checking and savings accounts held at the bank, as well as balances for all liabilities, including mortgages, personal loans, auto loans, credit cards, and overdrafts.[14] The data also include additional liabilities information, such as interest rate (as of August 2021), origination date, maturity, and monthly installment before the pandemic.

We merge the internal information of the bank with data from the Credit Register (*Central de Responsabilidades de Crédito*) managed by Bank of Portugal to obtain outstanding loans at other banks for each household. By matching these databases, we can fully track the liability side of the household balance sheet over the sample period and delinquency. While we have daily information on loan-level delinquency for all contracts held with this particular bank, we can only observe end-of-the-month overdue debt in other banks using the Credit Register.

Our data allow us to determine which households applied for and received forbearance and which did not. In addition, we use our data to infer whether a household was eligible to obtain forbearance according to program rules. Specifically, we consider that a household is formally eligible for forbearance if any household member: (1) suffered an income drop of at least 20%, as proxied by the change in wages from the first quarter of 2020 (i.e., the pre-pandemic period) to the second quarter of 2020 (i.e., the start of the pandemic); (2) was working in more affected industries during the first quarter of 2020 as given by the list of industries included in the program rules.[15]

[14] We are unable to compute account balances for financial assets (e.g., individual stocks, bonds, and mutual funds) due to data limitations. However, we see that about 12% of our sample households hold financial assets.

[15] The list considers a broad industry definition, which we then match to the Portuguese industry classification code list (*CAE*, Revision 3).

2.3.1 Summary Statistics

Table 2.A.1 presents pre-pandemic (as of December 2019) averages of variables for our sample of households, separately for households in and outside forbearance and eligible and ineligible households. This allows us to examine whether selection on observable characteristics plays an important role in applications for the government forbearance program at the beginning of the pandemic. Table 2.B.1 in the Internet Appendix presents detailed summary statistics for our full sample. Households in our sample comprised 1.7 mortgagors on average, with negligible differences between those who got forbearance and those who did not. The average household monthly total income in our full sample is €$2,527$, which is significantly higher than the average in the country, which in 2019 amounted to €$1,800$.[16] The 90th percentile of total income is €$4,659$ per month.[17]

The average wage is higher for households outside of forbearance, particularly in the case of eligible households. Total income, including pensions (for 40,000 of the 137,363 households in the sample), social security benefits, and other inbound transfers (i.e., rents, business or professional income) follow a similar pattern. For instance, the average total income for eligible households outside forbearance is substantially higher at €$2,759$ per month than that of eligible households in forbearance at €$2,449$. In addition, ineligible households in forbearance are the group with the lowest average wage and total income at €$1,416$ and €$2,046$, respectively.

Average household consumption is about €$1,500$ per month (from 39 monthly transactions per household, including cash withdrawals, on average). This compares to an average consumption expenditure per household of about €$1,560$ in the whole country.[18] Average household consumption follows a similar pattern to income across groups of

[16] Annual mean net income per household (€) by Deciles of income; INE - *Instituto Nacional de Estatística*, Statistics on Income and Living Conditions (*Inquérito às Condições de Vida e Rendimento*).

[17] The group of homeowners with mortgage comprised around 30% of all Portuguese households in 2021 (INE, Population and Housing Census (*Recenseamento da população e habitação*), 2021), with its median income being substantially higher (at least 25%) than the remaining households, per adult equivalent (Xerez, Pereira and Cardoso, 2019).

[18] Estimate for 2015, excluding actual or imputed rentals for housing (Peralta, Carvalho and Esteves, 2021).

households, with households outside forbearance exhibiting higher spending levels. In addition, ineligible households in forbearance are the group with the lowest average consumption at €$1,320$ per month.

Households, on average, maintain checking account balances of €6,700 and savings account balances of €17,300, conditional on having a savings account. However, median balances are substantially lower, at €2,000 for checking accounts and €5,700 for savings accounts, respectively (see Table 2.B.1). Importantly, households in forbearance exhibit significantly lower average balances in both checking and savings accounts, which aligns with the observation that these households are generally more financially fragile, irrespective of their eligibility status. Figure 2.B.2 of the Internet Appendix shows that total deposits are a particularly strong predictor of forbearance access. Indeed, in a penalized regression setting (LASSO), total deposits are more important in predicting forbearance access than changes in wages, even though the government eligibility criteria primarily focus on changes in wages and employer industry.

Table 2.B.2 of the Internet Appendix examines whether *future* outcomes differ significantly between eligible and ineligible households. The findings indicate that ineligible households in forbearance are the most likely to lose their job within the 12 months following the start of forbearance. Furthermore, among those who remain employed, ineligible households exhibit lower wage growth compared to eligible households. These results reinforce the notion that ineligible households in forbearance represent a particularly fragile group of the population.

Mortgage balances are, on average, €69,000, and households in forbearance have higher average balances. Almost all clients have a credit card or an overdraft, holding an average balance of about €420. In contrast, only about 1% of households in our sample hold student or auto loans, and 7% hold other types of loans, such as personal loans. Finally, most households in our sample have loans with other banks, with a balance of about €7,500 on average.

The average total loan payment (mostly mortgage payments), including principal and interest, is €315 per month, higher than the country's average by the end of 2019

(€248).[19] Moreover, households in forbearance have higher loan payment commitments (€377) than households outside forbearance (€311). By entering forbearance, the average household postpones €345 per month. Considering total income, we estimate an average debt payment-to-income (DTI) ratio of about 19% in 2019, slightly above the country's average in 2022 (17%).[20] As expected, the average DTI is higher for households in forbearance, in particular for ineligible households at 32%. Debt delinquency is infrequent in our sample, with just 1% of households having payments more than 30 days past due. We conclude that ineligible households in forbearance are the most fragile group with lower income, consumption, total deposits, and higher DTI.

2.4 Empirical Methodology

We estimate a difference-in-differences regression to compare the marginal propensities to consume, save, and borrow between households in forbearance and households outside forbearance around the start of the debt forbearance program:

$$Y_{i,t} - \overline{Y}_{i,2019} = \beta Forbearance\ Amount_i \times Post_t + \lambda X_{i,t} + \mu_{g,t} + \varepsilon_{i,t}, \tag{2.1}$$

where the outcome variable is either the change in monthly consumption expenditures ($\Delta Consumption$); change in saving in total deposits ($\Delta Saving\ in\ Deposits$); change in credit card and overdraft borrowing ($\Delta Borrowing\ Credit\ Card\ \&\ Overdraft$); and change in unsecured debt borrowing at other banks ($\Delta Borrowing\ Other\ Bank's\ Debt$) for household i at time t. Changes are calculated relative to each variable's 2019 average. Saving is the change in end-of-month checking and savings account balance ($\Delta Total\ Deposits$). Borrowing is the change in end-month credit card and overdraft balance or unsecured debt outstanding at other banks.

$Forbearance\ Amount_i$ is the amount of postponed debt payments (mostly mortgages, but it may include other loans for some households) for household i. $Post_t$ is

[19] Press Release INE, Interest rates implied in housing loans, January 19, 2022.

[20] Banco de Portugal, Relatório de Estabilidade Financeira, November 2022.

a dummy variable that takes a value of one for the period starting when mortgage payments are suspended and zero otherwise.[21] The coefficient of interest is β, which captures whether forbearance is associated with a differential effect on consumption, saving or borrowing around the program's start. The sample period is between January 2018 and September 2021 (i.e., the end of the government program).

We also estimate the effect at different horizons by replacing the *Post* dummy variable with three dummy variables: (1) *Immediate Effect* for months 1 through 3 after a household enters forbearance; (2) *Short-run Effect* for months 4 through 12 after forbearance; and (3) *Long-run Effect* for the period starting 12 months after forbearance and up to the end of the government program.

$X_{i,t}$ is a set of household-level time-varying controls, which includes changes in monthly total income ($\Delta Income$) relative to average monthly income in 2019, and the $Forbearance_i$ dummy variable that takes the value of one for households receiving forbearance, and zero otherwise. All the regressions include month-year fixed effect (μ_t) to absorb shocks that may affect all households in a given period or group-by-month-year fixed effects ($\mu_{g,t}$) to absorb time-varying shocks for households by quartile of pre-pandemic income and wealth (2019 averages). Thus, the regressions include a total of 16 group indicators (four quartiles of income by four quartiles of total deposits) interacted with dummy variables for each month-year. Standard errors are clustered two-way at the household and month-year levels.

We also estimate the dynamic effect of the forbearance by replacing the $Post_t$ variable with time dummies, $\mathbb{1}(\text{period} = \tau)$:

$$Y_{i,t} - \overline{Y}_{i,2019} = \sum_{\tau=-29}^{28} \beta_\tau \times Forbearance\ Amount_i \times \mathbb{1}(\text{period} = \tau) + \lambda X_{i,t} + \mu_{g,t} + \varepsilon_{i,t}. \tag{2.2}$$

The coefficients of interest are β_τ, which measure the change in consumption, saving, or

[21] We drop the household subscript from $Post_t$ for expositional purposes. The $Post_t$ dummy variable is household-specific since households entered forbearance between April and June 2020. However, most households in our sample start forbearance in April 2020 (65%), plus 28% in May and just 7% in June.

borrowing due to postponed debt payments in each month around the start of forbearance.

To estimate the average change in the consumption and saving rates, defined as monthly spending and saving divided by average total income, we estimate the following difference-in-differences regression:

$$\frac{Y_{i,t} - \overline{Y}_{i,2019}}{\overline{Income}_{i,2019}} = \alpha Forbearance_i \times Post_t + \lambda X_{i,t} + \mu_{g,t} + \varepsilon_{i,t}, \tag{2.3}$$

where the outcome variable is either the change in monthly consumption expenditures or the change in saving in total deposits for household i at time t, relative to the household's 2019 average, divided by average income in 2019. The coefficient of interest is α, which measures the average change in the consumption or saving rate associated with forbearance.

2.5 Effects of Debt Forbearance on Consumption, Saving, and Borrowing

In this section, we first show the evolution of the average income, consumption, and total deposits before and after the government debt forbearance program initiated in March 2020.

Figure 2.A.1 shows the evolution of average wages, social security benefits, and total income between July 2019 and the end of the program in September 2021 for households in forbearance and outside forbearance. We adjust for seasonality using month dummies but do not control for any other variables.

Panel A of Figure 2.A.1 shows that households in forbearance were, on average, more exposed to the pandemic shock, losing about €130 of monthly wages, on average, at the onset of the pandemic, compared with about €80 for households outside forbearance. Notice that households in forbearance had lower average wages to begin with, as shown in Table 2.A.1.

Panel B of Figure 2.A.1 shows that the evolution of social security benefits at the onset of the pandemic disproportionately benefited households in forbearance and that this gap persisted until 2022. Panel C shows total income evolution, including wages and social security transfers. The figure shows that income supplements and other government transfers were sufficient to stabilize total income during this period.

Figure 2.B.3 of the Internet Appendix shows the evolution of wages, social security benefits, and total income separately for households receiving forbearance who meet the eligibility criteria and for those who do not meet. We find that the large drop in wages for households in forbearance happens almost exclusively for eligible households, with almost no reduction for ineligible ones. This is somewhat mechanical, as one of the criteria for eligibility is a drop in income of at least 20%. Notably, we do not see virtually any drop for ineligible households who choose to enter forbearance. In addition, the figure shows that even after social security benefits, eligible individuals in forbearance still suffered a substantial drop in income.

Figure 2.A.2 shows the evolution of the average consumption and total deposits. Panel A shows that both groups of households cut spending right after the start of the pandemic in March 2020, likely due to a combination of demand and supply factors due to shutdowns. However, we find a positive and statistically significant difference in consumption for households in forbearance relative to households outside forbearance of about €200 per month by the summer of 2020. Interestingly, households in forbearance end up with a significantly higher average monthly consumption even compared to pre-pandemic levels. This is particularly noteworthy given that the total income was lower for households in forbearance (see Table 2.A.1).[22]

Figure 2.B.4 of the Internet Appendix shows the evolution of consumption and total deposits separately for eligible and ineligible households in forbearance. We find that ineligible households drive the positive gap in consumption that emerges for households in forbearance, whereas the consumption of eligible households in forbearance mostly tracks that of those outside of forbearance.

Panel B of Figure 2.A.2 shows the evolution of the average total deposits. The pandemic's beginning is associated with a slower growth in total deposits of households in

[22] The figure shows the evolution of consumption using equal weights among households. Table 2.B.3 of the Internet Appendix shows that the value-weighted evolution of consumption in our sample closely matches the evolution of consumption in Portugal for this period.

forbearance (mostly driven by checking accounts). By mid-2020, and even more so by early 2021, households in forbearance started increasing their total deposits, i.e., accumulating balances in their checking and savings accounts, faster than households outside forbearance.

2.5.1 Response of Marginal Propensity to Consume and Save

In this section, we present the estimates of the effect of the debt forbearance program on household consumption and saving in deposits. Table 2.A.2 shows difference-in-differences regression estimates based on equation (2.1). Columns (1)-(4) show the estimates for the effect on the marginal propensity to consume (MPC) measured as the change in consumption per euro of postponed debt payment in each month relative to the household's 2019 average, and columns (5)-(8) show the estimates for the effect on the marginal propensity to save in total deposits. The main explanatory variable is the amount of postponed debt payments in euros ($Forbearance\ Amount_i$). Columns (1) and (5) include month-year fixed effects. Columns (2)-(4) and (6)-(8) include 16 household group indicators using quartiles of income-by-total deposits interacted with month-year fixed effects. In columns (3), (4), (7), and (8), we control for $\Delta Income$. Additionally, since households in forbearance are on average more fragile, in columns (4) and (8) we include the $\Delta Income \times Forbearance$ interaction term to control for potential differences in the propensities to consume/save out of income.

Column (1) of Table 2.A.2 indicates that the MPC to consume out of payments in forbearance is both positive and statistically significant, amounting to 15 cents per euro of postponed payment. This effect translates to approximately €52 at the average forbearance amount. Columns (2)-(4), which include household group-by-month-year fixed effects and total income as controls, yield similar estimates, ranging from 13 to 15 cents, all of which are also significant.

Column (5) shows a positive effect on the marginal propensity to save of 12 cents per euro of postponed payment, although this effect is statistically insignificant. In contrast, when household group-by-month-year fixed effects are included in column (6), the coefficient increases to 18 cents per euro and becomes statistically significant. Further, when changes in total income are added as a control in columns (7) and (8), the marginal propensity to save in deposits rises to about 30 cents per euro.

Changes in total income exhibit a positive and significant impact on both consumption and total deposits. We estimate an MPC out of income changes of about 9 cents (lower than in Ganong et al. (2023) who obtain an MPC of 21 cents out of typical income fluctuations) and a marginal propensity to save of 70 cents per euro. In column (4), we include the $\Delta Income \times Forbearance$ interaction term and find that the combined MPC estimate is about 0.13. This effect is comparable in magnitude to that of forbearance, indicating that households adjust their consumption in response to increased liquidity from suspended debt payments in much the same way they respond to changes in income. It remains unclear whether households perceive these changes in liquidity as temporary or permanent.

Table 2.B.4 of the Internet Appendix presents robustness tests of the effect of forbearance on consumption and saving in Table 2.A.2. Column (1) shows that these results are robust to the inclusion of household-by-month fixed effects to absorb unobserved (time invariant) household-level heterogeneity and monthly seasonality. Moreover, columns (2) and (3) show that the estimated coefficients are robust when we include industry-by-month and municipality-by-month fixed effects, thus controlling for potential unobserved industry and regional shocks.

2.5.2 Response at Different Horizons

Next, we examine the response to the suspension of debt payments at different horizons after the start of forbearance. We estimate the regression in equation (2.1), replacing the *Post* dummy variable with three dummy variables: *Immediate Effect* (month 1 through month 3); *Short-run Effect* (month 4 through month 12); and *Long-run Effect* (after month 12).

Table 2.A.3 presents these estimates, which can be directly compared to those in Table 2.A.2. Columns (1)-(3) presents the estimates for the effect of forbearance on consump-

tion. In column (1), we find that the immediate effect on the MPC is close to zero and statistically insignificant. However, this estimate becomes significant and ranges from 13 to 15 cents per euro in forbearance for the short-term horizon. The long-term effect on consumption reaches approximately 22 cents per euro. This indicates that consumption did not respond to the amount of forbearance during the early months of the pandemic (possibly due to supply-side constraints) but increased over time.

Columns (4)-(6) of Table 2.A.3 presents the estimates for the effect of forbearance on saving in deposits. Controlling for observable differences is crucial in the saving regressions, as both income and wealth levels, along with changes in income, significantly impact the estimated saving behavior of households in forbearance (which is apparent from comparing columns (4)-(6)). Using our most comprehensive specification in column (6), we find that households save up to 35 cents per euro of postponed payments immediately following the onset of forbearance. Although the saving response to forbearance decreases to 32 cents per euro of postponed payment in the short run and 23 cents in the long run, it remains positive and strongly significant.[23]

Figure 2.A.3 shows the evolution of the marginal propensity to consume (Panel A) and save in deposits (Panel B) for households in forbearance and outside forbearance from 12 months before the start of the program (March 2020) up to 12 months after. The figure plots the estimates of the monthly β_τ coefficients obtained from the regression in equation (2.2). The coefficients measure the difference between households in forbearance and households outside forbearance relative to the month before the start of the forbearance. Despite significant differences in the average characteristics of the two groups, Panel A shows no evidence of preexisting differential trends in the MPC prior to the initiation of forbearance. Additionally, there is a positive and significant consumption response shortly after the forbearance program begins. This effect increases over the first six months of the forbearance period and is persistent in the long run.

[23] Table 2.B.5 in the Internet Appendix shows that the estimates of the consumption and saving response to forbearance are similar when we restrict the sample to individuals working in the private sector (i.e., we exclude public servants and other individuals working in public entities and state-owned firms). This sample includes households likely to have been more affected by the pandemic.

Panel B shows the response of the marginal propensity to save in deposits around the onset of forbearance. A positive and significant saving response is clear from the beginning of the forbearance period. The effect becomes smaller in magnitude over the short-term and long-term horizons but is still positive and significant.

2.5.3 Response of Consumption and Saving Rate

Our results are robust when we use alternative definitions of the consumption and saving response to debt forbearance. Table 2.A.4 shows the effect of forbearance on consumption and saving rates, i.e., change in monthly consumption expenditure and change in monthly saving as a fraction of pre-pandemic average income. Columns (1)-(3) present the estimates using the consumption rate. Using the most stringent specification in column (3), we find that households in forbearance increased the consumption rate by about 6 percentage points. As before, the effect is stronger at 9 percentage points in the long run, which compares with an unconditional average of 76% of income allocated to consumption before the pandemic (and about 88% for households in forbearance).

Columns (4)-(6) report the estimates using the saving rate. We find that the average saving rate response is positive and significant. Households increase the saving rate by about 5 percentage points over the forbearance period. When we control for changes in income in column (6), the impact on the saving rate is similar at different horizons, ranging from 4 (immediate effect) to 5 percentage points (short-run and long-run effects).

2.5.4 Response of Marginal Propensity to Borrow

In this subsection, we estimate the marginal propensity to borrow (unsecured debt) out of postponed debt payments. Table 2.A.5 presents the estimated coefficients for the $Forbearance\ Amount \times Post$ interaction term for two additional outcome variables: changes in credit card and overdraft borrowing at the bank in columns (1)-(3) and changes in unsecured debt borrowing from other banks in columns (4)-(6). Columns (1)-(3) indicate that households in forbearance reduced borrowing in credit card and overdraft compared to households outside forbearance. Although the overall effect on credit card and overdraft borrowing is statistically insignificant, we find that households during the first quarter of forbearance (immediate effect) allocated approximately 4 cents per euro of postponed payments to reduce short-term liabilities.

Conversely, columns (4)-(6) suggest that households in forbearance paid down unsecured debt held at other banks, compared to those outside forbearance, but this effect is statistically significant only in the long term. Our estimates across all specifications indicate that households reduced borrowing at other banks by about 4 cents per euro of postponed payment. Considering that all types of unsecured loans from other banks are included, these results are consistent with the idea that households initially prioritize deleveraging high-cost loans, gradually transitioning to longer-maturity (cheaper) loans.

2.5.5 Spending Categories

Our bank transaction-level data include merchant codes for debit and credit card transactions, which allow us to categorize most of the consumption expenditures.[24] Table 2.A.6 shows the estimates of the forbearance effect on the MPC by category. Panel A presents the estimates of the overall effect and Panel B presents the estimates by horizon (immediate, short run and long run). The sample period is from January 2020 to September 2021 (merchant codes are unavailable in 2018 and 2019). All regressions include household group-by-month-year fixed effects, as well as $\Delta Income$ as a control.

Column (1) shows that the estimates of the total consumption response are similar when we use the sample for which we can categorize consumption expenditures (i.e., starting in January 2020). The consumption effect is positive and significant at 10 cents per euro of postponed payment, ranging between 9 cents in the short run and 17 cents in the long run.

Columns (2)-(10) report the estimates of the consumption sensitivity to forbearance for each category. During the first year after the forbearance start (immediate and short-run effects), the main drivers of the consumption response to forbearance are "Groceries" and "Clothing", and to a smaller extent "House Maintenance", "Furniture", "Health Care" and "Entertainment and Education", which have a positive and significant effect. Notably,

[24] This is similar to the consumption categories in Cox et al. (2020) using credit card data from a large U.S. bank.

"Restaurants" initially have a negative effect, possibly due to COVID-19-related closures. Over the long term (beyond one year after the start of the forbearance), the effects are positive and significant across all categories. The consumption response to forbearance is more pronounced for "Groceries" at 6 cents per euro of postponed payments, and for "Clothing", "Transportation", and "Restaurants" at about 2 cents.

2.5.6 Heterogeneous Effects

We investigate the extent to which the marginal propensity to consume or save out of postponed debt payments is heterogeneous across households with different levels of financial fragility as measured by wealth, income, and indebtedness. We estimate the $Forbearance\ Amount \times Post$ interaction term coefficient using the regression in equation (2.1) separately for the sample of more fragile households and the sample of less fragile households. Specifically, we split households at the median of pre-pandemic wealth (proxied by total deposits), income, and indebtedness (proxied by the DTI ratio) in Panels A-C. Figure 2.A.4 reports the effects on the MPC for these groups separately, while Figure 2.A.5 provides the corresponding estimates for the marginal propensity to save in deposits.

Panels A-C of Figure 2.A.4 show that the consumption response is concentrated primarily in the most fragile households across all three financial fragility proxies. In Panel A, the low-deposits group consumption response is positive and significant at about 30 cents per euro of postponed payments, compared to about 7 cents for the high-deposits group. In Panel B, the consumption response is stronger for low-income households than for high-income households, with similar magnitudes to those in Panel A. Panel C shows a stronger consumption response for households with a high DTI ratio than a low DTI ratio. The effect is almost 20 cents for households with a high DTI ratio and only 6 cents for households with a low DTI ratio.

We also show how households with differing levels of income volatility react to forbearance: Panel D presents estimates for households with above- and below-median income volatility, defined as the standard deviation of total monthly income normalized by its average in 2019. Panel E presents estimates for employees working in the public and private sectors, based on the primary earner in the household. This analysis addresses whether the perception of income risk and unemployment risk influences the response to forbearance. In Panel D, 2.A.4, the consumption response is lower, at about 10 cents, for households with more volatile income prior to the pandemic, compared to about 21 cents for those households with low volatility of income. Similarly, in Panel E, the consumption response is about 10 cents per euro for households in the private sector, whereas it is significantly stronger for public sector households, at about 25 cents.

Conversely, Panels A-C of Figure 2.A.5 show that the average saving response in deposits is primarily driven by high-wealth, high-income, and low-debt burden households, respectively. The propensity to save per euro of postponed payment by less fragile households is about four times higher than for the more fragile households. In Panel A, the high-deposits group's saving response is positive and significant at almost 40 cents per euro of postponed payments, compared to about 10 cents for the low-deposits group. In Panel B, the saving response is stronger for high-income households than for low-income households, with similar magnitudes to those in Panel A. Finally, Panel C shows a stronger saving response for households with a low DTI ratio than a high DTI ratio. The effect is approximately 40 cents greater for the low-DTI group compared to the high-DTI group.

Panels D and E of Figure 2.A.5 show that households with more volatile earnings or employed by the private sector show a higher propensity to save, although the difference between the groups is not statistically significant. These findings suggest that anticipated income risk and employment risk, which is notably higher for private sector employees, play a role in shaping household responses to the debt forbearance program.

In summary, forbearance induces heterogeneous responses among households with different levels of financial fragility and income risk. The consumption response is concentrated among more fragile households and those facing lower income risk, whereas the saving response is concentrated among less fragile households and those facing higher income risk.

2.6 Forbearance Eligibility and Selection

Access to the debt forbearance program during the COVID-19 pandemic was relatively lenient, unlike the stringent criteria for loan modifications that characterized the 2008-2009 foreclosure crisis in the United States. (Adelino, Gerardi and Willen (2013)).

We estimate the effect of forbearance on consumption and saving in deposits using the regression in equation (2.1), focusing on four groups of households based on their forbearance status and program eligibility status: (1) ineligible households outside forbearance (the omitted group); (2) eligible households outside forbearance; (3) ineligible households in forbearance; and (4) eligible households in forbearance. Specifically, we define a *Eligible* dummy variable that takes the value of one for households eligible to the forbearance program according to program rules, and zero otherwise (see Section 2.3 for details on the eligibility definition). We then interact the *Eligible* dummy variable with the *Forbearance* and the *Post* dummy variables.

2.6.1 Number of Eligible and Ineligible Households

Table 2.A.7 (at the bottom of the table) presents the number of observations for each of the four groups. The distribution of households across these groups confirms that access to the forbearance program was relatively lenient during the pandemic, with implementation by banks favoring broader access to forbearance. In fact, we find that about 10% of households were eligible for forbearance, but only about 11% $[= 1.1 \div (9.1 + 1.1)]$ of those eligible households actually entered the program (representing 1.1% of the full sample). In contrast, 5.3% $[= 4.8 \div (85.0 + 4.8)]$ of the ineligible households entered the program (representing 4.8% of the full sample). This implies that over 80% of the households in forbearance were ineligible, while less than 20% met the eligibility criteria. These findings align with the lack of rigorous eligibility checks during the pandemic and the absence of strong incentives for bank officers to screen out ineligible forbearance applications.[25]

[25] While we recognize that our eligibility measure may not be perfect, the proportion of the sample identified as ineligible significantly exceeds what would be expected from merely assignment errors in our measures.

As discussed in Section 2.3.1, there are significant differences in observable characteristics between households in and out of forbearance, as well as between eligible and ineligible households. Ineligible households in forbearance exhibit the lowest levels of total income, consumption, and total deposits, coupled with the highest DTI ratios, among the four groups. A LASSO regression shows that total deposits are the most important factor in determining access to forbearance, even more so than wage reductions, which were part of the program's eligibility criteria, as shown in Figure 2.B.2 of the Internet Appendix. This indicates that ineligible households in forbearance were already the most fragile group at the onset of the pandemic crisis

2.6.2 Heterogeneus Effects by Eligibility Status

Table 2.A.7 shows substantial heterogeneity in the effects of forbearance on consumption among the four household groups. We find that eligible households outside forbearance exhibit a significantly lower MPC after the start of the forbearance period relative to ineligible individuals also outside of forbearance (the omitted group in these regressions, which constitutes 85% of the sample). This difference is about -14 cents per euro of postponed payment when we include household group-by-month-year fixed effects and total income as a control, as shown in column (3). This indicates that the burden of higher debt payments led these eligible households, who opted not to access forbearance, to significantly reduce consumption during the pandemic.[26] Eligible households in forbearance avoided this decline in consumption, showing a positive consumption response of 7 cents per euro in column (3); however, this response is not statistically different from that of ineligible households outside of forbearance.

In contrast, ineligible households that nonetheless entered forbearance exhibit a significantly higher MPC out of postponed payments, ranging from about 17 to 18 cents per euro of forbearance relative to the omitted group, as shown in columns (2) and (3). These

[26] The decision by these households to forgo the forbearance option and instead adjust their consumption to meet mortgage payments aligns with the model presented in Campbell, Clara and Cocco (2021). According to that model, opting for interest-only payments during recessions results in smaller reductions in consumption, which is consistent with our findings for borrowers who choose forbearance.

findings indicate that the significant MPC reported in Table 2.A.2 is primarily driven by ineligible households that applied for and received forbearance. Furthermore, concerns about future job loss may have influenced these households' decision to seek forbearance, as they are more likely to experience job loss within 12 months after entering forbearance, as shown in Table 2.B.2 of the Internet Appendix.

Column (6) of Table 2.A.7 shows that ineligible households in forbearance have a marginal propensity to save in deposits of about 28 cents per euro when controlling for changes in total income. In contrast, we find no significant relationship between the saving behavior of eligible households outside of forbearance and the amount of postponed payments, unlike the results observed for consumption. Additionally, forbearance is associated with a higher marginal propensity to save among eligible households, reaching about 49 cents per euro of forbearance in column (6).

Figure 2.A.6 shows the evolution of the marginal propensity to consume (Panel A) and the marginal propensity to save in deposits (Panel B) for households in forbearance, distinguishing between eligible and ineligible households (the omitted group consists of all households outside forbearance). In Panel A, the results indicate that ineligible households in forbearance are the primary contributors to the observed increase in consumption in response to forbearance. This effect increases during the first six months of the forbearance period and remains significant in the long term. Conversely, the consumption response among eligible households is statistically insignificant. Panel B depicts the response of the marginal propensity to save around the start of forbearance. From the beginning of the forbearance period, a positive and significant saving response is evident. Both eligible and ineligible households exhibit a similar sensitivity to forbearance.

Table 2.B.6 of the Internet Appendix shows the effects for eligible and ineligible groups on changes in credit card and overdraft borrowing at the bank, as well as unsecured debt at other banks. We do not find significant differences in the marginal propensity to borrow, except for eligible households who do not enter forbearance with a 4% effect on unsecured debt at other banks. The other estimates in the table are not statistically significant.

Selection plays an important role in our setting as over 80% of the households in forbearance in our sample are identified as ineligible based on our proxy. The observed differences in the sensitivity of consumption (as shown in column (3)) and saving (as shown in column (6)) between eligible and ineligible households indicate that differences in forbearance program participation, when access is lenient, significantly influence the overall effects of forbearance. Specifically, ineligible households that entered the forbearance program exhibited greater sensitivity in their consumption to the amount of postponed payments compared to eligible households. These findings imply that easier access to forbearance programs may lead households with a higher sensitivity of consumption to deferred debt payments to opt for forbearance.[27]

Table 2.A.8 examines the eligibility effects separately for more and less affected household groups according to the industry they work in. The more affected subsample comprises households whose primary employer industry had below-median revenue growth between 2019 and 2020. Even though this is not how the government selected industries for eligibility, a much larger fraction of the workers in these industries are eligible for forbearance according to the formal criteria (almost 30% in total).[28] Still, even for this group, only 14% of eligible households entered forbearance (4.2% of the sample of households in these industries). This implies that ineligible households make up a smaller fraction of households in forbearance in these industries (about 50% instead of 80% in the full sample). Column (1) shows that, within this group of more affected industries, the differential effect is similar to the average effect in the whole sample, with eligible households outside forbearance cutting consumption by 12 cents per euro of postponed payment; eligible households in forbearance avoiding to do so; and finally ineligible households in forbearance exhibit a positive and statistically significant MPC out of postponed payments of 14 cents.

Interestingly, a different pattern emerges when focusing on industries less affected by

[27] Table 2.B.7 in the Internet Appendix shows the response by spending category for each group, akin to Table 2.A.6.

[28] We measure revenue growth until December 2020, and this was only available after March 2020, the date of eligibility definition by the government.

the pandemic (column (2)), defined as those with above-median revenue growth between 2019 and 2020, or when focusing on public servants (column (3)), who experienced no wage changes and were ineligible under the program rules.[29] In these sectors, ineligible households constitute a larger share of those in forbearance—76% in less affected sectors and 90% among public servants—and their behavior closely mirrors that of eligible households. Additionally, the perception of income risk plays a significant role across all household groups, with the impact on consumption (saving) showing a monotonic decrease (increase) with income risk.

2.7 Effect of Exit and Additional Debt Relief Measures

We examine whether the effects of the forbearance program on household behavior persisted after the program ended in September 2021. To conduct this analysis, we extend the sample period through June 2022 and introduce a dummy variable, *Exit Effect*, that takes the value of one between September 2021 and June 2022 and zero otherwise. The regression also includes indicators for the three different horizons presented before (*Immediate Effect*, *Short-run Effect*, and *Long-run Effect*).

Table 2.A.9 presents the results. Column (1) shows that consumption is affected by the end of the forbearance program. The *Long-run Effect* dummy, which is set to one starting twelve months after the initiation of forbearance and lasting until the program's end in September 2021, is associated with a 22 cents increase in consumption per euro of forbearance. However, this effect diminishes to about 13 cents after the forbearance period ends, as indicated by the coefficient on the *Exit Effect* dummy. The estimates for saving in deposits in column (3) align with those for consumption. In fact, the long-run effect of forbearance on saving changes significantly after the forbearance period, with saving decreasing from 23 cents per euro to about -12 cents post-forbearance. These findings suggest that households increased their consumption during the forbearance period

[29] In these less affected industries, the proportion of households meeting the eligibility criteria decreases to 14%, and to just 5% among public servants. These public servants were eligible primarily due to meeting eligibility criteria through their *secondary* employer, i.e., the household's secondary source of income.

and did not fully adjust consumption levels downward after its termination, resulting in a drawdown of savings (Chetty and Szeidl, 2007). Table 2.B.8 of the Internet Appendix further extends the analysis of the propensity to consume upon exiting forbearance, indicating that the rigidity in reducing consumption is primarily driven by spending in "Groceries", "Clothing", and "House Maintenance and Utilities".

In the summer of 2021, and at the regulator's request, banks assessed the risk levels of borrowers in forbearance. For those identified as having a higher risk of default at the end of the forbearance based on a credit risk model, the bank conducted a survey to evaluate whether they should receive additional debt relief measures due to perceived default risk. Furthermore, all borrowers in forbearance were notified via SMS, email, and the bank's app that additional assistance was available if they had difficulties meeting their debt obligations. Similiar to the government forbearance program, access to these additional debt relief measures did not require on a formal verification of the borrower's income or financial hardship. In this section, we compare the evolution of consumption and saving for households that did and did not receive additional debt relief measures implemented by the bank in September 2021.

A more nuanced pattern emerges when examining the additional relief measures. Each of the three horizon dummies is interacted with an additional indicator, *Additional Relief*, to separately identify the effects on households exiting forbearance after September 2021 and and those receiving additional assistance. Columns (2) and (4) of Table 2.A.9 present the results. Only about 7.4% of ineligible households in forbearance requested additional relief, compared to about 6.1% of eligible households. Column (2) shows that households receiving additional relief in September 2021 did not adjust their consumption behavior after the forbearance period ended, as the point estimate for the long-run effect remains nearly identical to the estimate after the end of forbearance (15 cents per euro of postponed payment). This is unexpected, given the temporary nature of these debt relief measures, but it aligns with the "consumption commitments" model proposed by Chetty and Szeidl (2007) for this subset of borrowers. Despite this, these households that requested additional relief, on average, exhibit lower propensity to consume from forbearance funds and higher propensity to save, as shown in columns (2) and (4). This behavior continues after the transition from the initial government forbearance program to bank-provided assistance, with the marginal propensity to save being 52 cents higher for households that remain in forbearance compared to those who exit the program.

2.8 Conclusion

Government debt relief programs during the COVID-19 pandemic provide a unique laboratory to understand borrower selection into forbearance and borrower response to preemptive interventions even before large-scale defaults. Using comprehensive bank account transaction and balance sheet data, we show that forbearance programs have a positive and significant impact on household consumption and saving. Households in forbearance increased their spending by approximately 15 cents per euro of postponed debt payments compared to those outside forbearance, and increased their saving by around 30 cents. These effects are not only substantial but also persist for over a year following the initiation of forbearance.

Importantly, our findings reveal heterogeneity in responses across different household groups. Financially fragile households, characterized by lower wealth, income, and higher indebtedness, exhibit a higher marginal propensity to consume from postponed payments. In contrast, less fragile households exhibit a greater marginal propensity to save. The response is also heterogeneous based on program eligibility. Both eligible and ineligible households in forbearance were financially more fragile even before the pandemic. Eligible households benefit from forbearance by avoiding consumption reductions due to ongoing debt payments, while ineligible households in forbearance show a relatively higher marginal propensity to consume compared to their counterparts outside forbearance.

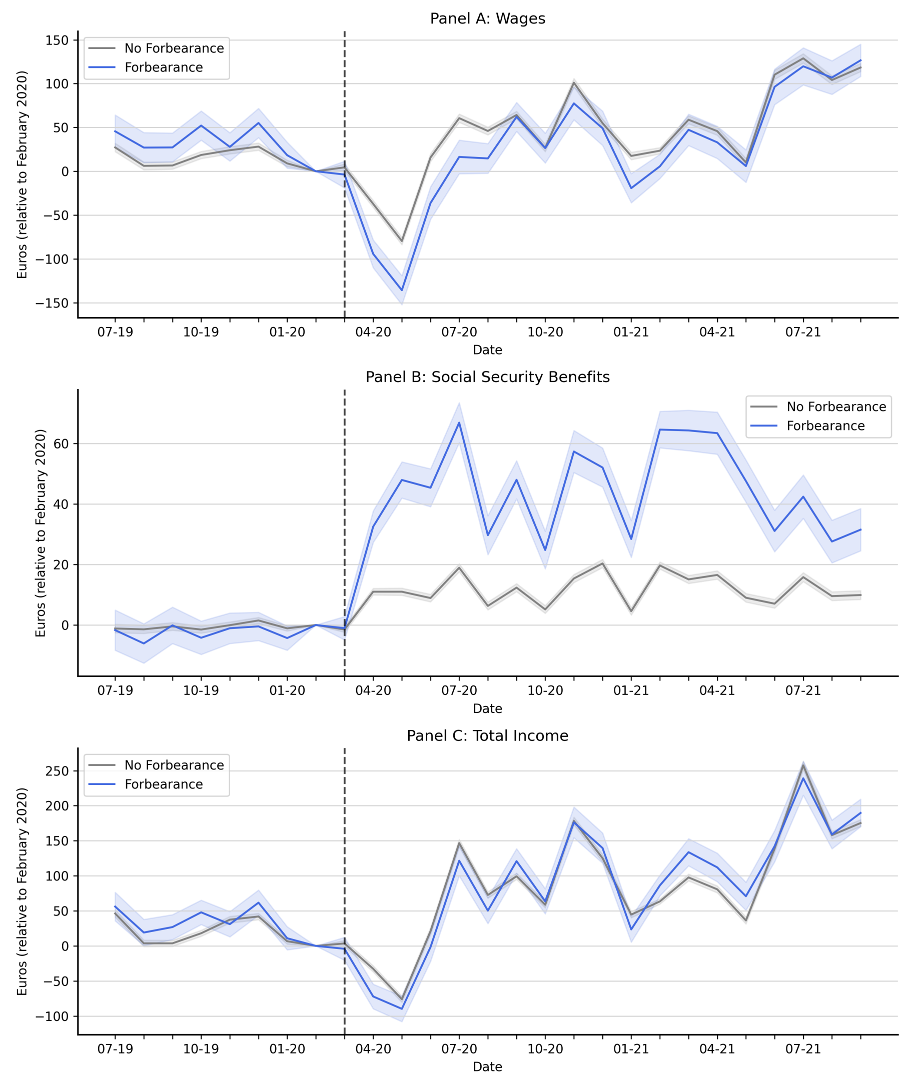
These findings have implications for the design of debt relief programs. Our research is the first to examine the consumption and saving responses of both eligible and ineligible households within a large-scale forbearance program, while accounting for key unobserved factors such as changes in income. The results suggest that, although the

Portuguese government (and many others globally) aimed to assist those most directly affected by the pandemic, the program was also accessed by households that were already financially fragile before the crisis, who were not the intended targets. Financially fragile households were also more likely to increase their consumption, leading many to exit forbearance with higher debt burdens (due to postponed payments) and only modest improvements in savings, potentially exacerbating their financial fragility.

Our study highlights a potential unintended consequence of broad-based forbearance programs: while the comprehensive measures implemented at the start of the pandemic provided temporary relief and helped stabilize household finances, likely preventing a wave of defaults globally, these programs may have also increased indebtedness among already fragile households. Policymakers could improve the effectiveness of debt relief measures by using observable household characteristics, commonly available to lenders, and considering how different groups respond to forbearance when designing future interventions. This targeted approach could be complemented by additional policies aimed at supporting household financial health, thereby reducing the risk of long-term financial instability and ensuring that the primary goal of these programs—providing relief without exacerbating debt burdens—is achieved.

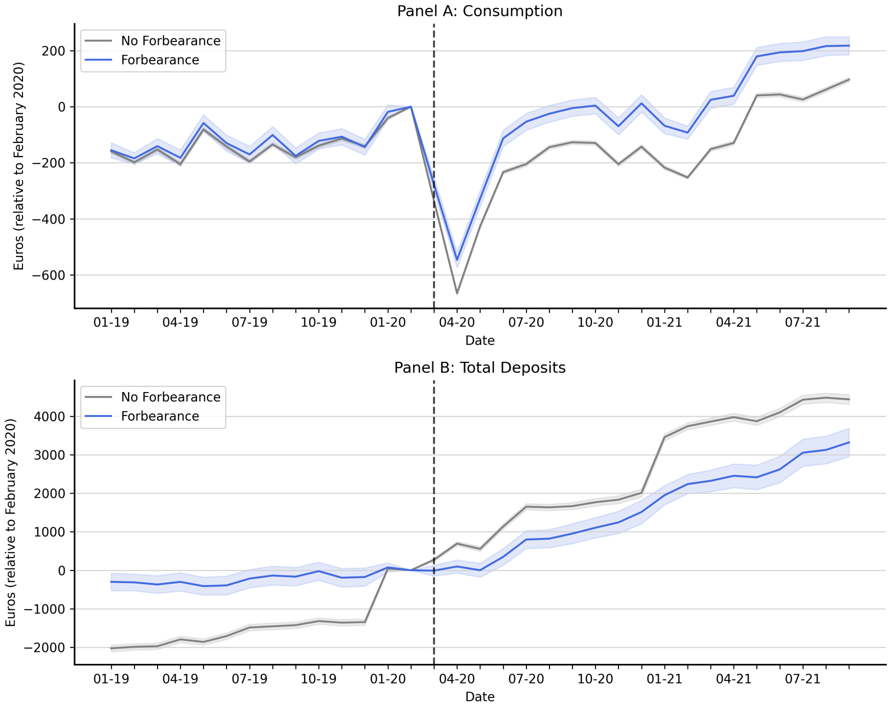
Appendix of Chapter 2

Figure 2.A.1: Evolution of Income by Forbearance Status



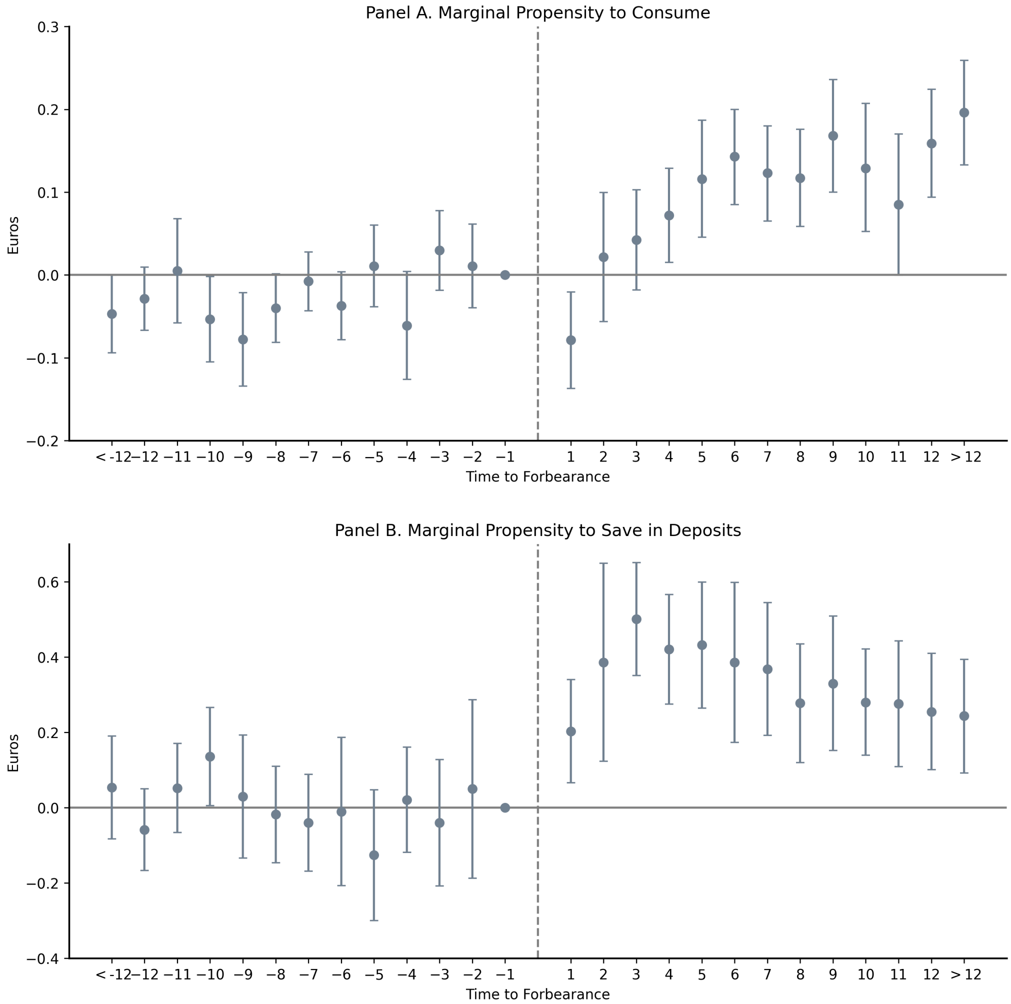
This figure shows the household average and 95% confidence interval for different components of monthly income from July 2019 to September 2021. All measures are reported in euros, seasonally adjusted and relative to a pre-pandemic baseline (February 2020). Panel A shows the change in monthly wages. Panel B shows the change in social security benefits. Panel C shows the change in total monthly income, computed as the sum between monthly wages, social security, and retirement benefits. In all panels, the average change is presented separately for households who received forbearance and those who never received forbearance. Standard errors are clustered by household.

Figure 2.A.2: Evolution of Consumption and Deposits by Forbearance Status



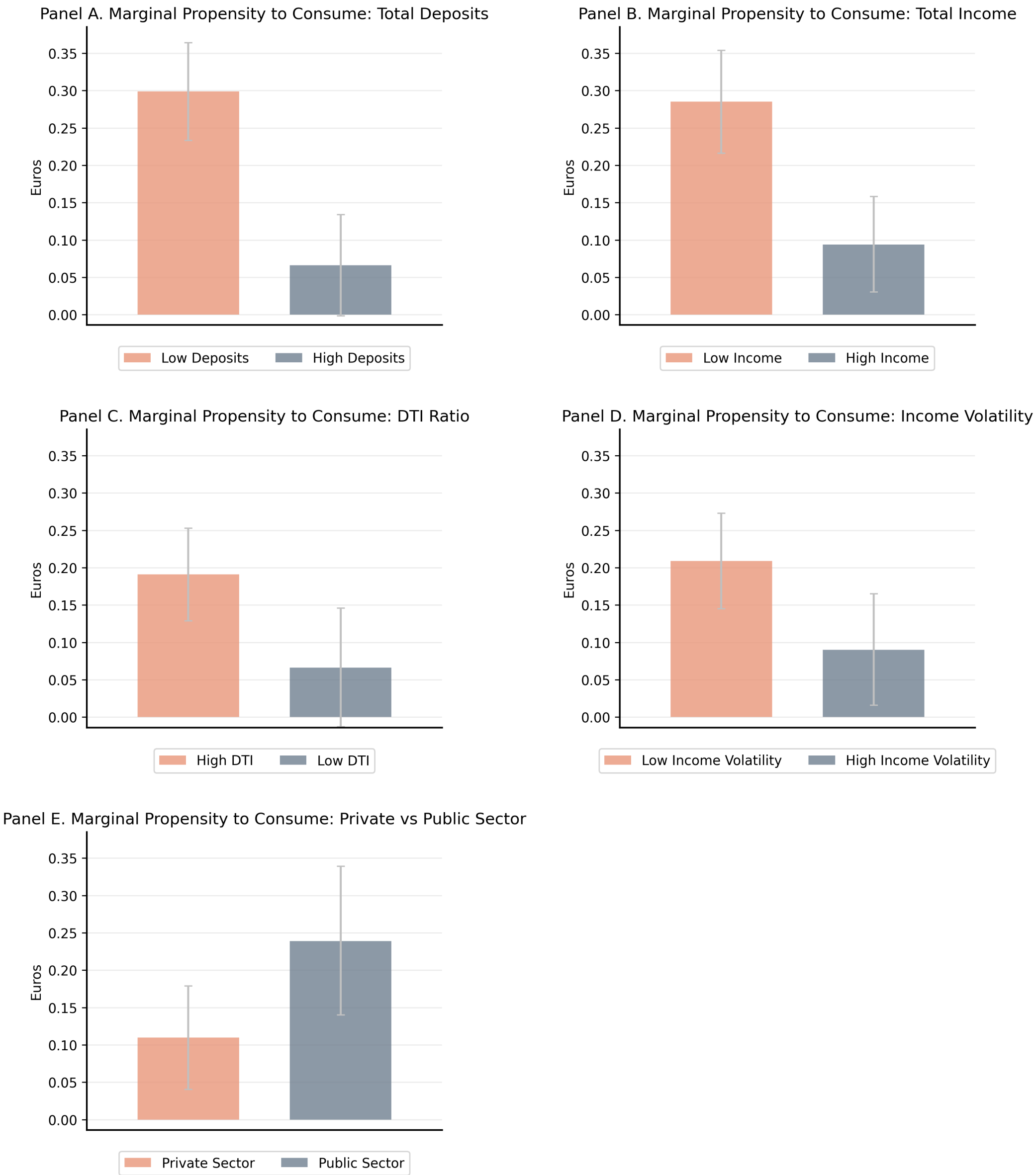
This figure shows the household average and 95% confidence interval for monthly consumption and total deposits from January 2019 to September 2021. All measures are reported in euros, seasonally adjusted, and relative to the pre-pandemic baseline (February 2020). Panel A shows the change in monthly consumption. Panel B shows the change in total deposits, computed as the sum between end-of-the-month checking and saving accounts' balances. In both panels, the average change is presented separately for households who received forbearance and those who never received forbearance. Standard errors are clustered by household.

Figure 2.A.3: Household Propensities to Consume and Save in Deposits



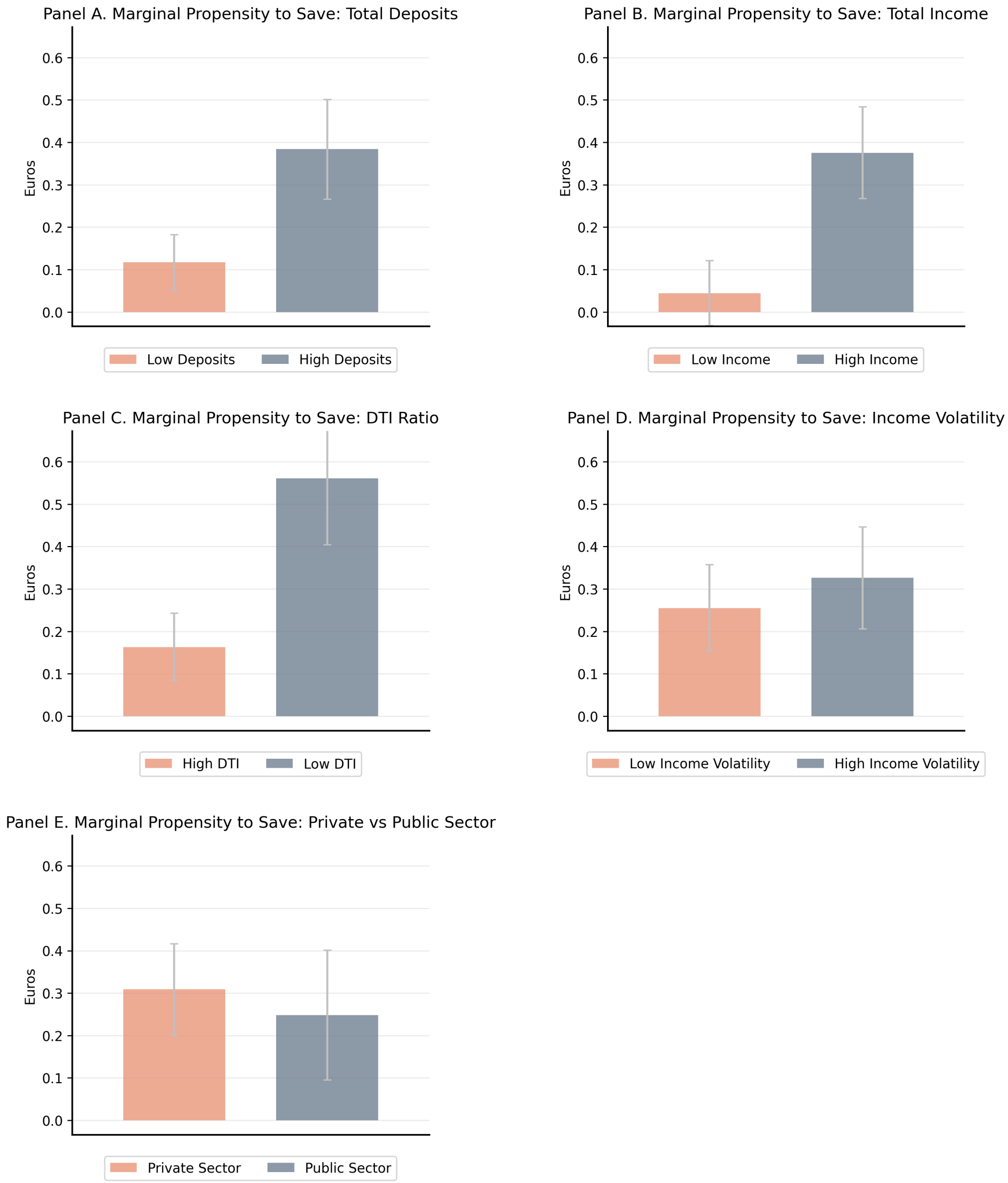
This figure shows the regression coefficients and 95% confidence intervals of the changes in monthly consumption and saving in total deposits using the difference-in-differences regression in equation (2.2). Panel A shows the estimates of the change in monthly spending per euro of postponed debt payment. Panel B shows the estimates of the change in saving in total deposits per euro of postponed debt payment. The specification includes group-month-year fixed effects and includes as control variables the changes in total income and the forbearance dummy variable that takes the value of one for households receiving forbearance, and zero otherwise. Standard errors are two-way clustered by household and month-year.

Figure 2.A.4: Household Propensity to Consume: Wealth, Income, Indebtedness and Employer Sector



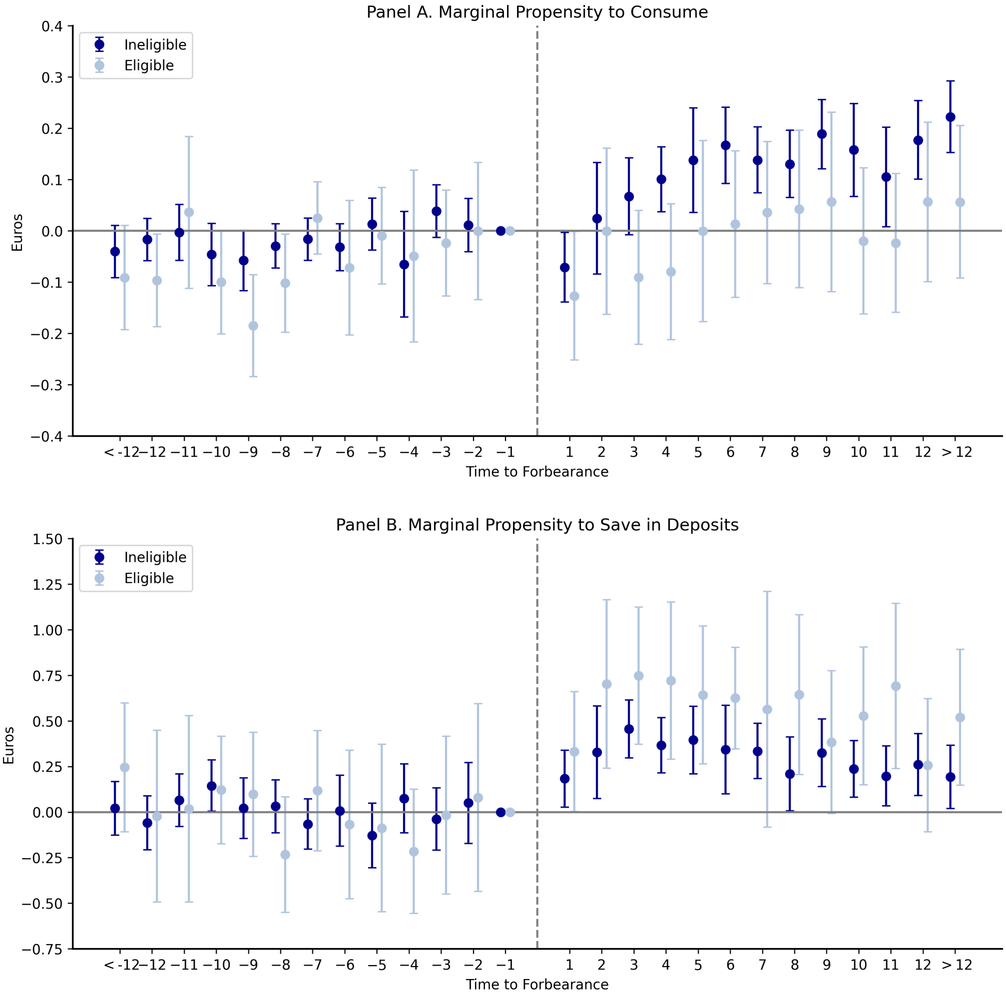
This figure shows the regression coefficients and 95% confidence intervals of the changes in monthly consumption using the difference-in-differences regression in equation (2.1). Panels A-D show the estimates for subgroups of households based on the pre-pandemic median of assets, income, debt payment-to-income ratio, and income volatility (2019 average). Panel E shows the estimates for subgroups of households whose primary employer is from the private and public sector. The specification includes group-month-year fixed effects and includes as control variables the changes in total income and the *Forbearance* dummy variable. Standard errors are two-way clustered by household and month-year.

FIGURE 2.A.5: Household Propensity to Save: Wealth, Income, Indebtedness and Employer Sector



This figure shows the regression coefficients and 95% confidence intervals of the changes in monthly saving in total deposits using the difference-in-differences regression in equation (2.1). Panels A-D shows the estimates for subgroups of households based on the pre-pandemic median of assets, income, debt payment-to-income ratio, and income volatility (2019 average). Panel E shows the estimates for subgroups of households whose primary employer is from the private or public sector. The specification includes group-month-year fixed effects and includes as control variables the changes in total income and the *Forbearance* dummy variable. Standard errors are two-way clustered by household and month-year.

Figure 2.A.6: Household Propensities to Consume and Save in Deposits: By Eligibility Status



This figure shows the regression coefficients and 95% confidence intervals of the changes in monthly consumption and saving in total deposits using the difference-in-differences regression in equation (2.2). The *Forbearance Amount* variable is further interacted with the *Eligibility* dummy variable. Panel A shows the estimates of the change in monthly spending per euro of postponed debt payment. Panel B shows the estimates of the change in saving in total deposits per euro of postponed debt payment. The specification includes group-month-year fixed effects and includes as control variables the changes in total income and the *Forbearance* dummy variable. Standard errors are two-way clustered by household and month-year.

Table 2.A.1: Average Household Characteristics by Groups

	No Forbearance			Forbearance		
	Total	Eligible	Ineligible	Total	Eligible	Ineligible
Wages	1,837	1,885	1,830	1,466	1,620	1,416
Social Security Benefits	346	350	345	300	303	299
Total Income	2,553	2,759	2,531	2,121	2,449	2,046
Consumption	1,516	1,615	1,506	1,343	1,441	1,320
Consumption Rate (%)	75.6	67.2	76.6	88.1	66.9	93.0
Total Deposits	18,855	17,854	18,962	7,581	7,449	7,612
Mortgage Loans	67,803	73,339	67,211	93,077	96,256	92,346
Credit Cards and Overdraft	399	375	401	749	654	771
Other Banks' Debt	7,044	7,417	7,005	13,885	13,457	13,984
Debt Payment	311	305	312	377	360	381
Debt Payment-to-Income (%)	18.7	14.7	19.1	29.8	19.6	32.2
Forbearance Amount	0	0	0	345	333	347
Observations	129,201	12,469	116,732	8,162	1,525	6,637

This table shows pre-pandemic (2019) averages for households who received forbearance and those who never received forbearance, further dividing those two groups on whether they were eligible or not according to program rules. Income, deposits, liabilities and consumption measures are winsorized at the top and bottom 1%.

TABLE 2.A.2: Household Propensities to Consume and Save in Deposits

	ΔConsumption				ΔSaving in Deposits			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Forbearance Amount × Post	0.152***	0.133***	0.147***	0.137***	0.122	0.182***	0.293***	0.321***
	(0.033)	(0.030)	(0.028)	(0.027)	(0.075)	(0.047)	(0.041)	(0.042)
ΔIncome			0.085***	0.083***			0.695***	0.704***
			(0.003)	(0.003)			(0.009)	(0.009)
ΔIncome × Forbearance				0.050***				-0.155***
				(0.003)				(0.012)
Month × Year FE	Yes	No	No	No	Yes	No	No	No
Group × Month × Year FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
R^2	0.062	0.082	0.102	0.102	0.018	0.026	0.157	0.157
Observations	6,181,335	6,181,335	6,181,335	6,181,335	6,043,972	6,043,972	6,043,972	6,043,972

This table presents difference-in-differences estimates of regressions of changes in monthly consumption and saving in total deposits using the difference-in-differences regression in equation (2.1) at the household-month level. The dependent variable in columns (1)-(4), Δ*Consumption*, is the difference between monthly spending at time t, relative to the corresponding household average in 2019. The dependent variable in columns (5)-(8), Δ*Saving in Deposits*, is the monthly saving in total deposits at time t, relative to the corresponding household average in 2019. *Forbearance Amount* is the amount of postponed debt payments. *Post* is a dummy variable that takes a value of one for the period starting when mortgage payments are suspended and zero otherwise. All specifications include the *Forberance* dummy variable as a control variable. In some specifications, the regressions include group-month-year fixed effects, with group referring to quartiles of pre-pandemic deposits and income (2019 averages), and changes in total income relative to the corresponding household average in 2019 as a control. The sample period is from January 2018 to September 2021. Two-way standard errors clustered by household and month-year are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 2.A.3: Household Propensities to Consume and Save in Deposits by Horizon

	ΔConsumption			ΔSaving in Deposits		
	(1)	(2)	(3)	(4)	(5)	(6)
Forbearance Amount ×						
Immediate Effect (1m-3m)	0.038	-0.019	0.018	-0.165	0.045	0.345***
	(0.039)	(0.032)	(0.035)	(0.144)	(0.080)	(0.055)
Short-run Effect (4m-12m)	0.153***	0.133***	0.146***	0.186**	0.213***	0.318***
	(0.029)	(0.024)	(0.023)	(0.092)	(0.056)	(0.042)
Long-run Effect (>12m)	0.211***	0.215***	0.218***	0.173	0.206***	0.226***
	(0.029)	(0.025)	(0.024)	(0.110)	(0.062)	(0.044)
ΔIncome			0.085***			0.695***
			(0.003)			(0.009)
Month × Year FE	Yes	No	No	Yes	No	No
Group × Month × Year FE	No	Yes	Yes	No	Yes	Yes
R^2	0.062	0.082	0.102	0.018	0.026	0.157
Observations	6,181,335	6,181,335	6,181,335	6,043,972	6,043,972	6,043,972

This table presents difference-in-differences estimates of regressions of changes in monthly consumption and saving in total deposits using the difference-in-differences regression in equation (2.1) at the household-month level, but replacing the *Post* indicator with three different time dummy variables: the *Immediate Effect* measures the impact over the first quarter after the start of forbearance; the *Short-run Effect* measures the average effect from the 4^{th} to the 12^{th} month; and the *Long-run Effect* measures the average effect after one year. The dependent variable in columns (1)-(3), $\Delta Consumption$, is the difference between monthly spending at time t, relative to the corresponding household average in 2019. The dependent variable in columns (4)-(6), Δ*Saving in Deposits*, is the monthly saving in total deposits at time t, relative to the corresponding household average in 2019. *Forbearance Amount* is the amount of postponed debt payments. All specifications include the $Forberance$ dummy variable as a control variable. In some specifications, the regressions include group-month-year fixed effects, with group referring to quartiles of pre-pandemic deposits and income (2019 averages), and changes in total income relative to the corresponding household average in 2019 as a control. The sample period is from January 2018 to September 2021. Two-way standard errors clustered by household and month-year are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 2.A.4: Effect of Forbearance on Consumption and Saving Rates

	Consumption Rate			Saving Rate		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Overall					
Forbearance × Post	0.118***	0.064***	0.063***	0.040*	0.048***	0.045***
	(0.011)	(0.008)	(0.007)	(0.020)	(0.014)	(0.010)
%ΔIncome			0.148***			0.486***
			(0.009)			(0.021)
	Panel B: Horizons					
Forbearance Amount ×						
Immediate Effect (1m-3m)	0.055***	0.017	0.024*	-0.023	0.013	0.037***
	(0.016)	(0.011)	(0.013)	(0.037)	(0.023)	(0.013)
Short-run Effect (4m-12m)	0.111***	0.063***	0.062***	0.050**	0.051***	0.048***
	(0.008)	(0.006)	(0.006)	(0.024)	(0.018)	(0.014)
Long-run Effect (>12m)	0.163***	0.092***	0.087***	0.060**	0.064***	0.045***
	(0.009)	(0.008)	(0.007)	(0.029)	(0.021)	(0.013)
%ΔIncome			0.148***			0.486***
			(0.009)			(0.021)
Month × Year FE	Yes	No	No	Yes	No	No
Group × Month × Year FE	No	Yes	Yes	No	Yes	Yes
R^2	0.052	0.084	0.129	0.012	0.015	0.093
Observations	6,170,985	6,170,985	6,170,985	6,033,852	6,033,852	6,033,852

This table presents difference-in-differences estimates of regressions of changes in the consumption rate and saving rate using the difference-in-differences regression in equation (2.3) at the household-month level. The dependent variable in columns (1)-(3), *Consumption Rate*, is the difference between monthly spending at time t and the corresponding household average in 2019, divided by the average income in 2019. The dependent variable in columns (4)-(6), *Saving Rate*, is the monthly saving in total deposits at time t and the corresponding household average in 2019, divided by the average income in 2019. *Forbearance* is a dummy variable that takes the value of one for households receiving forbearance, and zero otherwise. *Post* is a dummy variable that takes a value of one for the period starting when mortgage payments are suspended and zero otherwise. In Panel B, the *Post* indicator is replaced by three different time dummy variables: the *Immediate Effect* measures the impact over the first quarter after the start of forbearance; the *Short-run Effect* measures the average effect from the 4^{th} to the 12^{th} month; and the *Long-run Effect* measures the average effect after one year. All specifications include the *Forberance* dummy variable as a control variable. In some specifications, the regressions include group-month-year fixed effects, with group referring to quartiles of pre-pandemic deposits and income (2019 averages), and percentage changes in total income relative to the corresponding household average in 2019 as a control. The sample period is from January 2018 to September 2021. Two-way standard errors clustered by household and month-year are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 2.A.5: Household Propensity to Borrow

	ΔBorrowing Credit Card & Overdraft			ΔBorrowing Other Banks' Debt		
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: Overall			
Forbearance Amount × Post	-0.009	-0.009	-0.011	-0.053*	-0.033	-0.029
	(0.011)	(0.009)	(0.009)	(0.026)	(0.025)	(0.025)
ΔIncome			-0.007***			0.022***
			(0.001)			(0.002)
			Panel B: Horizons			
Forbearance Amount ×						
Immediate Effect (1m-3m)	-0.043**	-0.034	-0.037*	-0.036	-0.006	0.003
	(0.020)	(0.020)	(0.019)	(0.027)	(0.026)	(0.028)
Short-run Effect (4m-12m)	-0.001	-0.005	-0.006	-0.051	-0.034	-0.031
	(0.012)	(0.009)	(0.009)	(0.037)	(0.035)	(0.035)
Long-run Effect (>12m)	-0.005	-0.004	-0.004	-0.064***	-0.045**	-0.044**
	(0.015)	(0.011)	(0.011)	(0.021)	(0.021)	(0.021)
ΔIncome			-0.007***			0.022***
			(0.001)			(0.002)
Month × Year FE	Yes	No	No	Yes	No	No
Group × Month × Year FE	No	Yes	Yes	No	Yes	Yes
R^2	0.012	0.021	0.023	0.001	0.003	0.004
Observations	6,043,972	6,043,972	6,043,972	4,395,616	4,395,616	4,395,616

This table presents difference-in-differences estimates of regressions of changes in credit card and overdraft, and other banks' debt payments using the difference-in-differences regression in equation (2.1) at the household-month level. The dependent variable in columns (1)-(3), Δ*Borrowing Credit Card & Overdraft*, is the difference in monthly changes in end-of-the-month credit card and overdraft balances at time t at the bank, relative to the corresponding household average in 2019. The dependent variable in columns (4)-(6), Δ*Borrowing Other Banks' Debt*, is the difference between monthly changes in liabilities at other banks at time t, relative to the corresponding household average in 2019. *Forbearance Amount* is the amount of postponed debt payments. *Post* is a dummy variable that takes a value of one for the period starting when mortgage payments are suspended and zero otherwise. In Panel B, the *Post* indicator is replaced by three different time dummy variables: the *Immediate Effect* measures the impact over the first quarter after the start of forbearance; the *Short-run Effect* measures the average effect from the 4^{th} to the 12^{th} month; and the *Long-run Effect* measures the average effect after one year. All specifications include the $Forberance$ dummy variable as a control variable. All specifications include the $Forberance$ dummy variable as a control variable. In some specifications, the regressions include group-month-year fixed effects, with group referring to quartiles of pre-pandemic deposits and income (2019 averages), and changes in total income relative to the corresponding household average in 2019 as a control. The sample period in columns (1)-(3) is from January 2018 to September 2021. The sample period in columns (4)-(6), due to data limitations, is from January 2019 to September 2021. Two-way standard errors clustered by household and month-year are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 2.A.6: Household Propensity to Consume by Category

	(1) Total	(2) Groc.	(3) Cloth.	(4) House Maint.	(5) Furnit.	(6) Transp.	(7) Health Care	(8) Restau.	(9) Entert. & Educ.	(10) Misc.
Panel A: Overall										
Forbearance Amount × Post	0.095***	0.055***	0.014***	0.005***	0.006**	0.007	0.006**	-0.000	0.009**	0.002
	(0.029)	(0.006)	(0.003)	(0.002)	(0.002)	(0.006)	(0.003)	(0.006)	(0.004)	(0.013)
ΔIncome	0.078***	0.008***	0.003***	0.001***	0.003***	0.006***	0.002***	0.005***	0.003***	0.028***
	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Panel B: Horizons										
Forbearance Amount ×										
Immediate Effect (1m-3m)	-0.033	0.036***	0.004	0.005**	0.003	-0.009	-0.001	-0.025***	-0.003	-0.027*
	(0.039)	(0.008)	(0.004)	(0.002)	(0.004)	(0.008)	(0.003)	(0.005)	(0.004)	(0.015)
Short-run Effect (4m-12m)	0.092***	0.057***	0.015***	0.004**	0.005**	0.005	0.008**	-0.003	0.010**	0.002
	(0.025)	(0.006)	(0.003)	(0.002)	(0.002)	(0.005)	(0.003)	(0.007)	(0.004)	(0.013)
Long-run Effect (>12m)	0.167***	0.061***	0.020***	0.005**	0.009***	0.020***	0.008**	0.017**	0.013**	0.017
	(0.026)	(0.006)	(0.003)	(0.002)	(0.003)	(0.005)	(0.003)	(0.006)	(0.005)	(0.015)
ΔIncome	0.078***	0.008***	0.003***	0.001***	0.003***	0.006***	0.002***	0.005***	0.003***	0.028***
	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Group × Month × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.095	0.028	0.049	0.007	0.010	0.043	0.010	0.067	0.017	0.036
Observations	2,884,623	2,884,623	2,884,623	2,884,623	2,884,623	2,884,623	2,884,623	2,884,623	2,884,623	2,884,623

This table presents difference-in-differences estimates of regressions of changes in monthly consumption for different spending categories using the difference-in-differences regression in equation (2.1) at the household-month level. The dependent variable is measured as the difference between monthly spending at time t, relative to the corresponding household average in January and February of 2020, for each consumption category: (1) Total Consumption; (2) Groceries; (3) Clothing; (4) Housing Maintenance and Utilities; (5) Furniture; (6) Transport; (7) Health Care; (8) Restaurants; (9) Entertainment and Education; and (10) Miscellaneous Goods and Services. *Forbearance Amount* is the amount of postponed debt payments. *Post* is a dummy variable that takes a value of one for the period starting when mortgage payments are suspended and zero otherwise. In Panel B, the *Post* indicator is replaced by three different time dummy variables: the *Immediate Effect* measures the impact over the first quarter after the start of forbearance; the *Short-run Effect* measures the average effect from the 4^{th} to the 12^{th} month; and the *Long-run Effect* measures the average effect after one year. In all specifications, the regressions include group-month-year fixed effects, with group referring to quartiles of pre-pandemic deposits and income (2019 averages), and changes in total income relative to the corresponding household average in January and February 2020 as a control. The sample period is from January 2020 to September 2021. Two-way standard errors clustered by household and month-year are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 2.A.7: Household Propensities to Consume and Save in Deposits by Eligibility and Forbearance Status

	ΔConsumption			ΔSaving in Deposits		
	(1)	(2)	(3)	(4)	(5)	(6)
Debt Payment ×						
Forbearance=0 × Eligible=1 × Post	-0.242***	-0.152***	-0.135***	-0.131*	-0.133*	0.012
	(0.038)	(0.024)	(0.021)	(0.069)	(0.068)	(0.050)
Forbearance=1 × Eligible=0 × Post	0.195***	0.169***	0.177***	0.144*	0.210***	0.275***
	(0.036)	(0.033)	(0.030)	(0.085)	(0.051)	(0.044)
Forbearance=1 × Eligible=1 × Post	0.011	0.015	0.065	0.019	0.075	0.486***
	(0.056)	(0.052)	(0.048)	(0.112)	(0.105)	(0.083)
Controls	No	No	Yes	No	No	Yes
Month × Year FE	Yes	No	No	Yes	No	No
Group × Month × Year FE	No	Yes	Yes	No	Yes	Yes
R^2	0.062	0.082	0.102	0.018	0.026	0.157
Observations	6,181,335	6,181,335	6,181,335	6,043,972	6,043,972	6,043,972
Observations:						
Forbearance=0 × Eligible=0	116,732					
% of sample	*(85.0%)*					
Forbearance=0 × Eligible=1	12,469					
% of sample	*(9.1%)*					
Forbearance=1 × Eligible=0	6,637					
% of sample	*(4.8%)*					
Forbearance=1 × Eligible=1	1,525					
% of sample	*(1.1%)*					

This table presents difference-in-differences estimates of regressions of changes in monthly consumption and saving in total deposits using the difference-in-differences regression in equation (2.1) at the household-month date level. The dependent variable in columns (1)-(3), $\Delta Consumption$, is the difference between monthly spending at time t, relative to the corresponding household average in 2019. The dependent variable in columns (4)-(6), $\Delta Saving\ in\ Deposits$, is the monthly saving in total deposits at time t, relative to the corresponding household average in 2019. *Debt Payment* is the pre-pandemic amount of debt payments of each household. *Forbearance* is a dummy variable that takes the value of one for households receiving forbearance and zero otherwise. *Eligible* is a dummy variable that takes the value of one if the household satisfied the legal requirements for suspending mortgage payments. *Post* is a dummy variable that takes a value of one for the period starting when mortgage payments are suspended and zero otherwise. All specifications include the *Forberance* dummy variable as a control variable. In some specifications, the regressions include group-month-year fixed effects, with group referring to quartiles of pre-pandemic deposits and income (2019 averages), and changes in total income relative to the corresponding household average in January and February 2020 as a control. The sample period is from January 2018 to September 2021. Two-way standard errors clustered by household and month-year are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 2.A.8: Propensity to Consume and Save in Deposits by Eligibility and Selection Groups: More Affected versus Less Affected

	ΔConsumption			ΔSaving in Deposits		
	More Affected (1)	Less Affected (2)	Public Servants (3)	More Affected (4)	Less Affected (5)	Public Servants (6)
Debt Payment ×						
Forbearance=0 × Eligible=1 × Post	-0.123***	-0.085**	-0.076	0.013	0.072	-0.011
	(0.033)	(0.036)	(0.046)	(0.077)	(0.083)	(0.107)
Forbearance=1 × Eligible=0 × Post	0.139***	0.190***	0.230***	0.180*	0.236**	0.269***
	(0.051)	(0.061)	(0.053)	(0.094)	(0.088)	(0.081)
Forbearance=1 × Eligible=1 × Post	0.030	0.196**	0.299**	0.654***	0.135	0.273
	(0.069)	(0.085)	(0.114)	(0.119)	(0.113)	(0.263)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Group × Month × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.109	0.105	0.106	0.176	0.167	0.163
Observations	919,080	1,327,095	1,719,855	898,656	1,297,604	1,681,636
Observations:						
Forbearance=0 × Eligible=0	13,485	23,899	35,241			
% of sample	*(66.0%)*	*(81.0%)*	*(92.2%)*			
Forbearance=0 × Eligible=1	5,176	4,103	1,775			
% of sample	*(25.3%)*	*(13.9%)*	*(4.6%)*			
Forbearance=1 × Eligible=0	904	1,076	1,096			
% of sample	*(4.4%)*	*(3.6%)*	*(2.9%)*			
Forbearance=1 × Eligible=1	859	413	107			
% of sample	*(4.2%)*	*(1.4%)*	*(0.3%)*			

This table presents difference-in-differences estimates of regressions of changes in monthly consumption and saving in total deposits using the difference-in-differences regression in equation (2.1) at the household-month level. The dependent variable in columns (1)-(3), $\Delta Consumption$, is the difference between monthly spending at time t, relative to the corresponding household average in 2019. The dependent variable in columns (4)-(6), $\Delta Saving\ in\ Deposits$, is the monthly saving in total deposits at time t, relative to the corresponding household average in 2019. The *More Affected* subsample corresponds to households whose primary employer operates in an industry with revenue growth from 2019 to 2020 below the median. The *Less Affected* subsample corresponds to households whose primary employer operates in an industry with revenue growth from 2019 to 2020 above the median. The *Public Servants* subsample is defined as households whose primary employer operated in the public sector. *Debt Payment* is the amount of pre-pandemic debt payments made by households. *Forbearance* is a dummy variable that takes the value of one for households receiving forbearance and zero otherwise. *Eligible* is a dummy variable that takes the value of one if the household satisfied the legal requirements for suspending mortgage payments. *Post* is a dummy variable that takes a value of one for the period starting when mortgage payments are suspended and zero otherwise. All specifications include the *Forberance* dummy variable as a control variable. In some specifications, the regressions include group-month-year fixed effects, with group referring to quartiles of pre-pandemic deposits and income (2019 averages), and changes in total income relative to the corresponding household average in 2019 as a control. The sample period is from January 2018 to September 2021. Two-way standard errors clustered by household and month-year are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

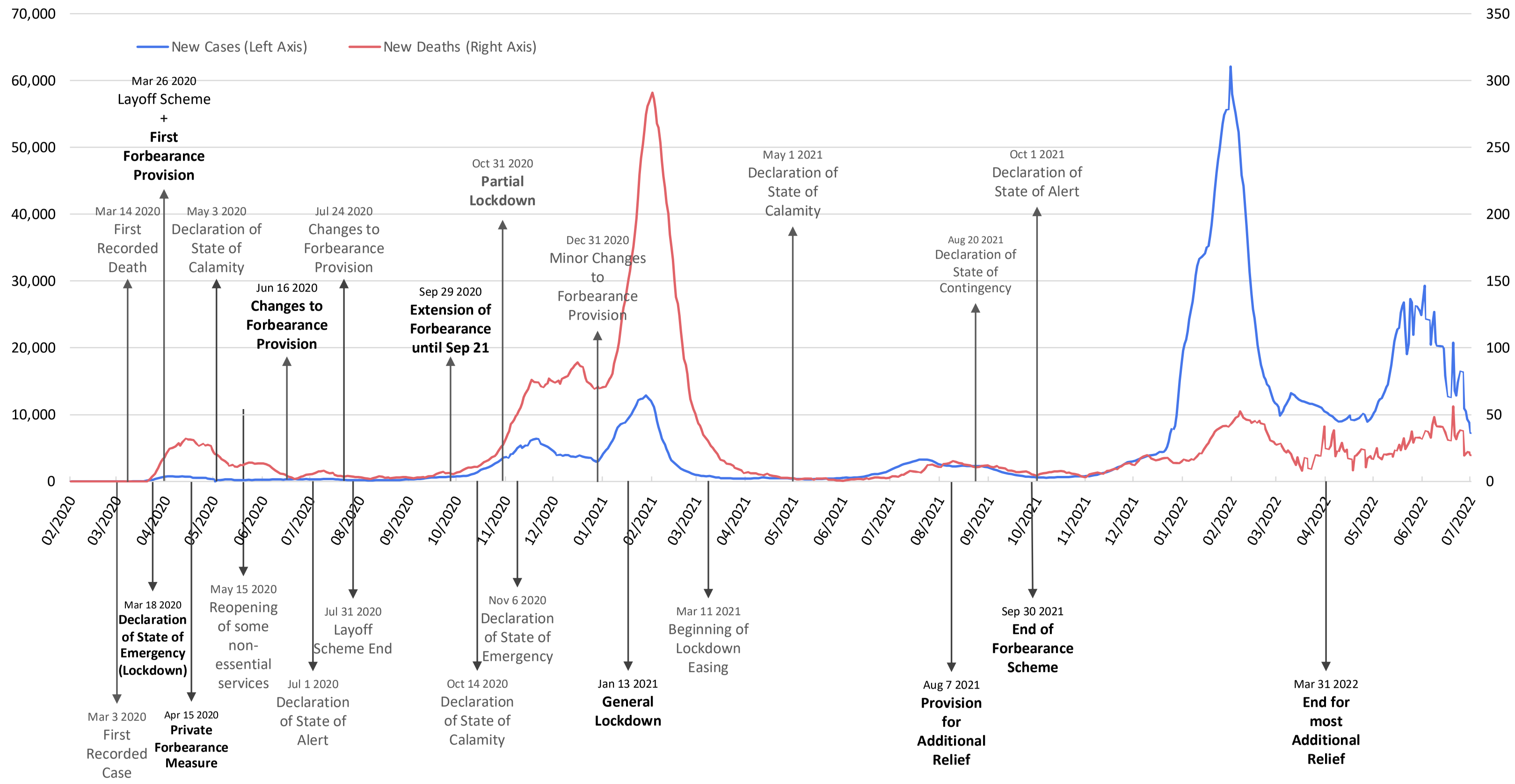
TABLE 2.A.9: Household Propensities to Consume and Save in Deposits on Exit

	ΔConsumption		ΔSaving in Deposits	
	(1)	(2)	(3)	(4)
Forbearance Amount ×				
Immediate Effect (1-3)	0.024	0.026	0.343***	0.336***
	(0.036)	(0.038)	(0.056)	(0.058)
Short-run Effect (4-12)	0.150***	0.157***	0.319***	0.296***
	(0.024)	(0.025)	(0.045)	(0.045)
Long-run Effect (>12)	0.221***	0.228***	0.228***	0.206***
	(0.025)	(0.026)	(0.046)	(0.047)
Exit Effect	0.126***	0.124***	-0.120**	-0.164***
	(0.028)	(0.029)	(0.054)	(0.056)
Immediate Effect (1-3) × Additional Relief		-0.029		0.080
		(0.077)		(0.070)
Short-run Effect (4-12) × Additional Relief		-0.083		0.273**
		(0.084)		(0.123)
Long-run Effect (>12) × Additional Relief		-0.075		0.267*
		(0.107)		(0.142)
Exit Effect × Additional Relief		0.026		0.522***
		(0.100)		(0.152)
Controls	Yes	Yes	Yes	Yes
Group × Month × Year FE	Yes	Yes	Yes	Yes
R^2	0.101	0.101	0.152	0.152
Observations	7,417,602	7,417,602	7,280,239	7,280,239
Observations:				
Forbearance=1 × Eligible=0		6,637		
Forbearance=1 × Eligible=0 × Additional Relief=1		490		
% of group		*(7.4%)*		
Forbearance=1 × Eligible=1		1,525		
Forbearance=1 × Eligible=1 × Additional Relief=1		93		
% of group		*(6.1%)*		

This table presents difference-in-differences estimates of regressions of changes in monthly consumption and saving in total deposits using the difference-in-differences regression in equation (2.1) at the household-month level, but replacing the *Post* indicator with four different time dummy variables: the *Immediate Effect* measures the impact over the first quarter after the start of forbearance; the *Short-run Effect* measures the average effect from the 4$^{\text{th}}$ to the 12$^{\text{th}}$ month; the *Long-run Effect* measures the average effect after one year and until the end of the payment suspension; and the *Exit Effect* measures the average effect after the end of the payment suspension. The dependent variable in columns (1)-(2), $\Delta Consumption$, is the difference between monthly spending at time t, relative to the corresponding household average in 2019. The dependent variable in columns (3)-(4), $\Delta Saving\ in\ Deposits$, is the monthly saving in total deposits at time t, relative to the corresponding household average in 2019. *Forbearance Amount* is the amount of postponed debt payments. *Additional Relief* is a dummy variable that takes a value of one if the household requested additional relief after the forbearance end. All specifications include the *Forberance* dummy variable as a control variable. All specifications include group-month-year fixed effects, with group referring to quartiles of pre-pandemic deposits and income (2019 averages), and changes in total income relative to the corresponding household average in 2019 as a control. The sample period is from January 2018 to June 2022. Two-way standard errors clustered by household and month-year are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

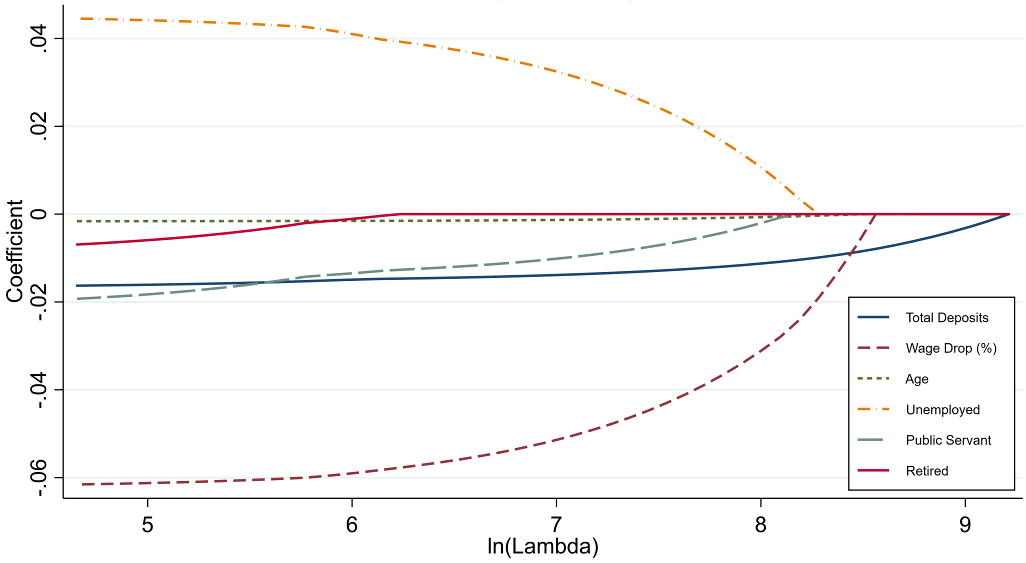
Internet Appendix of Chapter 2

FIGURE 2.B.1: Timeline of Events



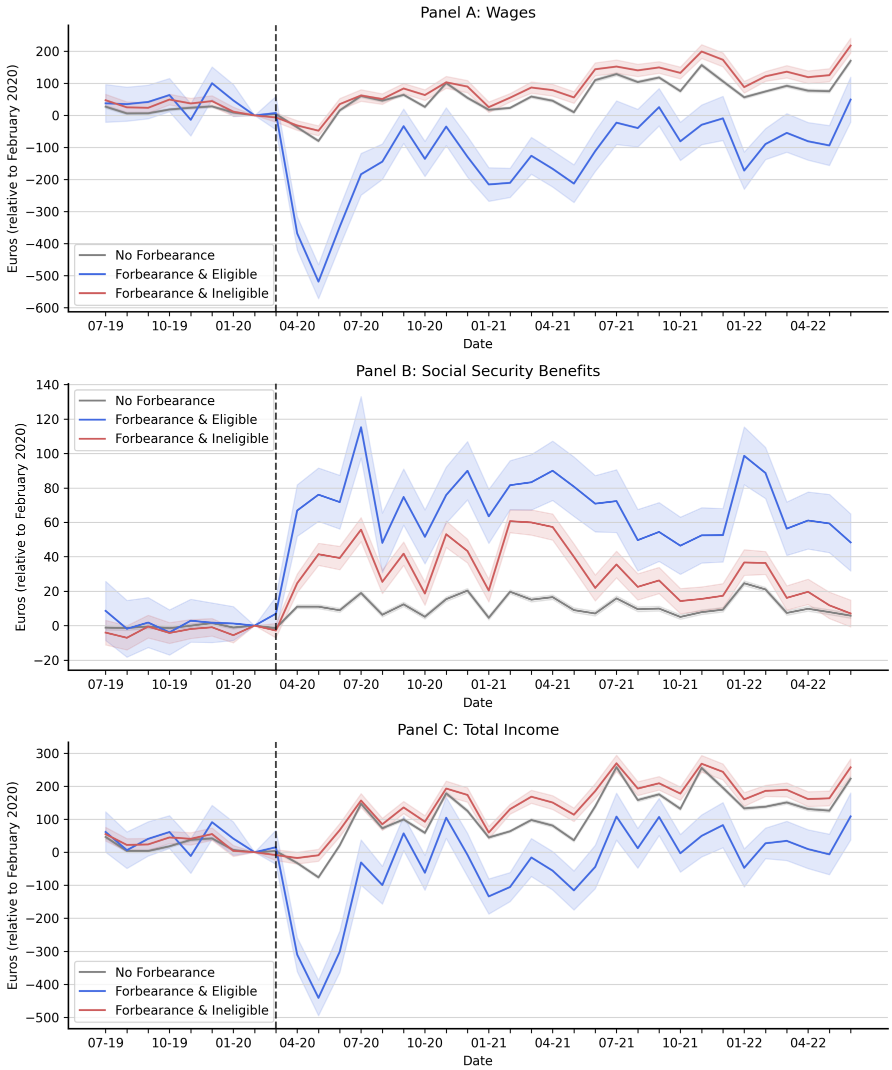
This figure shows the timeline of events (key events being identified in bold) from February 2020 until July 2022. The left axis variable (in blue) is the number of new COVID-19 cases. The right axis variable (in red) is the number of new deaths due to COVID-19.

FIGURE 2.B.2: Probability of Accessing Forbearance: Coefficient Path



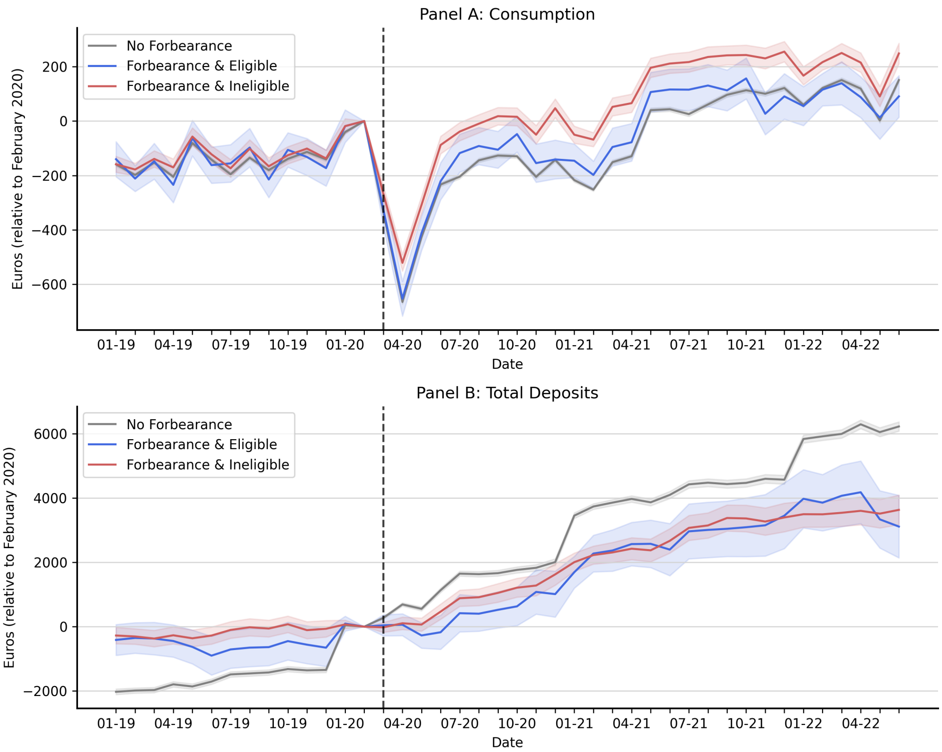
This figure plots the coefficient path of the selected variables in a LASSO regression, considering a set of pre-pandemic measures, for the probability of accessing forbearance. Coefficients of each variable are shown relative to λ, the overall penalty level of the regularized regression. Variables are shown in the legend according to the order by which they are selected.

Figure 2.B.3: Evolution of Income by Eligibility and Forbearance Status



This figure shows the household average and 95% confidence interval for different components of monthly income from July 2019 to June 2022. All measures are reported in euros, seasonally adjusted, and relative to the pre-pandemic baseline (February 2020). Panel A shows the change in monthly wages, while Panel B shows the change in social security benefits received. Panel C shows the change in total monthly income, computed as the sum between monthly wages, social security, and retirement benefits. In all panels, the average change is presented separately for eligible households who received forbearance, ineligible households who received forbearance, and households who never received forbearance. Standard errors are clustered by household.

Figure 2.B.4: Evolution of Consumption and Deposits by Eligibility and Selection Status



This figure plots the household average and 95% confidence interval for monthly consumption and total deposits from January 2019 to June 2022. All measures are reported in euros, seasonally adjusted, and relative to the pre-pandemic baseline (February 2020). Panel A reports monthly consumption. Panel B shows total deposits, computed as the sum between end-of-the-month checking and saving accounts' balances. In all panels the average change is presented separately for eligible households who received forbearance, ineligible households who received forbearance, and households who never received forbearance. Standard errors are clustered by household.

Table 2.B.1: Summary Statistics of Household Characteristics

Variable	Mean	SD	p10	p25	p50	p75	p90	Observations
Average Age	47.9	9.1	37.0	41.5	47.0	54.0	60.5	137,363
Number of Mortgagors	1.7	0.5	1.0	1.0	2.0	2.0	2.0	137,363
Wages	1,816.1	1,067.3	756.1	1,075.3	1,566.6	2,250.9	3,216.9	111,979
Pensions	1,313.9	928.4	390.2	629.2	1,056.7	1,767.7	2,539.4	40,258
Social Security Benefits	341.7	439.8	33.6	63.4	163.9	446.1	882.3	42,761
Other Inbound Transfers	663.2	976.0	25.6	107.1	297.5	803.0	1,693.8	137,363
Total Income	2,527.1	1,754.6	870.0	1,394.4	2,090.1	3,176.0	4,658.7	137,363
Consumption	1,505.9	932.2	559.0	860.2	1,298.3	1,915.2	2,704.5	137,363
Consumption Rate	0.76	0.75	0.32	0.46	0.62	0.80	1.13	137,133
Total Deposits	18,185.0	30,787.9	302.0	1,159.5	5,567.4	20,738.0	51,399.2	137,363
Checking Accounts	6,710.8	12,490.4	195.2	696.8	2,010.5	6,528.3	17,853.7	137,363
Savings Accounts	17,356.5	28,834.9	0.0	431.5	5,757.9	20,541.7	49,559.6	90,241
Mortgage Loans	69,304.6	52,000.4	15,173.5	30,724.2	57,206.5	95,048.2	137,247.8	137,363
Credit Cards and Overdraft	419.6	784.2	0.0	0.0	87.5	473.3	1,224.8	137,328
Other Banks' Loans	7,451.0	17,692.4	0.0	0.0	470.0	7,507.7	19,463.5	137,363
Total Debt Payment	315.3	170.1	148.7	207.4	279.4	378.1	523.5	137,363
Debt Payment-to-Income	0.19	0.25	0.06	0.09	0.14	0.21	0.32	137,133
7 Day Delinquency	0.02	0.13	0.00	0.00	0.00	0.00	0.00	137,363

This table shows pre-pandemic (2019) mean, standard deviation (SD), the 10% (p10), 25% (p25), 50% (p50), 75% (p75) and 90% (p90) percentiles, and number of households. Income, deposits, liabilities, and consumption measures are winsorized at the top and bottom 1% by date.

TABLE 2.B.2: Forbearance, Eligibility and Future Outcomes

	Employment Status Change				Wage Growth			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Forbearance	-0.009***	-0.008***	-0.008***	-0.007**	3.114***	2.962***	2.766***	2.044***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.631)	(0.634)	(0.635)	(0.631)
Eligible	-0.006**	-0.006**	-0.006**	-0.003	21.310***	21.360***	21.210***	20.810***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.541)	(0.541)	(0.540)	(0.569)
Forbearance × Eligible	0.004	0.004	0.003	0.004	1.821	1.914	2.091	1.518
	(0.009)	(0.009)	(0.009)	(0.009)	(1.679)	(1.678)	(1.676)	(1.655)
Additional Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Group FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Location FE	No	No	Yes	Yes	No	No	Yes	Yes
Industry FE	No	No	No	Yes	No	No	No	Yes
R^2	0.004	0.006	0.011	0.014	0.113	0.114	0.121	0.141
Observations	65,658	65,658	65,658	65,658	64,351	64,351	64,351	64,351

This table presents estimates of linear probability models of losing the job and wage growth between the first quarter of 2020 and 2021, as a function of predetermined variables. Observations are at the household level and only include households employed by a single employer during the first quarter of 2020. In columns (1)-(4) the dependent variable is the difference between a dummy variable that takes the value of one if the household receives no wage payment, comparing the dummy variable value during 2021:Q1 relative to 2020:Q2. In columns (5)-(8), the dependent variable corresponds to the household wage growth between 2020:Q2 and 2021:Q1. *Forbearance* is a dummy variable that takes the value of one for households receiving forbearance and zero otherwise. *Eligible* is a dummy variable that takes the value of one if the household satisfied the legal requirements for suspending mortgage payments. In all specifications, the regressions include pre-pandemic controls such as age, total income, total deposits, credit card and overdraft balances, mortgage loan balance, balances for loans held at other banks, and debt payment. We also control for employment risk by including a private sector dummy that takes the value of one if the household's employer in the first quarter of 2020 operated in the private sector, and a measure of employer's industry volatility, computed as the standard deviation of sales at the industry level and for the previous thee years, normalized by the industry's total assets. Robust standard errors are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 2.B.3: Household Consumption Growth: Sample and Population

	Sample	Population
2019	7.2%	4.2%
2020	-4.1%	-4.7%
2021	14.8%	13.8%

This table shows the annual growth rate of consumption for the average household in our sample and the corresponding statistic for the population. The population average is the yearly growth rate of the average consumption by all resident households, measured as the final consumption expenditure divided by the number of households. National accounts data are from INE.

Table 2.B.4: Household Propensities to Consume and Save in Deposits: Robustness

	ΔConsumption			ΔSaving in Deposits		
	(1)	(2)	(3)	(4)	(5)	(6)
Forbearance Amount × Post	0.167***	0.150***	0.159***	0.282***	0.298***	0.294***
	(0.024)	(0.028)	(0.027)	(0.030)	(0.040)	(0.041)
ΔIncome	0.091***	0.086***	0.085***	0.701***	0.694***	0.695***
	(0.003)	(0.003)	(0.003)	(0.007)	(0.009)	(0.009)
Group × Month × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Household × Month FE	Yes	No	No	Yes	No	No
Industry × Month FE	No	Yes	No	No	Yes	No
Municipality × Month FE	No	No	Yes	No	No	Yes
R^2	0.423	0.103	0.107	0.508	0.158	0.159
Observations	6,181,335	6,180,996	6,181,335	6,043,972	6,043,639	6,043,972

This table presents difference-in-differences estimates of regressions of changes in monthly consumption and saving in total deposits using the difference-in-differences regression in equation (2.1) at the household-month level. The dependent variable in columns (1)-(3), $\Delta Consumption$, is the difference between monthly spending at time t, relative to the corresponding household average in 2019. The dependent variable in columns (4)-(6), $\Delta Saving\ in\ Deposits$, is the monthly saving in total deposits at time t, relative to the corresponding household average in 2019. *Forbearance Amount* is the amount of postponed debt payments. *Post* is a dummy variable that takes a value of one for the period starting when mortgage payments are suspended and zero otherwise. Specifications in columns (2), (3), (5), and (6) include the *Forberance* dummy variable as a control variable. All specifications include group-month-year fixed effects, with group referring to quartiles of pre-pandemic deposits and income (2019 averages), and changes in total income relative to the corresponding household average in 2019 as a control. In columns (2) and (5) we define industry as the two-digit industry code of the primary employer, in case of employed households; and for non-employed households, the current status (either unemployed or retired). The sample period is from January 2018 to September 2021. Two-way standard errors clustered by household and month-year are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

TABLE 2.B.5: Household Propensities to Consume and Save in Deposits by Horizon: Sample of Individuals Working in the Private Sector

	ΔConsumption			ΔSaving in Deposits		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Overall					
Forbearance Amount × Post	0.129***	0.110***	0.131***	0.061	0.120**	0.302***
	(0.045)	(0.040)	(0.038)	(0.079)	(0.058)	(0.059)
ΔIncome			0.085***			0.711***
			(0.003)			(0.010)
	Panel B: Horizons					
Forbearance Amount ×						
Immediate Effect (1m-3m)	0.020	-0.032	0.013	-0.192*	0.015	0.396***
	(0.049)	(0.040)	(0.039)	(0.098)	(0.049)	(0.054)
Short-run Effect (4m-12m)	0.136***	0.116***	0.137***	0.090	0.117*	0.294***
	(0.044)	(0.037)	(0.036)	(0.093)	(0.069)	(0.065)
Long-run Effect (>12m)	0.175***	0.175***	0.185***	0.151	0.180**	0.262***
	(0.045)	(0.038)	(0.036)	(0.123)	(0.084)	(0.077)
ΔIncome			0.085***			0.711***
			(0.003)			(0.010)
Month × Year FE	Yes	No	No	Yes	No	No
Group × Month × Year FE	No	Yes	Yes	No	Yes	Yes
R^2	0.062	0.086	0.106	0.017	0.026	0.170
Observations	2,246,175	2,246,175	2,246,175	2,196,260	2,196,260	2,196,260

This table presents difference-in-differences estimates of regressions of changes in monthly consumption and saving in total deposits using the difference-in-differences regression in equation (2.1) at the household-month level. Panel A considers a single *Post* indicator, while in Panel B this indicator is replaced with three different time dummy variables: the *Immediate Effect* measures the impact over the first quarter after the start of forbearance; the *Short-run Effect* measures the average effect from the 4^{th} to the 12^{th} month; and the *Long-run Effect*, measures the average effect after one year. The dependent variable in columns (1)-(3), $\Delta Consumption$, is the difference between monthly spending at time t, relative to the corresponding household average in 2019. The dependent variable in columns (4)-(6), $\Delta Saving\ in\ Deposits$, is the monthly saving in total deposits at time t, relative to the corresponding household average in 2019. *Forbearance Amount* is the amount of postponed debt payments. *Post* is a dummy variable that takes a value of one for the period starting when mortgage payments are suspended and zero otherwise. All specifications include the *Forberance* dummy variable as a control variable. In some specifications, the regressions include group-month-year fixed effects, with group referring to quartiles of pre-pandemic deposits and income (2019 averages), and changes in total income relative to the corresponding household average in 2019 as a control. The sample is restricted to households whose primary employer in the first quarter of 2020 is in the private sector. The sample period is from January 2018 to September 2021. Two-way standard errors clustered by household and month-year are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 2.B.6: Household Propensity to Borrow by Eligibility and Forbearance Status

	ΔBorrowing Credit Card & Overdraft			ΔBorrowing Other Banks' Debt		
	(1)	(2)	(3)	(4)	(5)	(6)
Debt Payment ×						
Forbearance=0 × Eligible=1 × Post	0.002	0.001	-0.000	0.014	0.033*	0.039**
	(0.009)	(0.008)	(0.007)	(0.017)	(0.017)	(0.017)
Forbearance=1 × Eligible=0 × Post	-0.011	-0.011	-0.012	-0.051*	-0.029	-0.028
	(0.012)	(0.009)	(0.009)	(0.028)	(0.027)	(0.027)
Forbearance=1 × Eligible=1 × Post	0.000	-0.000	-0.004	-0.109*	-0.080	-0.067
	(0.018)	(0.017)	(0.017)	(0.054)	(0.054)	(0.054)
Controls	No	No	Yes	No	No	Yes
Month × Year FE	Yes	No	No	Yes	No	No
Group × Month × Year FE	No	Yes	Yes	No	Yes	Yes
R^2	0.012	0.021	0.023	0.002	0.003	0.005
Observations	6,043,972	6,043,972	6,043,972	4,395,616	4,395,616	4,395,616
Observations:						
Forbearance=0 × Eligible=0	116,732					
% of sample	*(85.0%)*					
Forbearance=0 × Eligible=1	12,469					
% of sample	*(9.1%)*					
Forbearance=1 × Eligible=0	6,637					
% of sample	*(4.8%)*					
Forbearance=1 × Eligible=1	1,525					
% of sample	*(1.1%)*					

This table presents difference-in-differences estimates of regressions of changes in credit card and overdraft, and other banks' debt payments using the difference-in-differences regression in equation (2.1) at the household-month level. The dependent variable in columns (1)-(3), ΔBorrowing Credit Card & Overdraft, is the difference in monthly changes in end-of-the-month credit card and overdraft balances at time t at the bank, relative to the corresponding household average in 2019. The dependent variable in columns (4)-(6), ΔBorrowing Other Banks' Debt, is the difference between monthly changes in liabilities found in the Credit Register held at other banks at time t, relative to the corresponding household average in 2019. *Debt Payment* is the amount of pre-pandemic debt payments made by households. *Forbearance* is a dummy variable that takes the value of one for households receiving forbearance and zero otherwise. *Eligible* is a dummy variable that takes the value of one if the household satisfied the legal requirements for suspending mortgage payments. *Post* is a dummy variable that takes a value of one for the period starting when mortgage payments are suspended and zero otherwise. All specifications include the *Forberance* dummy variable as a control variable. In some specifications, the regressions include group-month-year fixed effects, with group referring to quartiles of pre-pandemic deposits and income (2019 averages), and changes in total income relative to the corresponding household average in 2019 as a control. The sample period in columns (1)-(3) is from January 2018 to September 2021. The sample period in columns (4)-(6), due to data limitations, is from January 2019 to September 2021. Two-way standard errors clustered by household and month-year are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 2.B.7: Household Propensity to Consume by Category and by Eligibility and Forbearance Status

	(1) Total	(2) Groc.	(3) Cloth.	(4) House Maint.	(5) Furnit.	(6) Transp.	(7) Health Care	(8) Restau.	(9) Entert. & Educ.	(10) Misc.
Debt Payment ×										
Forbearance=0 × Eligible=1 × Post	-0.160***	0.005	-0.007*	0.001	-0.002	-0.028***	-0.010***	-0.023***	-0.015***	-0.065***
	(0.023)	(0.006)	(0.003)	(0.002)	(0.003)	(0.006)	(0.003)	(0.006)	(0.004)	(0.012)
Forbearance=1 × Eligible=0 × Post	0.121***	0.062***	0.015***	0.005***	0.007**	0.003	0.009**	0.003	0.013***	0.008
	(0.032)	(0.007)	(0.004)	(0.002)	(0.003)	(0.006)	(0.003)	(0.007)	(0.004)	(0.014)
Forbearance=1 × Eligible=1 × Post	0.016	0.055***	0.014*	0.004	0.004	0.029**	-0.005	-0.015	-0.006	-0.040
	(0.053)	(0.012)	(0.007)	(0.004)	(0.006)	(0.010)	(0.007)	(0.012)	(0.010)	(0.031)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Group × Month × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.095	0.028	0.049	0.007	0.010	0.043	0.010	0.067	0.018	0.036
Observations	2,884,623	2,884,623	2,884,623	2,884,623	2,884,623	2,884,623	2,884,623	2,884,623	2,884,623	2,884,623

This table presents difference-in-differences estimates of regressions of changes in monthly consumption for different spending categories using the difference-in-differences regression in equation (2.1) at the household-month level. The dependent variable is measured as the difference between monthly spending at time t, relative to the corresponding household average in January and February of 2020, for each consumption category: (1) Total Consumption; (2) Groceries; (3) Clothing; (4) Housing Maintenance and Utilities; (5) Furniture; (6) Transport; (7) Health Care; (8) Restaurants; (9) Entertainment and Education; and (10) Miscellaneous Goods and Services. *Debt Payment* is the pre-pandemic amount of debt payments of each household. *Forbearance* is a dummy variable that takes the value of one for households receiving forbearance and zero otherwise. *Eligible* is a dummy variable that takes the value of one if the household satisfied the legal requirements for suspending mortgage payments. *Post* is a dummy variable that takes a value of one for the period starting when mortgage payments are suspended and zero otherwise. All specifications include the *Forberance* dummy variable as a control variable. In all specifications, the regressions include group-month-year fixed effects, with group referring to quartiles of pre-pandemic deposits and income (2019 averages), and changes in total income relative to the corresponding household average in January and February 2020 as a control. The sample period is from January 2020 to September 2021. Two-way standard errors clustered by household and month-year are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

TABLE 2.B.8: Household Propensity to Consume on Exit by Category

	(1) Total	(2) Groc.	(3) Cloth.	(4) House Maint.	(5) Furnit.	(6) Transp.	(7) Health Care	(8) Restau.	(9) Entert. & Educ.	(10) Misc.
Forbearance Amount ×										
Immediate Effect (1m-3m)	-0.030	0.036***	0.004	0.005**	0.003	-0.009	-0.000	-0.025***	-0.002	-0.026*
	(0.039)	(0.007)	(0.004)	(0.002)	(0.004)	(0.008)	(0.003)	(0.005)	(0.004)	(0.015)
Short-run Effect (4m-12m)	0.093***	0.058***	0.015***	0.004**	0.005**	0.005	0.008**	-0.003	0.010**	0.002
	(0.025)	(0.006)	(0.003)	(0.002)	(0.002)	(0.005)	(0.003)	(0.007)	(0.004)	(0.013)
Long-run Effect (>12m)	0.167***	0.061***	0.020***	0.005***	0.009***	0.020***	0.008**	0.017**	0.013**	0.017
	(0.026)	(0.006)	(0.003)	(0.002)	(0.003)	(0.005)	(0.003)	(0.006)	(0.005)	(0.015)
Exit Effect	0.070**	0.021***	0.014***	0.003**	0.001	0.007	0.004	0.001	0.004	0.016
	(0.027)	(0.006)	(0.004)	(0.002)	(0.002)	(0.005)	(0.003)	(0.006)	(0.004)	(0.016)
ΔIncome	0.085***	0.008***	0.004***	0.001***	0.003***	0.007***	0.003***	0.006***	0.004***	0.031***
	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Group × Month × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.087	0.029	0.044	0.006	0.010	0.037	0.009	0.053	0.015	0.037
Observations	4,120,890	4,120,890	4,120,890	4,120,890	4,120,890	4,120,890	4,120,890	4,120,890	4,120,890	4,120,890

This table presents difference-in-differences estimates of regressions of changes in monthly consumption for different spending categories using the difference-in-differences regression in equation (2.1) at the household-month level, but replacing the *Post* indicator with four different time dummy variables: the *Immediate Effect* measures the impact over the first quarter after the start of forbearance; the *Short-run Effect* measures the average effect from the 4^{th} to the 12^{th} month; the *Long-run Effect* measures the average effect after one year and until the end of the payment suspension; and the *Exit Effect* measures the average effect after the end of the payment suspension. The dependent variable is measured as the difference between monthly spending at time t, relative to the corresponding household average in January and February of 2020, for each consumption category: (1) Total Consumption; (2) Groceries; (3) Clothing; (4) Housing Maintenance and Utilities; (5) Furniture; (6) Transport; (7) Health Care; (8) Restaurants; (9) Entertainment and Education; and (10) Miscellaneous Goods and Services. *Forbearance Amount* is the amount of postponed debt payments. In all specifications, the regressions include group-month-year fixed effects, with group referring to quartiles of pre-pandemic deposits and income (2019 averages), and changes in total income relative to the corresponding household average in January and February 2020 as a control. The sample period is from January 2020 to June 2022. Two-way standard errors clustered by household and month-year are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

3

Capital Structure and Employee Consumption

3.1 Introduction

Financial leverage can impose significant costs on employees by increasing the likelihood of corporate bankruptcy. These costs include the immediate loss of income, which leads to economically significant reductions in consumption (Gruber, 1997), as well as nonpecuniary distress costs associated with unemployment spells (Oswald, 1997; Helliwell, 2003). Moreover, the costs of corporate bankruptcy for employees far exceed those endured during unemployment, as the destruction of firm-specific human capital results in persistent income losses for the displaced workers.[1]

The existing literature studying the effect of financial leverage on wages is inconclusive regarding the question of whether employees care about leverage and firm risk. The key issue with prior analyses is that at least two opposing effects operate: while leverage increases the risk borne by employees, it also raises the bargaining power of the firm when setting wages. The dominant force then depends on the specific model and/or empirical setting.[2] Additionally, selection effects hamper the analysis. For instance, highly lever-

[1] Graham et al. (2023) estimate the present value of lost earnings to be around 87% of pre-bankruptcy annual pay. Davis and Von Wachter (2011) relate these costs to the business cycle and show that men lose an average of 1.4 years of pre-layoff earnings in normal times, increasing to 2.8 years during recessions.

[2] For example, two recent studies looking at public firms in the United States find opposing results: Michaels, Beau Page and Whited (2019) suggest that employer leverage depresses wages,

aged firms may, on average, employ more low-skill employees (Qian, 2003), or there may be equilibrium matching between more risk-averse workers and low-leverage firms (Berk, Stanton and Zechner, 2010; He et al., 2022), resulting in different bargaining outcomes.

I show how firm leverage affects employee consumption and saving behaviors, where theory offers a clear prediction: employees in riskier, more leveraged firms are expected to increase precautionary savings. I address this question using transaction-level data provided by a leading Portuguese bank and merged with employers' financial variables, providing granular data about firm risk, employer-employee matching, and employee consumption and saving patterns. I find that workers recognize firm risk *ex ante*: those employed by highly leveraged firms exhibit lower marginal propensities to consume (MPC). Taken together, the evidence suggests that financial distress costs are partially borne by employees, who optimally cut consumption to hedge their exposure to firm risk.

The effect of leverage on the MPC holds both across households and *within* households. To further mitigate concerns about omitted variables, I show that these results are robust to the inclusion of industry-by-year and employer fixed effects. Notably, these results hold even *within* employment-spell, where two-sided selection bias is less of a concern. Using the interquartile range of the leverage ratio, the results indicate that the marginal propensity to consume falls by about 3% (7% between the top and bottom deciles). Consistently, this behavior leads employees to deleverage by increasing liquid saving. Given that pay is a major determinant of employee motivation (Rynes, Gerhart and Minette, 2004), which together with job security constitutes one of the most important job characteristics from the employees' perspective (Clark, 2001), these results suggest that the use of leverage can lead to lower employee motivation, arguably imposing an additional cost on the firm.

The overall average effect on consumption conceals an important degree of heterogeneity, driven by household and employer characteristics. Specifically, the consumption response is substantially greater for low-wealth households. Additionally, since the costs faced by employees depend not only on the probability of employer bankruptcy but also

while Graham et al. (2023) find a wage premium for highly leveraged firms.

on the "loss given default," the decrease in the propensity to consume is more pronounced among employees working in more volatile industries and in slack labor markets. These findings suggest that households are particularly sensitive to their employers' indebtedness when the consequences of unemployment are more severe or the expected separation rate is higher. Due to data limitations, I do not propose specific channels through which information about financing decisions flows from employers to households. However, I document that the sensitivity of consumption to leverage is much stronger for households working in publicly listed companies, where information asymmetries tend to be lower due to financial disclosure requirements. As such, informational frictions may impose further costs on uninformed households, who are unable to optimally adjust for firm risk.

I further decompose the overall average effect by examining how leverage influences the household consumption basket. Interestingly, the effect is driven by non-essential, or "luxury," goods and services. Specifically, I find a significant and negative effect for clothing, dining out, and transportation expenditures, all of which have been associated with an income elasticity above one.[3] On the other hand, the effect is negligible for groceries, health care, and housing maintenance or utility expenditures. In an external validity exercise using data at the municipality level, I show that the turnover of the luxury goods and services sector is negatively correlated with the leverage of companies in the non-luxury sector. Additionally, evidence suggests that leverage helps to propagate regional shocks: whenever nearby municipalities experience a productivity shock, the luxury sector suffers, but only if companies in those municipalities are highly leveraged. The consumption response then suggests a new channel through which costs of financial distress spill over to other, potentially unrelated firms: the "employee-spending channel".

To rule out alternative explanations, I examine the possibility that households working for high-leverage firms are compensated for such risk through higher wages. I find a negative relationship between wages and employer leverage. Thus, households working for high-leverage firms exhibit lower propensities to consume, although in my sample they earn *less*–which would predict a higher MPC out of income. Additionally, I find

[3] See, for example, Clements, Wu and Zhang (2006) and Clements et al. (2020).

that the impact of imperfect risk-sharing between firms and employees is not limited to consumption or saving decisions but also extends to employment choices. Specifically, I show that households also react with their feet: those employed by highly leveraged firms are more likely to leave their jobs, even after accounting for the increased likelihood of these firms going bankrupt. While I do not directly observe the underlying motive for job termination, patterns in future income and unemployment benefits are consistent with higher voluntary and involuntary termination rates.

Even though these results suggest that leverage and firm risk are associated with lower consumption, the endogeneity of leverage is a potential concern (as it could bias these findings in either direction). To address these concerns, I propose a "quasi-experiment" in which I identify industry-wide negative shocks to sales. The idea of this setting is that while the average firm faces economic distress, highly leveraged firms also suffer financial distress, in the spirit of Opler and Titman (1994). I find that following such industry-wide shocks, only households working for high-leverage firms cut consumption, although there is no differential effect on wages. The effect on consumption is both statistically and economically significant, implying that, following a negative sales shock to their employer, households working for firms with above-median leverage cut their consumption by 3 percentage points more relative to other households working in low-leverage firms.

To better understand the economic mechanisms behind these empirical findings, I propose a matching model with two-sided heterogeneity where wages are determined by a Nash bargaining procedure, in the spirit of Bils, Chang and Kim (2011). Specifically, the model rationalizes apparently inconsistent empirical findings, notably (1) high-leverage firms paying lower wages and (2) employees working at such firms displaying lower MPC. The literature has identified two main channels through which leverage determines wages. On the one hand, within the scope of the implicit contract model (Baily, 1974; Azariadis, 1975), the risk-neutral employer plays the role of providing insurance to risk-averse employees, insulating them from adverse wage and employment shocks. As such, unemployment risk should drive wage premia, as workers demand compensation for limited risk-sharing with their employer (Abowd and Ashenfelter, 1981; Topel, 1984; Hamermesh and Wolfe, 1990). As leverage increases the probability of firm failure, employees effectively pay for insurance–lower employer leverage–by accepting a wage discount (Berk, Stanton and Zechner, 2010) and ultimately a positive relation between leverage and wages should be observed.

On the other hand, financial constraints might be used strategically by employers to limit the bargaining power of workers.[4] For instance, using the state-level adoption of right-to-work laws and changes in the unemployment insurance system in the United States as exogenous variation in union bargaining power, Matsa (2010) finds a positive relation between union power and financial leverage. In a related study, using a comprehensive panel of publicly listed firms from 29 countries, Ellul and Pagano (2019) provide evidence that firms respond to higher workers' bargaining power by increasing leverage. Michaels, Beau Page and Whited (2019) find a negative correlation between leverage and employee pay and propose a dynamic model of labor and capital in which leverage restricts wages through bargaining.

In my model, risk-averse workers exhibit heterogeneous job-match quality, savings levels, and relative risk aversion. To the best of my knowledge, I am the first to endogenously determine the matching process between risk-averse workers and leveraged firms.[5] Job-match quality is then subject to exogenous shocks, which might lead either the firm or the employee to terminate the match. Part of this risk is treated as idiosyncratic and workers cannot insure against it, besides boosting their savings to ensure consumption smoothing. Consequently, the model partially replicates the dynamics proposed by Berk, Stanton and Zechner (2010), where risk-neutral firms pay a premium for losses incurred by the risk-averse workers in case of separation. On the other hand, potential employers differ in their leverage ratio, with leverage acting as a counterweight to the risk-sharing mechanism. In my model, leverage decreases pledgeable cash flows to workers and thus

[4] Several papers have explored the idea of firms using capital structure as a bargaining tool. For early contributions, see, for example, Baldwin (1983), Dasgupta and Sengupta (1993), and Perotti and Spier (1993); and, more recently, Matsa (2010) and Michaels, Beau Page and Whited (2019).

[5] In a related model, Liu (2019) proposes a matching model assuming risk neutrality, where the focus is on capital structure choices. In contrast, my model focuses on worker responses, where risk aversion and precautionary savings are central.

has a depressing effect on wages through the bargaining procedure. When I calibrate the model to replicate stylized facts of the Portuguese economy, these bargaining frictions introduce a wage discount from using leverage. Interestingly, even though workers at high-leverage firms are paid less, they optimally choose to lower consumption and increasingly do so when unemployment is particularly painful–i.e., when households are relatively uninsured. As such, the model theorizes that the aggregate effect of leverage on consumption is mainly driven by low-wealth households, which resonates with my own empirical findings.

My paper contributes to several strands of the literature. First, I complement the emerging literature studying the impact of capital structure on employees and labor markets.[6] While mixed evidence has been found for the effect of leverage on wages (Chemmanur, Cheng and Zhang, 2013; Akyol and Verwijmeren, 2013; Agrawal and Matsa, 2013; Michaels, Beau Page and Whited, 2019; Graham et al., 2023; Dore and Zarutskie, 2023; Gill, Choi and John, 2024), recent empirical findings suggest that employees perceive financial distress and recognize this source of risk. Such knowledge seems to be prevalent not only among insiders, who react to their employer's credit deterioration by increasing networking activity (Gortmaker, Jeffers and Lee, 2022), but also among outsiders, who can reasonably perceive an employer's financial strength (Brown and Matsa, 2016). Baghai et al. (2021) find that this effect may be more pronounced for top talent, who, following an exogenous export shock, are more likely to abandon the firm–but only if the employer is highly leveraged. My paper contributes to this literature by showing that employees react to employment risk by reducing spending and insuring themselves through precautionary saving.

Second, I complement the literature on income risk and household saving by examining how capital structure affects precautionary saving behavior. Kantor and Fishback (1996) examine how the introduction of workers' compensation for workplace accidents crowded out private insurance and led to a decline in precautionary savings. While the

[6] Although I focus on compensation and leverage, the latter might affect employee welfare through alternative channels such as workplace safety investments (Cohn and Wardlaw, 2016).

empirical literature has found mixed evidence on the importance of precautionary saving,[7] Fuchs-Schündeln and Schündeln (2005) suggest that self-selection of risk-averse workers into low-risk jobs may result in underestimating the importance of precautionary saving. In a related paper, Alfaro and Park (2020) measure the impact of volatility in employers' stock returns on employee spending. While their results highlight a strong link between employer stock-level volatility and labor income risk, I extend their findings by showing how financial leverage may amplify this channel.

Third, though the focus of my paper is on the employees' response to financial leverage, it is also related to the literature on the indirect costs of financial distress (Titman, 1984). While these indirect costs are difficult to measure, previous evidence suggests they are greater than direct ones, manifesting through the loss of customers (Opler and Titman, 1994; Hortaçsu et al., 2013; Custódio, Ferreira and Garcia-Appendini, 2023), suppliers (Sautner and Vladimirov, 2017), and through fire sales of firms' assets (Pulvino, 1998). Additionally, there is evidence that the loss of human capital and its impact on employee pay are also an important component of the indirect costs of financial distress (Graham et al., 2023). I contribute to this literature by providing evidence that financial distress costs are partially shifted to employees, who are paid less and have to cut back on their consumption.

Finally, I present a novel channel through which financial distress costs spill over to other firms in potentially unrelated industries, namely those associated with non-essential goods and services. While previous work has focused on the transmission of shocks through input-output linkages (Acemoglu et al., 2012; Barrot and Sauvagnat, 2016) or financial networks (Allen and Gale, 2000; Acemoglu, Ozdaglar and Tahbaz-Salehi, 2015), my results show how idiosyncratic shocks can propagate across the economy through employee-consumer networks, even if no supply chain or centralized borrowing/lending entity is shared between firms or sectors.

[7] See, for example, Dynan (1993) for evidence of no significant effect and Carroll and Samwick (1997, 1998) for evidence of a precautionary saving motive of households.

3.2 Data

This data set consists of household-employer pairs, covering clients with an outstanding mortgage loan at a large Portuguese bank, from January 2018 to June 2022. As in prior work (Adelino, Ferreira and Oliveira, 2024), the sample is restricted to households who (1) regularly use this bank's accounts through either credit or debit cards for making purchases and payments (requiring a minimum average of 10 payments per month); and (2) choose direct deposit of wages, which is crucial in identifying the households' employers. The final sample is restricted to households in which at least one member is employed–either in the private or public sector–at any point during the sample period.

From the perspective of the household, I can partially describe the asset side of their balance sheet by observing the end-of-month balances for all checking and savings accounts held at the bank. Moreover, I observe transaction-level data for all payments and purchases made using a credit or debit card at this bank, as well as cash withdrawals. Conversely, I observe the complete liability side of the household balance sheet. From the bank's internal information, I have data about household liabilities with this bank, including outstanding debt, interest rate, date of origination, maturity, and monthly installments. Additionally, from the Portuguese Credit Register, managed by the Bank of Portugal, I obtain data on outstanding debt for loans held at other financial institutions, providing a full picture of household liabilities.

In addition to tracking payments and purchases, the data also include all inbound Single Euro Payments Area (SEPA) transfers. Since all households in the original sample hold an outstanding mortgage at this bank and are offered a reduction in the interest rate spread if they request direct deposit of their wages at the bank, I observe a large number of wage payments. Furthermore, by making use of the transfer description–namely, the name of the entity ordering the SEPA transfer–I can match each transfer to the universe of companies operating in Portugal. To achieve this, I apply the Levenshtein Distance string metric to compare the name of the entity to the names of all companies operating in Portugal, validating its accuracy through multiple random manual checks.

Having identified the name and thus the unique tax identifier of each employer, I then use the firm-level database SABI INFORMA (Sistema de Análisis de Balances Ibéricos), provided by Bureau van Dijk. The database contains detailed accounting data from IES (*Informação Empresarial Simplificada*), allowing me to retrieve accounting measures for every employer found.

3.2.1 Household Statistics

Panel A of Table 3.A.1 presents a summary of the main household-level variables for the final sample, which includes approximately 87 thousand households. This sample consists of all households with a valid employer match during the sample period, whether in the public or private sector.

The average household is composed of 1.7 members and has a monthly consumption expenditure of about 1,615 euros. This measure includes all purchases and payments made using the bank's credit or debit cards, including cash withdrawals. Table 3.B.1 in the Internet Appendix shows that households whose main wage earner is employed in the public sector consume around 150 euros more than those working for the private sector. Additionally, within the latter group, those working for firms in the bottom quintile of leverage appear to consume about 90 euros less compared to households working for firms in the top quintile of the leverage distribution.

The average household income is about 2,170 euros per month, and the average monthly wage is approximately 1,860 euros. These figures are slightly above the after-tax average household income at the national level, which in 2019 amounted to 1,800 euros per month. This sample of borrowers differs from the average Portuguese household, as I am focusing on homeowners with mortgages. This group represented about 30% of all Portuguese households in 2021,[8] and earns on average higher wages than the remaining Portuguese population (Xerez, Pereira and Cardoso, 2019). Households working in the public sector earn significantly higher wages–about 270 euros more per month–and about 490 euros more in total income, as shown in Table 3.B.1. Within the private sector, those

[8] INE (*Instituto Nacional de Estatística*), Population and housing census 2021.

working for the most leveraged firms earn about 100 euros less in wages, compared to households working for the least leveraged firms (a similar difference is observed in total household income).

While I am able to capture a significant fraction of monthly household income and consumption, I do not observe outbound SEPA transfers or wealth held at other financial institutions. As such, measures of saving are noisier in my sample when compared to consumption and income. Nonetheless, these households hold, on average, 6,700 euros in net liquid assets, i.e., checking account balance net of outstanding credit card and overdraft debt. About 67% of households have a savings account at this bank, holding about 17.9 thousand euros on average, conditional on having this type of account. Looking at liabilities, households have on average a mortgage balance of 73.6 thousand euros. Only a small fraction of households hold auto or student loans (about 1%), or personal loans (about 7%). Conditional on having auto or student loans, these households have an outstanding balance of about 7 thousand euros; and conditional on having personal loans, their outstanding balance is about 6.4 thousand euros. However, around 71% of households have loans with other banks, with an average outstanding balance of about 10.7 thousand euros (although the median is much lower, at about 3.2 thousand euros).

As before, households working for the public sector carry higher levels of savings and liquid assets and hold higher credit card balances. Notably, they have lower outstanding mortgage balances, partially explained by the fact that these households are, on average, four years older than households working in the private sector. Furthermore, those working for more leveraged firms carry about 650 euros less in net liquid assets when compared to the households working for firms in the bottom quintile of leverage, and have a lower outstanding mortgage balance, at about 5 thousand euros. I also introduce a measure of debt payment-to-income, corresponding to the ratio between the monthly debt payments made by the household and their total income, which stands at around 14%. Finally, about 45% of households in this sample work for a state-owned company or institution.[9]

[9] This is a significantly higher fraction compared to the national average, which stands at about 15%. This fact is explained by the selection of the sample, which only includes households with an outstanding mortgage—who were consequently selected by a lender according to their ability

3.2.2 Firm Statistics

Panel B of Table 3.A.1 reports the financial characteristics of in-sample firms. Sample statistics are reported for the variables used either as controls or in defining subsamples for empirical tests, following previous literature on the effect of leverage on wage determination (see, for example, Akyol and Verwijmeren (2013) or Graham et al. (2023)). I compute a measure of industry volatility at the three-digit industry code level, given by the standard deviation of sales over the previous three years, normalized by the industry's total book assets. The leverage ratio corresponds to total (current and non-current) debt financing, net of cash holdings, normalized by book assets. Profitability is the return on assets, given by net income divided by total assets, and tangibility is the ratio between fixed assets and total assets. Finally, I define employee productivity as sales divided by the number of employees, and average employee expenses as total wage bills divided by the number of employees. While I mostly focus my analysis on the observed employers (the "in-sample" firms), in some robustness checks I extend the analysis to include all Portuguese firms (including "out-of-sample" firms).

Since I include lagged variables as controls in my empirical design, the sample of firms runs from 2015 to 2022.[10] Financial firms are excluded from the sample (CAE codes 64 to 66), as well as any firm observations with a negative book value of assets or negative value of sales. The average employer has book assets of about 11.3 million euros, though the median employer is much smaller, at about 1.8 million euros. Annual turnover for the average firm is about 9.8 million euros, resulting in a net income of about 380 thousand euros. The average employer is thus a medium-sized firm, employing about 75 workers in 2019, while the median one would be a small-sized firm, employing about 24 workers. The average total debt is about 2.4 million euros (6.7 million euros in total liabilities), costing on average about 77 thousand euros in interest payments per year. Employee productivity is measured at about 145 thousand euros of generated sales

to meet debt payments, namely, by considering their income risk—and the market positioning of this particular bank.

[10] For some aggregate tests, I further expand this sample to include all fiscal years starting in 2012 and ending in 2022.

per worker, and firms face an average annual wage bill of about 22 thousand euros per worker.

Table 3.B.2 in the Internet Appendix presents these averages while splitting in-sample firms according to the quintile of the leverage distribution to which they belong. Highly leveraged firms, defined as those belonging to the top quintile of leverage, are, on average, larger in asset value than those belonging to the bottom quintile. Highly leveraged firms are also less profitable, exhibit higher tangibility of assets, and generally pay less to employees.

As most comparable studies focus on U.S. publicly held firms, it is instructive to compare in-sample firms with the standard data set for such U.S.-focused studies. Figure 3.B.1 presents the distribution of in-sample firms, *vis-à-vis* the distribution of Compustat firms.[11] As expected, these households' employers are much smaller than most Compustat firms with respect to book assets (the average US public firm has book assets of about 4.2 billion euros, as opposed to about 11.3 million euros for in-sample firms). Companies in-sample also use less leverage, as defined above (average of 11% for firms in-sample versus 33%).[12] Additionally, they are more profitable (0% versus -31%) and exhibit higher tangibility of assets (about 26% versus 22%). However, these in-sample employers are larger when compared to the remaining universe of Portuguese firms, as the average firm in the latter has about 510 thousand euros in book assets. As shown in Figure 3.B.3, not only are in-sample firms larger than the country average, but they are also more leveraged, more profitable, and have higher tangibility of assets.

3.3 Empirical Methodology

I begin by testing whether households working for more leveraged firms adjust their consumption and saving decisions. I use a monthly panel and define the primary employer

[11] To construct this sample, all firms from the Compustat Fundamentals data set in 2018 are included. Firms with negative book assets or negative turnover are excluded, as well as firms operating in the financial sector (SIC codes 6000 to 6999) and utilities (SIC codes 4900 to 4999).

[12] Figure 3.B.2 shows the median leverage ratio at the industry level for both Compustat firms and in-sample firms, demonstrating that differences in levels also reflect substantial industry and institutional differences.

by considering the main source of income over the previous quarter. I then focus on two outcome variables: the household consumption expenditure and the change in net liquid assets. In particular, to describe household behavior, I estimate marginal propensities to consume and save, using the following baseline specification:

$$\begin{aligned} Y_{h,e,t} &= \beta_0 Income_{h,t} + \lambda Income_{h,t} \times Leverage_{e,t-12} \\ &\quad + \beta_1 Income_{h,t} \times Z_{e,t-12} + \mu_h + \nu_t + \varepsilon_{h,e,t}, \end{aligned} \tag{3.1}$$

where $Y_{h,e,t}$ is consumption or change in net liquid assets for household h, working for employer e at date t. To estimate their marginal propensities, I am primarily interested in how coefficient β_0 changes while working for a relatively more leveraged firm, an effect measured by coefficient λ. As such, the main explanatory variable is the interaction between income and the lagged leverage ratio, computed as total debt, net of cash, to book assets, capturing the sensitivity of employee wages to the employer's financial leverage.[13]

I also include in this specification the interaction between income and a set of additional controls for the employer, denoted by $Z_{e,t-12}$. This vector includes other lagged explanatory variables used in previous empirical studies (Akyol and Verwijmeren, 2013), namely, the natural logarithm of the employer's book assets, to account for a potential large-firm wage premium; the employer's profitability, which should capture surplus to be shared with employees; tangibility, which by working as a proxy for capital-intensity may be correlated with the probability of bankruptcy (Berk, Stanton and Zechner, 2010); the average employee productivity, to account for the possibility that more productive workers are paid more; and the industry volatility measured in the three previous years, which by being correlated to the worker's willingness to bear risk may determine consumption and saving decisions.

While I do not observe education levels in the data, in some specifications I include household fixed effects (μ_h) to absorb time-invariant characteristics of the household. I also include month-year fixed effects (ν_t) to control for common shocks affecting all

[13] I exclude the main effect of leverage from this specification, as my focus is on changes in the marginal propensity to consume/save, rather than the nonlinearities in MPC/MPS. Nonetheless, applying a first-difference transformation yields similar results, which I further validate using the simulated data set.

households. Finally, in more stringent specifications, I include industry-by-year, employer, and employer-by-household fixed effects to mitigate further concerns about omitted industry or employer-level variables.

To address whether households working for relatively more leveraged firms receive higher wages, I compute the net wage paid by the household's primary employer over each calendar year and use this measure as the outcome variable in the following baseline specification:

$$Log(Earnings)_{h,e,y} = \lambda Leverage_{e,y-1} + Z_{e,y-1} + \nu_y + \varepsilon_{h,e,y}, \tag{3.2}$$

where the unit of observation is at the household-year level, with household h, working for employer e at year y.

To explore how households react to an industry-wide revenue shock, which constitutes an arguably exogenous shock, I also employ a difference-in-differences regression to compare consumption and wages. In particular, I consider the following baseline specification:

$$\begin{aligned} Y_{h,e,i,t} &= \lambda High\ Leverage_{e,t-12} \times Industry\ Shock_{i,t} + \beta_0 High\ Leverage_{e,t-12} \\ &\quad + \beta_1 Industry\ Shock_{i,t} + Z_{e,t-12} + \mu_h + \nu_{i,t} + \varepsilon_{h,e,i,t}. \end{aligned} \tag{3.3}$$

where $Y_{h,e,t}$ is either the inverse hyperbolic sine of wages or consumption. This specification allows for changes in both the intensive and extensive margins expressed as percentage changes. Additionally, to take advantage of the high frequency of the data, the unit of observation is at the household-month level, with household h, working for employer e in industry i, at date t. An industry is classified as being treated if the year-on-year change in industry sales (at the two-digit code) is in the bottom 5% in a given year. The key assumption here is that while firms operating in such industries are facing economic distress, those firms with above-median leverage face greater costs of financial distress. In all specifications, I include household and industry-by-month-year fixed effects.

3.4 Effects of Capital Structure on Employees

3.4.1 Effect on the Marginal Propensities to Consume and Save

Is there any evidence that household consumption and saving correlate with employer leverage? To answer this question, I first estimate the effect of leverage on household consumption and saving by studying the marginal propensities to consume and save liquid assets, as per equation (3.1).

Table 3.A.2 reports the estimates for the marginal propensity to consume, showing that income and unemployment risk are important drivers of this sensitivity.[14] In columns (1)–(4), I report the marginal propensity to consume for households whose main employer is a private-sector firm, focusing on the effect of leverage.[15] Column (1) shows a negative and marginally significant effect of leverage, which becomes highly significant after including industry-by-year fixed effects, as shown in column (2). I also show that the results are robust to controlling for employer fixed effects in column (3), and, notably, for employment-spell fixed effects in column (4). Notice that this last analysis thus bypasses most concerns about two-sided selection effects, as these results are not biased by the endogeneity of time-invariant firm and employee characteristics that determine a job match.

Overall, these results imply that households working for employers in the top 10% of the leverage ratio distribution reduce their marginal propensity to consume by about 7% when compared to households working for firms in the bottom 10%. Interestingly, I also find a negative and statistically significant effect from increased industry volatility. Households working for more labor-intensive companies, measured by their tangibility ratio, exhibit lower marginal propensities to consume.[16] Finally, higher employee produc-

[14] As a robustness check in estimating the MPC, Table 3.B.3 employs a specification in first differences. Overall, the estimated effects are of similar magnitude to the coefficients from the baseline specification.

[15] Table 3.B.4 considers an alternative specification using the inverse hyperbolic sine of consumption expenditure. To account for differences in average propensities to consume, I include group-by-month-year fixed effects. Nonetheless, results are broadly consistent, as leverage is associated with lower consumption levels.

[16] For example, Palacios (2013) finds that labor intensity is positively correlated with the market beta at the industry level.

tivity is associated with lower propensities to consume, which may capture the positive correlation between productivity and wages, as shown in section 3.4.3.

Column (5) extends this analysis to households working in the public sector. Specifically, it shows that households primarily working for firms or institutions belonging to the public sector have a higher marginal propensity to consume, roughly an increase of 10% relative to private sector households. Interestingly, this is true even if they earn *higher* wages on average, as shown in section 3.4.3.[17] Although this is only tangentially connected to the theoretical framework presented here, this result is consistent with the main hypothesis developed in this paper: households recognize income and employment risk and act on these through consumption decisions, consequently exhibiting precautionary saving behavior.

However, a caveat is in order regarding the potential causal effect of leverage. So far, we cannot attribute these results solely to the use of leverage, as firms endogenously decide to issue and retire debt, and therefore capital structure may be capturing time-varying, firm-specific omitted variables. However, the main contribution of the paper is *not* about capital structure determinants,[18] but whether capital structure is perceived as a potential source for income and unemployment risk, and whether these risks induce a response from households. Nonetheless, in section 3.4.4 I try to ameliorate these concerns by exploring an arguably exogenous shock.

Table 3.A.3 decomposes the overall result on consumption according to different spending categories. Due to data limitations, this panel covers only the period from January 2020 to June 2022. Moreover, I consider a single specification that includes month-by-year, household, and industry-by-year fixed effects, while controlling for the same set of firm-level variables presented before. As we observe in columns (1), (3), and (6), households working for more leveraged employers do not appear to decrease their propensity to consume necessary goods and services, such as groceries, house main-

[17] To the best of my knowledge, I am the first to provide transaction-level evidence about the heterogeneity in consumption and saving response to income changes between public and private-sector employees.

[18] Though in equilibrium firms would respond to the imperfect insurance provided to workers and adjust their leverage ratio accordingly.

tenance and utilities, or health care, respectively. Instead, the negative effect described before appears to be driven by decreases in clothing, transportation, and restaurant expenditures, as seen in columns (2), (5), and (7), respectively.[19] These findings are then consistent with households exhibiting lower propensities to consume in categories that the literature has described before as luxury goods and services, i.e., those with an income elasticity greater than one.[20]

Mechanically, I observe that households employed by highly leveraged firms increase their propensity to save in liquid assets, as shown in Table 3.A.4. Columns (1)–(4) show that leverage is correlated with higher propensities to save, though the result becomes insignificant in columns (3) and (4). Nonetheless, the loss in statistical power may be partially explained by the fact that saving is measured with greater error than consumption, as I only observe saving within this specific bank. Consistently, column (5) shows that households employed by the public sector exhibit lower precautionary saving.

Interestingly, aggregate behavior shows similar patterns. In Tables 3.B.5 and 3.B.6 in the Internet Appendix, I examine whether the total turnover of the "luxury" goods and services sector is affected by the financing decisions of other firms in the economy. To test this channel, firms are first divided into two sectors: the luxury sector, corresponding to CAE codes 4751, 4771, and 4772 (clothing retailers), 49–51 (transportation), and 55–56 (hotels and restaurants), intended to closely represent the consumption categories where a negative reaction was found in Table 3.A.3–while all other firms are included in the non-luxury sector. For each Portuguese municipality and for each sector as defined here, a set of municipality-by-sector measures are computed, including total turnover, the number of employees, and total employee expenses, as well as the average leverage, profitability, and tangibility ratios of local firms.[21]

[19] Additionally, the effect is also negative and significant in column (9), corresponding to miscellaneous goods and services, which considers undefined spending (for example, cash withdrawals or purchases at large online retailers) and transactions that do not fit in the remaining categories.

[20] Though the decomposition of consumption into spending categories varies between studies, see for example Clements, Wu and Zhang (2006), where clothing and transportation exhibit an income elasticity well above one.

[21] More specifically, for the latter variables, an industry-adjusted measure is first computed by subtracting the corresponding two-digit industry mean in each sample year. All measures are then

Table 3.B.5 in the Internet Appendix reports that the total turnover of the luxury sector is lower in municipalities where the non-luxury sector is more leveraged. Columns (1)–(2) show that even after controlling for other financial ratios by sector, turnover in the luxury sector is about 2% lower in municipalities where the rest of the companies exhibit high leverage ratios. As shown in both columns, this effect is robust to controlling for changes in the employment level and total employee pay, ameliorating concerns that results are driven by higher unemployment or pay cuts in municipalities with higher leverage levels. Finally, column (3) includes district-by-year fixed effects to ensure that common regional shocks are not driving these findings.

Finally, Table 3.B.6 in the Internet Appendix reports how leverage amplifies the effect when other municipalities in the same region suffer a productivity shock (measured by changes in total turnover). For each municipality, regional values are computed considering all the other municipalities in the same district (excluding itself). Columns (1)–(2) report the effect on total turnover in the luxury sector at the municipality level. Consistent with the previous results, the luxury sector turnover is lower in municipalities where the non-luxury sector is highly leveraged, and also if firms in other municipalities of the same region are highly leveraged, albeit to a smaller degree. Notably, there is a strong interaction effect between regional leverage and changes in regional turnover. This result suggests that whenever nearby municipalities suffer a productivity shock, the luxury sector suffers, *but only* if companies in nearby municipalities are highly leveraged. Nonetheless, no amplification effect occurs in the non-luxury sector, as the interaction between regional leverage and changes in turnover is statistically insignificant in columns (3)–(4). Taken together, these results further suggest that an employee-spending channel exists, through which productivity shocks are amplified by the financing decisions of a given employer and then transmitted through employee-consumer networks.

computed as a weighted average by the number of employees of each firm.

3.4.2 Heterogeneous Effects

To characterize how different households perceive this source of risk, I re-estimate the model in equation (3.1), decomposing the effect of leverage on the propensity to consume by interacting it with group indicators.[22] Figure 3.A.1 plots the λ coefficient in equation (3.1) for different groups of households, splitting the sample according to household and firm characteristics.

Panel A shows that the effect of leverage on the marginal propensity to consume is statistically indistinguishable when comparing households in the bottom quartile of total income to the rest of the sample. However, resonating with the model's predictions (introduced in section 3.5), Panel B shows that the response is mainly driven by households in the bottom quartile of assets, with this difference in coefficients being statistically significant at the 5% level. Thus, Panels A and B are broadly consistent with the model results presented in this paper: according to the model, when unemployment is particularly painful because households are in a low-liquidity state, the precautionary saving motive becomes relatively more important.

Panel C then shows that there is no difference in behavior depending on the size of the firm. While these data are rich enough to decompose the effect of employer financial distress on household consumption behavior, pinpointing the specific channels through which households acquire information about the employer's financial strength is challenging. For instance, one might expect different occupations within the company to have varying exposures to the firm's actual financial condition, but the anonymized nature of the data makes testing this hypothesis unfeasible. However, Panel D of Figure 3.A.1 shows that the household sensitivity to employer debt is much stronger when working for a publicly listed company.[23] Whatever the specific channel through which households acquire this information, either directly or indirectly (for example, due to the increased visibility of these companies), this result suggests that the reduction of informational

[22] Additionally, in these regressions, I include the interaction effect between income and the group indicator.

[23] Notably, this result appears not to be driven by firm size, as it still holds after controlling for the triple interaction between income, leverage, and firm size.

asymmetries between households and employers leads to a much stronger effect of employer debt on household consumption.

Finally, in Panels E and F, I consider how leverage and expected costs of unemployment jointly change the consumption decision. In Panel E, to capture changes in the probability of separation, I consider the impact of industry volatility and find that employees working in more volatile industries are the most sensitive to the use of leverage, with this effect being marginally significant at the 10% level. Nonetheless, expected costs are also affected by the "loss given default," which I proxy by the vacancies-to-unemployment ratio at the regional level.[24] In Panel F, I find that households working in slack labor markets exhibit lower propensities to consume, with this effect being marginally significant as well.

3.4.3 Risk and Wages

In this section, I rule out alternative explanations for the previous findings. One possible concern is that leverage is positively associated with employee outcomes, both in terms of current pay and future outcomes.

I first investigate the extent to which households *should* receive any compensating differential– that is, whether they face higher unemployment or income risk by working for highly leveraged employers. Table 3.A.5 shows the estimates for a linear probability model, where the outcome variable is a dummy variable that takes the value of one if the firm goes bankrupt and zero otherwise. First, in columns (1)–(3), I estimate the probability of in-sample firms going bankrupt during the whole sample period (between 2018 and 2022), as a function of the explanatory variables described before and using values at the end of the 2017 fiscal year. The main explanatory variable is a dummy variable, *High Leverage*, that takes the value of one for firms with above-median leverage ratios and zero otherwise.[25] Column (1) shows that firms with above-median leverage ratios are more

[24] Data are retrieved from *Instituto do Emprego e Formação Profissional*, which provides data on new vacancies and unemployment stock by two-digit industry code and region (NUTS II), at a monthly frequency. The measure is then computed by considering new vacancies over the previous quarter, normalized by the total unemployment stock.

[25] Results are robust for the same specification using the original continuous variable.

likely to go bankrupt during the sample period, an increase of 1.2 percentage points *vis-à-vis* an unconditional mean of 1.7%. Column (2) adds industry fixed effects at the two-digit level, and column (3) adds additional firm-level controls. Across all columns, the coefficient estimate of the high-leverage dummy variable is positive and both statistically and economically significant, suggesting that employees working for firms with above-median leverage are exposed to higher unemployment risk.[26]

In columns (4)–(6), I consider a panel counterpart where the outcome variable is a dummy variable taking the value of one if the firm goes bankrupt in the following year. Once again, leverage is statistically and economically significant across all specifications.[27]

However, after excluding bankrupt firms from the analysis, I fail to find evidence that highly leveraged firms exhibit worse employment growth, both in the short run (after one year) and in the long run (after three years). Table 3.B.9 presents the results. Interestingly, this null result does not hold when considering all Portuguese firms, as shown in Table 3.B.10 in the Internet Appendix. While the magnitudes in columns (1)–(3) are significantly higher, columns (4) and (5) show comparable magnitudes to Table 3.B.9, and column (6) exhibits even lower point estimates. Consequently, evidence suggests that among in-sample firms, which are larger and more profitable than the average Portuguese firm, highly leveraged firms are not more likely to shed employees outside of bankruptcy, neither in the immediate nor in the long-run periods.[28]

In fact, in contrast to most US states, where firms are not obliged to provide a reason for dismissal, unilateral termination of regular employees in Portugal entails stricter procedural requirements, as well as severance pay costs to the firm (OECD, 2020). More-

[26] Indeed, in this sample only a small fraction of households (less than 5%) continue to work for a firm after bankruptcy, with the remainder transitioning to unemployment or a new job spell.

[27] Table 3.B.7 shows comparable results even when using the overall universe of Portuguese firms, and Table 3.B.8 shows consistent results by running a logistic regression model.

[28] For example, most collective dismissals between 2017 and 2022 were applied by micro, small, and medium-sized companies (source: DGERT - *Direção-Geral do Emprego e das Relações de Trabalho*). Nonetheless, such termination mechanisms are still costly to firms and constitute a small fraction of dismissals (about 14% of the total), with the non-renewal of temporary contracts being the main source of registered unemployment (about 50% of the total).

over, Portuguese employment protection requires such dismissal to be grounded on "fair" reasons, such as collective dismissal, redundancy of tasks, employee ineptitude, or breach. Although structural reforms were implemented within the scope of the international bailout in 2011, Portuguese employment protection remains high. For example, in 2019, the Organisation for Economic Co-operation and Development (OECD) ranked Portugal as having the third-strictest employment regulation for regular workers, while also being among the top 10 countries with the strictest regulations for temporary employment. This rigidity might explain the absence of differential employee growth, as firms avoid incurring such costs and complexity outside of bankruptcy.

Regardless of the exact mechanism used by firms to dismiss their employees, Table 3.A.6 provides evidence that employees of highly leveraged firms are more likely to become unemployed. Columns (1)–(3) show that households employed by high-leverage employers are more likely to have no recorded wage payment during the following quarter while being the recipient of social security payments.[29] This result suggests that these households are more likely to lose their jobs by about 60% relative to the unconditional average (which stands at about 0.13% per quarter), based on the results in column (3). In columns (4)–(6), I introduce a less strict definition of unemployment, identifying households who are currently employed but show no recorded wage payments in the following quarter, irrespective of whether they are receiving social security benefits. Households may opt to receive unemployment benefits through a different bank or by mail; however, this definition might also include alternative events, such as voluntary unemployment. Nonetheless, results are broadly consistent, as households working for highly leveraged companies are more likely to lose their current job, representing an increase in column (6) of about 25% relative to the unconditional mean of about 0.72% per quarter.

Given that households face additional income and unemployment risk when working for highly leveraged firms, it would also be natural to observe higher voluntary separation

[29] These payments include–but may not be limited to–unemployment insurance benefits. However, to exclude alternative explanations, such as short-term leaves (e.g., due to sickness or maternity leave), households who return to the original employer within one year are not classified as being unemployed.

rates. Columns (1)–(3) of Table 3.B.11 in the Internet Appendix provide evidence that households working for above-median leverage firms are more likely to switch to a new employer in the following year. Compared to the unconditional mean of around 4.3%, households whose main employer has an above-median leverage ratio are more likely to switch jobs by about 1.5 percentage points in the most stringent specification. In columns (4)–(6), I also examine the income behavior of movers and the differential effect for those previously working in a highly leveraged firm.[30] I fail to find evidence that households switching employers suffer a negative impact on their annual total income, which might suggest that those departures are either anticipated or voluntary. Additionally, I find no differential effect on earnings for those previously working for highly leveraged firms.

Moreover, could higher leverage also signal worse managerial quality or firm prospects? Table 3.B.12 in the Internet Appendix provides evidence on the ex post performance as a function of leverage, both in the short run (the following year) and the long run (after three years). While leverage does not seem to matter for turnover growth in the short and long run in columns (1) and (4), respectively, a negative and statistically significant effect is found after controlling for industry-by-year fixed effects, as shown in columns (2) and (5) for the short- and long-run effects, respectively). Finally, adding employer fixed effects reverses the direction of the effect in the short run, and renders the magnitude over the long run statistically insignificant. However, when considering all Portuguese firms, Table 3.B.13 suggests that indeed more leveraged firms have worse turnover growth prospects, both in the short and the long run, with this effect being either positive in the short run or insignificant in the long run for *within-firm* increases in leverage.[31]

Taken together, these findings suggest that leveraged firms indeed impose higher income and unemployment risk on households. Households working for highly leveraged firms are more likely to see their employer go bankrupt and have a higher likelihood of

[30] To rule out alternative explanations, such as household members switching jobs following a positive shock to other members within the household, I only consider those households with a single employer. However, unreported results show that adding this restriction does not change the conclusions.

[31] Consistently, Table 3.B.14 shows that, in the long run, highly leveraged firms are no more likely to end up in the top decile of the turnover distribution.

involuntary termination of their job. Additionally, results suggest that these households arguably search more intensively for other jobs, providing evidence of more frequent *voluntary* terminations (quits).

With these results in mind, I then run the regression in equation (3.2) to understand how wages are determined and, in particular, how they are affected by the use of leverage. Table 3.A.7 shows the estimates for the effect of firm-level variables on wage determination, using the net wage receipts recorded in this bank. Columns (1) to (4) suggest there is no leverage wage premium. When adding industry-by-year and household fixed effects, the effect of leverage on household earnings is negative (about a 4% wage *discount* when comparing firms in the top decile with the bottom decile of the leverage distribution) and statistically significant. Consequently, I find, if anything, that employees in highly leveraged firms suffer a penalty in terms of wages. Additionally, in column (5), I show that households whose main employer operates in the public sector earn, on average, a 24% premium.[32]

Finally, in Table 3.B.15 in the Internet Appendix, I support these findings by running a regression at the firm-year level in which the outcome variable is the natural logarithm of the average gross wage, computed as the total wage bill of a firm in a given year divided by its number of employees. Although, in this case, I use firm-level data, as opposed to the household-level data used before, the results are broadly consistent with the previous findings. Column (1), which includes only year fixed effects, shows that the average wage discount imposed by firms in the top decile of the leverage distribution is about 7% when compared to firms in the bottom decile. Column (2) then shows that the wage discount remains significant even after including other firm-level controls. The results in column (3) show that this negative relationship is robust to controlling for industry-by-year fixed effects. However, I fail to find evidence that leverage exerts a negative pressure on wages *within* firms, as the coefficient of interest in column (4) is statistically insignifi-

[32] While being a secondary finding not directly related to the study in hand, households working for the public sector exhibit a *higher* marginal propensity to consume (and lower marginal propensity to save), providing further evidence on how households perceive income and unemployment risk when making consumption and saving decisions.

cant after controlling for firm fixed effects. Table 3.B.16 in the Internet Appendix shows that estimates of this effect are generally smaller when considering the whole universe of Portuguese firms but still negative and statistically significant.

Evidence provided so far suggests that workers are more likely to face unemployment due to their employer's use of corporate debt. On average, more indebted firms also exhibit worse prospects, further increasing the risk of a job match termination. Overall, the evidence suggests that workers should receive compensation for the use of leverage, but in equilibrium employers impose a wage discount. While these results should be interpreted with caution, as high leverage could be a signal of firm quality, the absence of a wage premium still holds even *within* employer.

3.4.4 Responses to Exogenous Shock

In this section, I provide additional evidence that households take employer leverage into account when making consumption and saving decisions, by employing an arguably exogenous industry shock. Specifically, I use industry-wide revenue shocks as an exogenous instrument for financial distress. To construct a monthly measure of industry-wide shocks, I match employer's data with year-on-year monthly changes in the industry's calendar-unadjusted turnover, using Eurostat's Short-term business statistics at the two-digit NACE Rev.2 level.[33] However, these data are only available for a subset of my sample, specifically for manufacturing and service activities.

The shock is constructed using the monthly measure of year-on-year changes in turnover, selecting the bottom 5% industry-month observations.[34] The rationale for selecting this shock is that, while on average firms experience economic distress, the highly leveraged companies are more likely to experience financial distress as well.

[33] NACE (*Nomenclature statistique des Activités économiques dans la Communauté Européenne*) refers to the Statistical Classification of Economic Activities in the European Community. The CAE (*Classificação de Actividades Económicas*) Rev.3, which I use for classifying industries at the five-digit level, is integrated into NACE.

[34] To address concerns that the COVID-19 pandemic might be driving this selection, I perform this exercise for each year in sample, i.e., I identify the worst performing industry-month pairs *by year*. Nonetheless, in a robustness check, I exclude all observations starting in March 2020 and obtain similar results.

Before characterizing the consumption response, I first examine whether there is any differential effect on wages, as shown in Table 3.B.17 in the Internet Appendix. If these firms are experiencing economic distress, wage payments might be delayed, causing the pass-through of the shock to be felt by households at the extensive margin. Therefore, in the following tests, I consider the inverse hyperbolic sine of wages as the dependent variable.[35] However, columns (1) and (2) indicate that the wage drop following such shocks is statistically insignificant. Furthermore, all specifications show no differential effect for households employed by above-median leverage firms.

Interestingly, Table 3.A.8 shows that while low-leverage employers do not induce any consumption response by their employees, households working for highly leveraged firms reduce consumption when experiencing this industry-wide shock. This consumption drop is both economically and statistically significant at about 2% in the most stringent specification. However, these average estimates overlook how the likelihood of bankruptcy and financial distress realizing shapes the response of households. As a proxy for this probability, I consider the liabilities repayment share, computed as the ratio of current liabilities to total liabilities. Figure 3.A.2 shows that the consumption response is primarily driven by households working in highly leveraged firms with an above-median fraction of short-term liabilities.

To address concerns that the COVID-19 pandemic response might partially drive these results I report in the Internet Appendix identical wage and consumption responses when considering only 2018-2019 (Tables 3.B.19 and 3.B.20, respectively). Finally, Table 3.B.21 in the Internet Appendix presents the estimated effect of this industry shock on the probability of going bankrupt within the sample period, i.e., from 2018 to 2022. In all specifications, high-leverage firms are more likely to go bankrupt, and this likelihood further increases if they are exposed to such industry shocks, raising the probability of bankruptcy by about 1.5 percentage points.

[35] Alternative specifications, such as the natural logarithm of $y + 1$, yield similar results. To address further concerns about the use of the hyperbolic sine as a dependent variable, I decompose the effect between the intensive and extensive margins in Table 3.B.18.

3.5 Theory

In this section, I introduce a matching model of endogenous job creation and destruction, building on the work of Bils, Chang and Kim (2011). In contrast to their approach, I calibrate the model to match key stylized facts of the Portuguese economy, while also incorporating two important sources of heterogeneity. Specifically, in the model I propose here, workers have different sensitivities to risk, with varying levels in the coefficient of relative risk aversion, whereas firms differ in their leverage levels.

The goal of the model is to understand whether bargaining frictions can help explain the empirical findings and to examine how endogenous matching between workers and firms may contribute to the heterogeneity in these findings. Unemployed individuals search for a job and are assumed to have perfect knowledge about the exogenously determined level of debt held by the potential employer.[36] On the other hand, entrepreneurs have perfect knowledge about workers' characteristics, including risk-aversion and wealth levels.[37] Workers are risk averse and can save to partially insure themselves against idiosyncratic job-match shocks, and they can also borrow, subject to an exogenous borrowing constraint. Furthermore, I assume they are further insured by unemployment benefits, which facilitates the calibration of the model to the Portuguese economy. Thus, the model includes two counteracting forces in determining wages: on the one hand, risk-averse workers dislike unemployment risk, and negotiate for a higher wage as compensation, in the spirit of Berk, Stanton and Zechner (2010); on the other hand, while increasing unemployment risk, leverage also reduces the available surplus to be shared with the employee–an effect, although modeled differently, resembles the intuition of Michaels, Beau Page and Whited (2019).

[36] Although a simplifying assumption, work by Brown and Matsa (2016) suggests that applicants have at least *some* knowledge of the financial condition of potential employers.

[37] Previous job experience and age could be seen as proxies for these two variables. However, how information flows between parties is outside the scope of this paper.

3.5.1 Model Setting

Consider a labor market in discrete time, populated by a continuum of infinitely-lived, risk-averse households of measure one, and a continuum of infinitely-lived, risk-neutral entrepreneurs.

Households

Households are ex ante heterogeneous in their risk-aversion and initial wealth and maximize their lifetime utility according to constant relative risk aversion (CRRA) utility function with two separable goods–consumption and leisure–defined by

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta_h^t \left[\frac{c_t^{1-\gamma} - 1}{1-\gamma} + (1 - \mathbb{1}_e) l \right],$$

with $0 < \beta_h < 1$. The indicator function $\mathbb{1}_e$ represents employment status, with unemployed households deriving utility from l, the exogenous value of leisure.[38] In each period, consumption must be nonnegative, and households are subject to a traditional budget constraint, as follows

$$c_t \leq (1+r)a_t + (1 - \mathbb{1}_e)\zeta + \mathbb{1}_e w_t - a_{t+1}, \quad \forall t \in [0, \infty), \tag{3.4}$$

$$c_t \geq 0, \quad \forall t \in [0, \infty). \tag{3.5}$$

Employed households earn a wage w_t and unemployed workers receive an unemployment insurance benefit equal to ζ. Households can smooth consumption and partially insure against unemployment risk by saving and investing in a short-term risk-free bond. Additionally, households are allowed to borrow, subject to an exogenous borrowing constraint, such that

$$a_t \geq \underline{a}, \quad \forall t \in [0, \infty). \tag{3.6}$$

Entrepreneurs and Firms

Entrepreneurs maximize the discounted present value of match surplus, given by

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta_f^t \left(z_t x_t - b \right), \tag{3.7}$$

[38] Allowing the value of leisure to depend on employment status helps calibrate the model to match data moments.

with $0 < \beta_f < 1$. Match surplus evolves over time according to two Markov processes, one governing aggregate productivity, denoted by z_t, and the other determining idiosyncratic job-match quality, denoted by x_t. I assume a standard autoregressive process of order one (AR(1)) for both variables. The persistence of the aggregate process is represented by ρ_z, with corresponding innovations normally distributed as $\varepsilon_z \in \mathcal{N}(0, \sigma_z^2)$. Similarly, ρ_x denotes the persistence of the idiosyncratic process, and σ_x represents the standard deviation of the normally distributed idiosyncratic shocks.

For new matches, x_t is assumed to be equal to the unconditional mean of job-match quality, $\overline{x}$. I assume that entrepreneurs issue a perpetual bond that costs b per unit of time, which reduces the surplus available to be shared with the worker. This amount is not micro-founded but is instead exogenously set at firm inception, as my primary concern is not on capital structure choice itself, but rather its effects on worker behavior.

Labor Market

Job matches are obtained through a Cobb-Douglas matching function, as follows

$$m(v_t, u_t) = m_0 u_t^{1-\eta} v_t^{\eta},$$

where m_0 represents the efficiency of the matching technology, u_t represents the number of unemployed workers, v_t denotes the number of posted vacancies, and η is the elasticity of job matchings with respect to vacancies (with $0 \leq \eta \leq 1$). Thus, the job-filling rate, i.e., the rate at which vacancies become filled, is $q(\theta_t) = m(v_t, u_t)/v_t = m_0 \theta_t^{\eta-1}$, where θ_t represents the vacancy-unemployment ratio. The job-finding rate, i.e., the rate at which unemployed workers find a match, is $\theta_t q(\theta_t) = m(u_t, v_t)/u_t = m_0 \theta_t^{\eta}$.

At the beginning of each period, matches are formed and both idiosyncratic and systematic shocks are realized. Following a match, households and entrepreneurs decide whether to continue or separate. If they choose to continue, production takes place and the agreed wage–which depends on the household type and wealth, job-match quality, and employer's leverage–is paid. If they decide not to continue the current match, households join the measure of unemployed workers searching for a new match. Finally, assume that the distribution of employed and unemployed households is given by $\lambda_e(\gamma, a_t, x_t, b)$ and

$\lambda_u(\gamma, a_t)$, respectively.

In characterizing the worker and entrepreneur's problem, let the value functions for employed and unemployed households be represented as W and U, while the value functions for a new vacancy and a matched job be denoted by V and J. Let $\phi_t = (\gamma, a_t)$ represent the vector of household-specific states for households, and let $\Phi = (z_t, \lambda_e, \lambda_u)$ denote the vector of aggregate states.

Wage Setting

Wages are set endogenously through a bargaining procedure in which the matched household and entrepreneur split the generated surplus. Given the value functions defined above, for a job match to form, the household gives up U (the household's threat point) in exchange for W; while the entrepreneur gives up V (the entrepreneur's threat point) in exchange for J. Consequently, the Nash bargaining solution for $w_t(x_t, b_t, \phi_t, \Phi_t)$ is determined by solving the following problem

$$\arg\max_{w_t} \left\{ \left[W_t(x_t, b_t, \phi_t, \Phi_t) - U_t(\phi_t, \Phi_t)\right]^{\delta} \left[J_t(x_t, b, \phi_t, \Phi_t) - V_t(b, \Phi_t)\right]^{1-\delta} \right\}, \quad (3.8)$$

where $0 \leq \delta \leq 1$, which may be interpreted as a relative measure of the worker's bargaining power.

Optimization Problem

Households solve their optimization problem by choosing the optimal level of consumption and consistently how much to borrow or lend. Consequently, the optimization problem for an employed household, subject to conditions (3.4) to (3.5), can be summarized as follows

$$W_t(x_t, b_t, \phi_t, \Phi_t) = \max_{\{c_t, a_{t+1}\}} \left\{ \frac{c_t^{1-\gamma} - 1}{1-\gamma} + \beta_h \mathbb{E}_t \max\left[W_{t+1}, U_{t+1}\right] \right\}, \quad (3.9)$$

where for notational convenience I drop the value functions dependence on $t+1$. Notice that the last term captures the household's uncertainty about whether to remain within the same match or join the pool of unemployed workers. In the latter case, the value of being unemployed, subject to conditions (3.4) to (3.5), is given by

$$U_t(\phi_t, \Phi_t) = \max_{\{c_t, a_{t+1}\}} \left\{ \frac{c_t^{1-\gamma} - 1}{1-\gamma} + l + \beta_h \left\{ (1 - \theta_t q(\theta_t))\, \mathbb{E}_t \left[U_{t+1} \right] + \theta_t q(\theta_t) \mathbb{E}_t \left[W_{t+1} \right] \right\} \right\}. \tag{3.10}$$

Finally, from the entrepreneur's perspective, the value of a match with a household is given by

$$J_t(x_t, b, \phi_t, \Phi_t) = z_t x_t - b - w(x_t, b, \phi_t, \Phi_t) + \beta_f \mathbb{E}_t \left[\max \left\{ J_{t+1}, V_{t+1} \right\} \right], \tag{3.11}$$

where the last term relates to the entrepreneur's uncertainty of whether to continue the current match or post a new vacancy. The value of posting a new vacancy is as follows

$$V_t(b, \Phi_t) = -\kappa + \beta_f q(\theta_t) \int \mathbb{E}_t \left[J_{t+1} \right] \mathrm{d}\lambda'_u(\phi_{t+1}) + \beta_f (1 - q(\theta_t)) \mathbb{E}_t \left[V_{t+1} \right], \tag{3.12}$$

where κ denotes the fixed cost of posting the vacancy, and λ'_u represents the measure of unemployed households at the end of each period, after borrowing and lending decisions have been made.

Equilibrium

In equilibrium, all profit opportunities must be exhausted, so I impose a free-entry condition such that $V_t(b, \Phi_t) = 0$. With this condition in mind, the stationary equilibrium of the model implies the following job creation condition, which corresponds to the first-order maximization condition of the bargaining problem (3.8):

$$J_t(x_t, b, \phi_t, \Phi_t) = \frac{1-\delta}{\delta} \left[W_t(x_t, b_t, \phi_t, \Phi_t) - U_t(\phi_t, \Phi_t) \right] c_t^{\gamma}. \tag{3.13}$$

Therefore, a stationary equilibrium consists of a set of value functions, as described in equations (3.9) to (3.12); decision rules for consumption and, consequently, saving; a full characterization of the wage schedule; the population distributions and their laws of motion; and, finally, a labor-market tightness ratio, such that:

1. Given θ_t, conditions (3.9) to (3.10) are met;
2. Given the wage schedule and optimal saving decision rules, condition (3.11) is met, with the value of a new posting for each firm type being zero;

3. The wage schedule satisfies the first-order maximization condition (3.13).

3.5.2 Quantitative Analysis

This section presents some numerical examples based on the baseline calibration reported in Table 3.A.9. Additionally, by simulating a panel of search and match dynamics on the steady state, I provide estimates for the impact of leverage on wage determination and household consumption and saving behavior.

Calibration

The model is calibrated in a steady state, with parameters chosen based on a model period of one month. I begin by normalizing the unconditional mean of aggregate productivity, assuming $z = 1$ in the steady state. Additionally, I normalize job market tightness to $\theta = 1$. The annual risk-free rate is set at 4%, and the household's monthly discount factor, β_h, is set to 0.996. The latter is calibrated to generate a realistic level of average financial holdings to average household income, approximately equal to 13 for Portugal in 2017.[39] I assume two values for the coefficient of relative risk aversion, $\gamma \in \{1, 2\}$, both within the typical range used in this literature. Also consistent with standard practice, I assign symmetric bargaining power for sharing the job-match surplus, equal to the elasticity of the matching technology, i.e., $\delta = \eta = 0.5$. For the idiosyncratic process, I set $\rho_x = 0.98$ to match the high persistence of observed earnings, with a standard deviation of innovations of about 0.035, both comparable with the calibration in Fujita and Moscarini (2017). I then choose a debt cost, b, of 0.1 for leveraged firms, to align the model's wage leverage gap with the empirical counterpart presented in section 3.4.

Compared to the US economy, Portugal is characterized by significantly longer unemployment spells, even when unemployment rates are comparable. Therefore, consistent with Blanchard and Portugal (2001), I set the matching technology parameter m_0 to be equal to 0.11, resulting in an average unemployment spell duration of about nine months. The utility from leisure, l is set to 0.15, following Bils, Chang and Kim (2011), so that

[39] Annual mean net income per household, INE-Instituto Nacional de Estatística, Statistics on Income and Living Conditions; and average value of financial assets of private households; Bank of Portugal, Household Finance and Consumption Survey 2017.

leisure is comparable to a 15% higher consumption level. In this calibration, the unemployment insurance benefit is higher than the benchmark in Bils, Chang and Kim (2011), to reflect the lower observed wedge between wages and unemployment benefit in Portugal compared to the United States.[40] Specifically, the unemployment benefit is chosen to target an unemployment rate of 6.5%, as in Blanchard and Portugal (2001). Finally, the parameter κ, the cost of posting a vacancy, is allowed to vary according to the free-entry condition.

The computational methodology employed in solving and simulating the model is described in section 3.B.1 of the Internet Appendix.

Wage Schedule

Figure 3.A.3 plots the wage schedule for a constant job-match quality–equal to the unconditional mean of x–as a function of the household's savings. Panel A compares the average wage across all household and firm types with the wage earned by households with different levels of risk aversion, while Panel B provides the same comparison for households working in unleveraged versus leveraged firms.

First, note that wages increase in household savings, as holding assets partially insures the household against unemployment, making this outside option relatively less costly, as in Krusell, Mukoyama and Şahin (2010) and Bils, Chang and Kim (2011). Interestingly, the model generates differences in how risk aversion affects wages. For sufficiently low levels of wealth, there is a *negative* association between risk aversion and wages, a point previously made, for example, in Acemoglu and Shimer (1999), where increases in risk aversion make households prefer low-wage jobs with lower unemployment risk. However, for sufficiently high wealth, so that households have high enough bargaining power in the wage negotiation procedure, there is a *positive* relationship between wages and risk aversion. In this region, more risk-averse households negotiate higher wages, as they require higher compensation for unemployment risk–and have enough relative bargaining

[40] For the 2000–2022 period, the average unemployment benefit after two months of unemployment, as a share of previous income, was about 76% in Portugal and 61% for the United States (data retrieved from the OECD).

power to do so.

Panel B presents an equivalent exercise but with the wage schedule split by employer leverage. In this numerical example, leverage has an unambiguous effect: it depresses wages. All else being equal, higher debt payments by the entrepreneur directly reduce the value of a match, which feeds back into the bargaining process and results in lower wages. Less obviously, an offsetting force to this direct channel also exists. By increasing debt payments and reducing the surplus generated by a match, leverage also makes employment riskier, thereby decreasing the value of employment to the household, as the probability of reaching a separating threshold is now greater. Thus, through this channel, wages could actually increase.

Distribution of Wealth

Figure 3.A.4 shows the wealth distribution for the same calibrated parameters, first by splitting households based on their risk aversion coefficient (Panel A), and then by employer leverage (Panel B). As expected, there are significant differences in Panel A, as more risk-averse individuals increase savings to insure themselves against unemployment risk. However, the interplay between wages and unemployment risk–both influenced by employer leverage–makes the differences in wealth distribution by employer leverage less pronounced, as seen in Panel B. This motivates an empirical approach focused not on levels but on flows, specifically on *propensities* to consume and save.

Simulated Panel

In this section, I generate a panel of households in a stationary equilibrium. Specifically, I simulate 250,000 household paths and randomly keep 50,000 households to create an artificial panel of consumption, saving, and employment decisions. To ensure stationarity, I simulate 5,000 periods, but keep only the last 60 periods, making the data comparable to the sample period. I then conduct a series of empirical tests designed to mirror those performed on the empirical data.

Table 3.A.10 shows that, in the simulated panel, households working for leveraged employers receive lower wages, consistent with the wage schedule and the channels dis-

cussed above. However, despite receiving lower wages on average, the need for insurance dominates, leading households working for leveraged employers to significantly decrease their propensities to consume, as shown in columns (1)–(2) of Table 3.A.11. Correspondingly, this consumption response is accompanied by an increase in the propensity to save earned wages, as reported in columns (3)–(4).

Furthermore, according to this model, the impact of leverage on consumption and saving decisions is driven primarily by household wealth rather than income. Panel A of Figure 3.A.5 shows that in the model the effect of leverage on the propensity to consume is virtually the same for low- and high-income households. In contrast, as shown in Panel B, leverage has a much stronger effect on the propensity to consume for low-wealth households, compared to wealthier households. Consistent with the empirical findings in this paper, the model helps to understand who is primarily concerned about leverage: as leverage increases the rate at which employers and employees endogenously separate, households in a low liquidity state, who struggle to smooth consumption during unemployment, exhibit greater sensitivity to employer leverage.

3.6 Conclusion

I provide novel evidence on the spillover effects of a firm's capital structure on its employees using a matched employer-employee data set from Portugal. Specifically, I show that employees facing higher income and unemployment risk due to their employer's higher leverage adjust their consumption and saving decisions. To explore the channels through which leverage affects household decisions, I propose a Diamond-Mortensen-Pissarides model with a precautionary saving motive that incorporates wage bargaining frictions. In the model, leverage has opposing effects on wage bargaining: on the one hand, risk-averse households demand compensation for the increased separation rate; on the other hand, leverage depresses job-match surplus, thereby lowering wages. After calibrating the model to the Portuguese economy, leverage has a negative effect on wages, and the increase in unemployment risk leads households to decrease (increase) their propensity to consume (save).

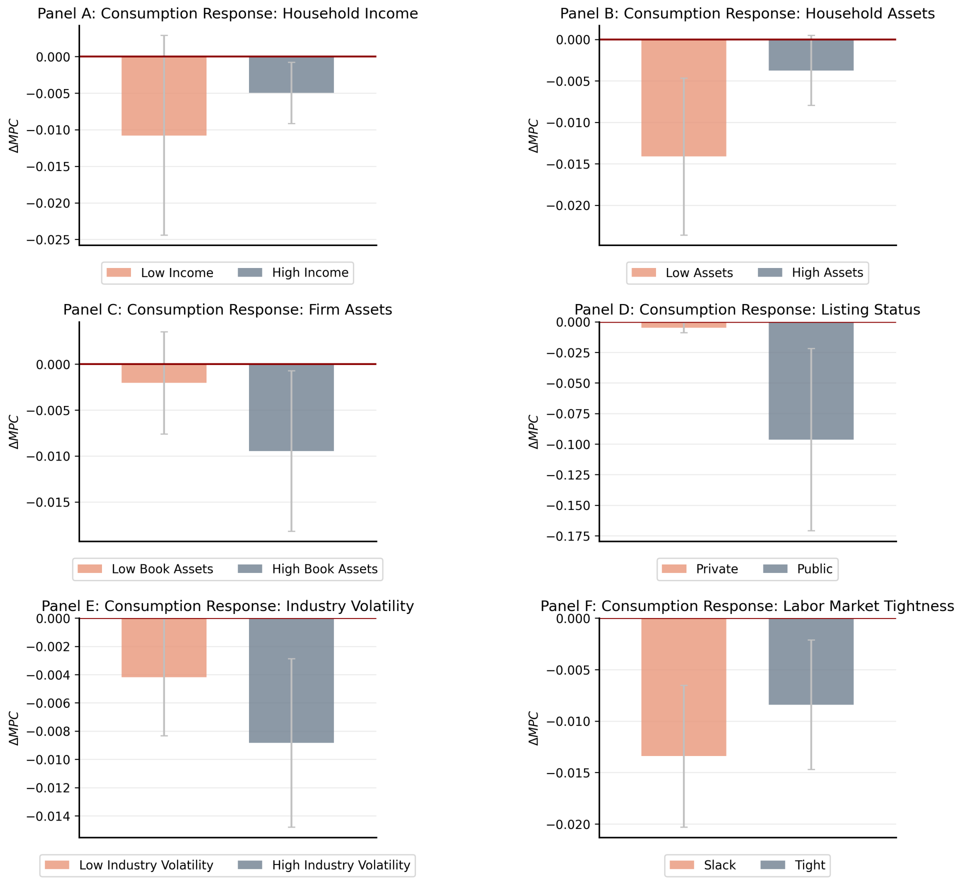
Consistent with the model, my empirical analysis indicates that leverage is associated with lower wages. Despite this, individuals working for highly leveraged firms exhibit a lower marginal propensity to consume. This effect is particularly strong when unemployment is especially painful, for instance, due to low wealth. This sensitivity to the use of leverage is amplified when individuals work for employers in highly volatile industries, where separations are more likely, or in slack labor markets, where unemployment costs for individuals are higher. I complement these findings by showing that individuals working for highly leveraged employers immediately cut consumption when exposed to a contemporaneous industry-wide shock, despite facing no differential effect on wages. Taken together, these results align with the proposed model, suggesting that by increasing job separation rates, leverage imposes a cost on households, who are forced to reduce consumption and increase precautionary savings.

Moreover, the response is highly heterogeneous across the consumption basket: as the effect is statistically insignificant for goods and services typically identified as essential, the overall consumption effect is mostly driven by reductions in the consumption of luxury goods and services. Consequently, by altering the consumption basket of employees, I further contribute to the literature on the spillover effects of capital structure by suggesting an indirect impact on other firms. Notably, these affected firms might not be competitors or part of the same supply chain as the leveraged firm and may be concentrated in specific industries. Although outside the scope of this paper, these results imply that "employee-consumer" networks might be important in explaining aggregate economic movements, while being substantially different from the traditional supply and financial networks previously studied in the literature.

My results raise broader questions about firms' financing decisions and their societal impact. Recently, concerns about the high levels of private-sector indebtedness have led to restrictions on the tax deductibility of interest, and further efforts are being made to reduce the equity-debt tax bias. By providing evidence that capital structure can shift costs of financial distress to employees and distort employee behavior, my findings raise further questions on the optimality of the interest tax deductibility from a societal perspective.

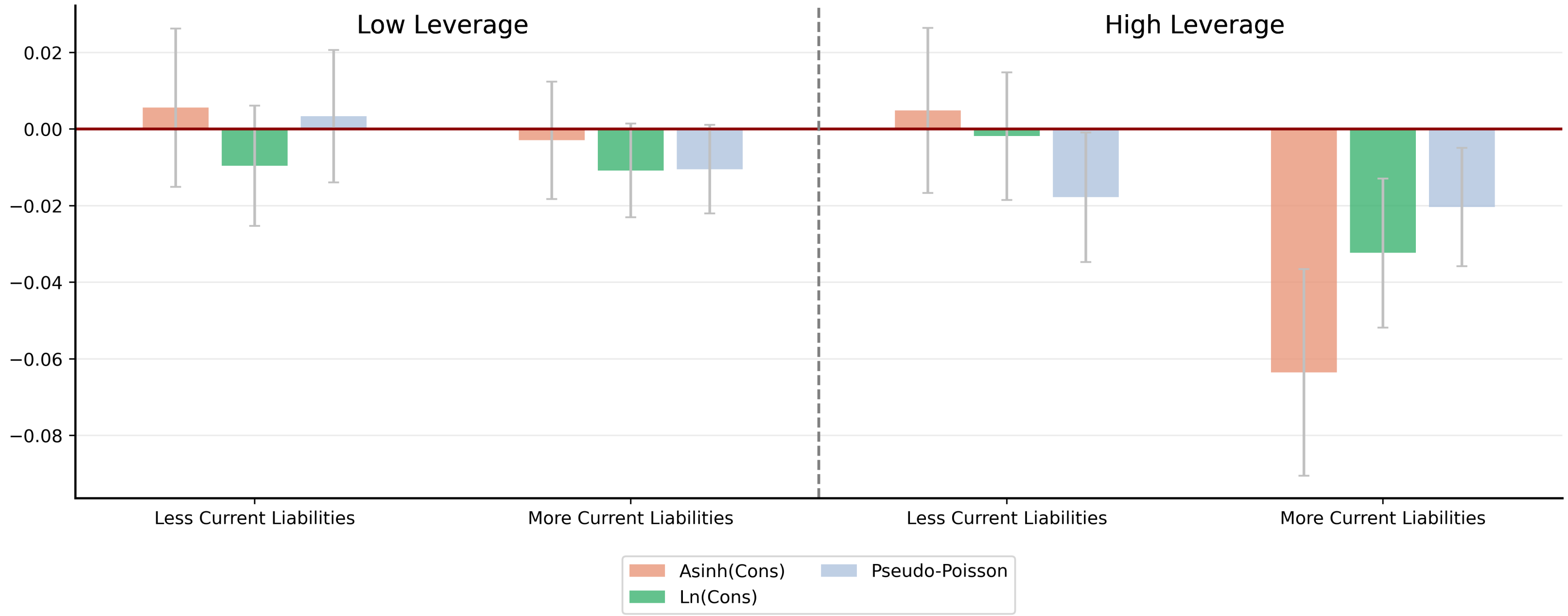
Appendix of Chapter 3

Figure 3.A.1: Heterogeneity in the Consumption Response



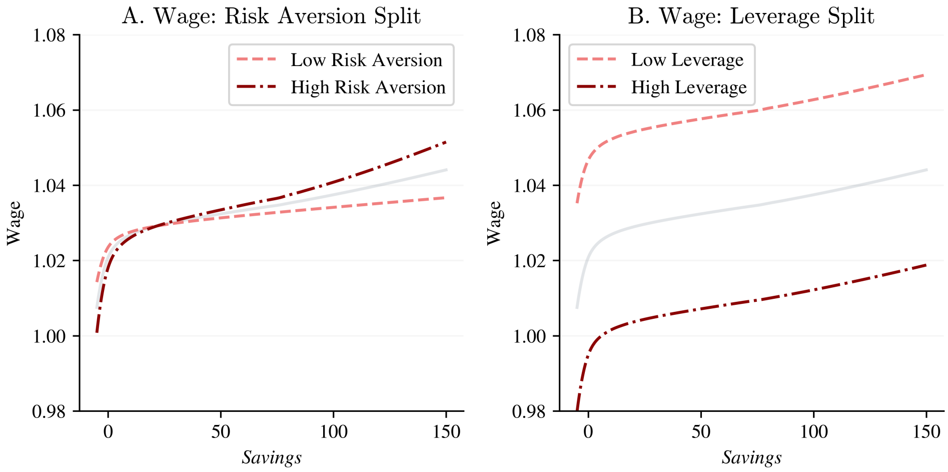
This figure plots the regression coefficients and 95% confidence intervals effect of leverage on consumption, based on different household and firm characteristics. The regression is based on equation (3.1), where the main explanatory variable is the interaction between income and *Leverage*, defined as the ratio of total debt financing, net of cash, to total assets, measured in book value. This variable is further interacted with dummy variables indicating the group a household or employer belongs to. The dependent variable in all panels, consumption, is measured as the sum between purchases and payments from either a debit or credit card at this bank. Panel A shows the estimated coefficient for $Income \times Leverage$, interacted with a dummy variable that takes the value of one if the household belongs to the bottom quartile in the income distribution and zero otherwise. In Panel B, the interacted dummy variable takes the value of one for households belonging to the bottom quartile in the asset distribution and zero otherwise. Panel C uses a dummy variable that takes the value of one for firms in the bottom quartile in size distribution, measured by book assets, and zero otherwise. Panel D considers a dummy variable that takes the value of one if the household's employer is publicly listed and zero otherwise. Panel E splits the sample by considering households whose employer operates in a highly volatile industry (defined as being in the top quartile of this distribution, according to the industry volatility measure described in Table 3.A.2). Finally, Panel F splits the sample depending on whether the vacancy-to-unemployment ratio is in the bottom quartile of its distribution and zero otherwise. This specification includes household, month-year, and industry-year fixed effects. Firm-level characteristics, the household contemporaneous income, and the remaining interaction terms are added as controls. Standard errors are computed using two-way clustering (household and employer level).

FIGURE 3.A.2: Heterogeneity on the Household Reaction to Industry Shock



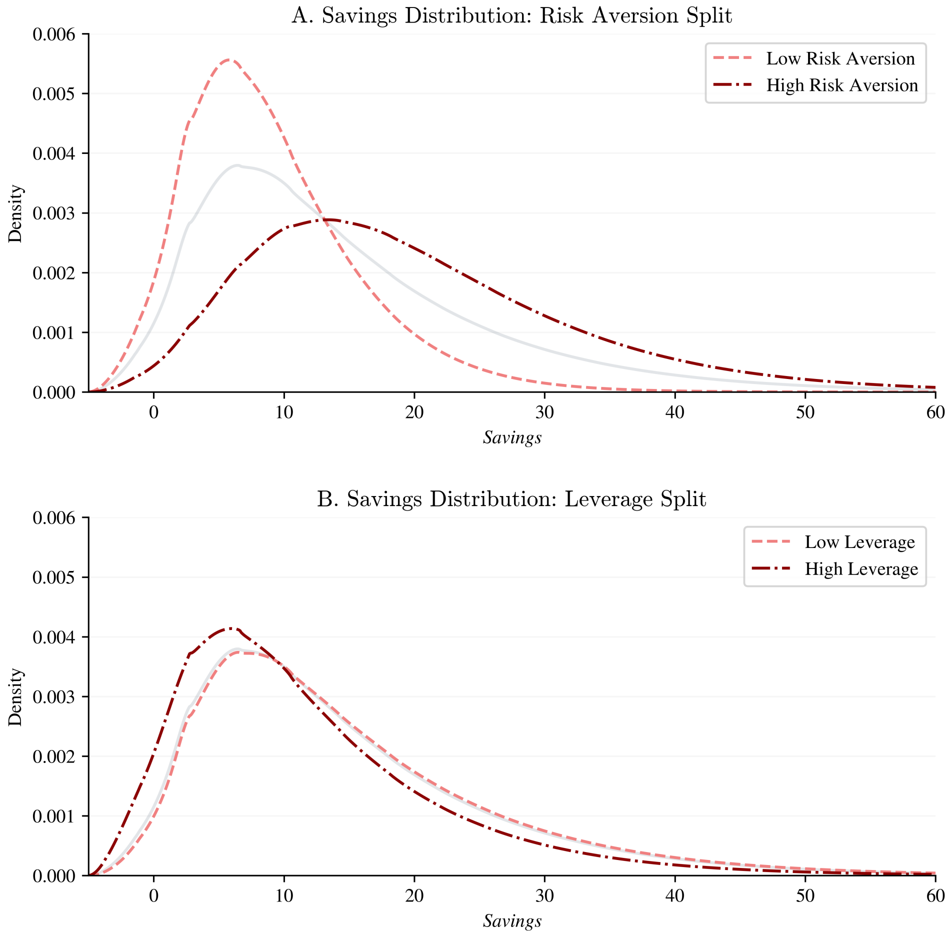
This figure plots the household consumption response to industry-wide shocks, following the specification in equation (3.3). The dependent variable, is the inverse hyperbolic sine of consumption, defined as the sum between purchases and payments from either a debit or credit card at this bank (red columns). Additional estimates are also presented for a specification in which the natural logarithm of consumption is considered, thus dropping zero values (green columns); and for a pseudo-Poisson regression (blue column). Observations are at the household-calendar date level and the panel runs from January 2018 to June 2022. All firm-level variables correspond to the primary employer over the past quarter and are lagged by one year. The figure plots, for different specifications, the coefficients for the interaction between *Industry Shock* and a group indicator, splitting employers according to their leverage and the maturity of liabilities. Additional controls include *Firm's Total Assets*, corresponding to book assets; *Profitability* is defined as net income divided by total sales; and *Tangibility* is given by fixed assets divided by total assets. In all specifications, month-by-year, household, and industry fixed-effects are considered. Standard errors in parentheses are clustered at the industry-date level. *p< 0.1;**$p < 0.05$;***p< 0.01.

Figure 3.A.3: Wages as a Function of Savings: Risk Aversion and Employer's Leverage Splits



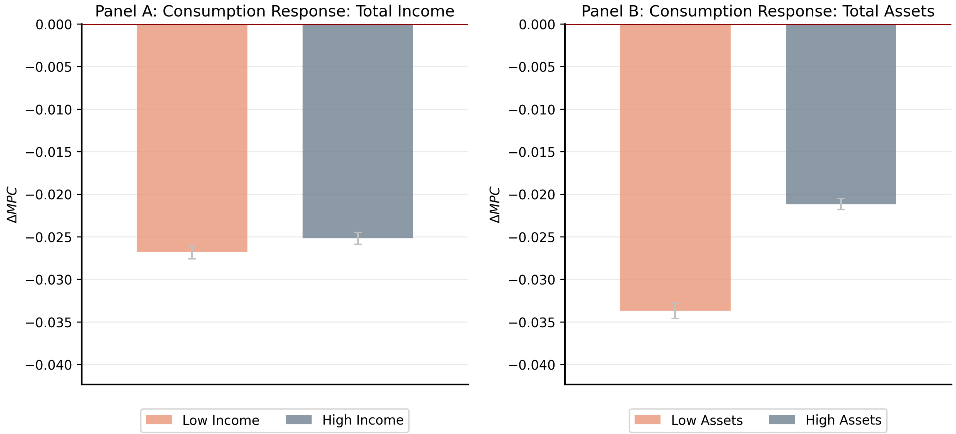
This figure shows the wage schedule as a function of household savings, based on the calibration reported in Table 3.A.9. In both panels, the average wage for different types of households and firms, assuming a job-match quality equal to the unconditional mean of x, is represented in gray (solid line). Keeping the level of idiosyncratic productivity (x) constant, Panel A then shows in orange (dashed line) the wage function for a lower coefficient of risk aversion ($\gamma = 1$) and in red (dash-dotted line) for a higher coefficient of risk aversion ($\gamma = 2$). Panel B also keeps the level of idiosyncratic productivity (x) constant, but plots in orange (dashed line) the wage function for an unleveraged firm ($b = 0$), and in red (dash-dotted line) the same function for a leveraged firm ($b = 0.1$).

FIGURE 3.A.4: Wealth Distribution: Risk Aversion and Employer's Leverage Splits



This figure plots the wealth distribution, based on the calibration reported in Table 3.A.9. In both panels, the solid gray line represents the density for each wealth level, across all levels of productivity, risk aversion, and leverage. Panel A illustrates in orange (dashed line) the wealth distribution for a lower coefficient of risk aversion ($\gamma = 1$) and in red (dash-dotted line) for a higher coefficient of risk aversion ($\gamma = 2$). Panel B shows in orange (dashed line) the wealth distribution for an unleveraged firm ($b = 0$), and in red (dash-dotted line) for a leveraged firm ($b = 0.1$).

FIGURE 3.A.5: Heterogeneity in the Consumption Response: Simulated Data



This figure plots the regression coefficients and 95% confidence intervals for the effect of leverage on consumption, according to different splits of household characteristics, based on a simulated panel as described in Section 3.5.2. The empirical methodology is comparable to the real data analysis and is based on the model defined in equation (3.1). The main explanatory variable is the interaction between wages and *Levered*, a dummy variable that takes the value of one for leveraged employers and zero otherwise. This variable is further interacted with a dummy variable which takes the value of one for households in the bottom quartile of income, and zero otherwise (Panel A); and a dummy which takes the value of one for households in the bottom quartile of savings, and zero otherwise (Panel B). Standard errors are clustered at the household level.

Table 3.A.1: Summary Statistics of Household and Firm Characteristics

Panel A: Households Summary Statistics								
Variable	N	Mean	SD	p10	p25	p50	p75	p90
Average Age	87,258	46.8	8.0	37.0	41.0	46.0	52.5	58.0
N. of Mortgagors	87,258	1.7	0.5	1.0	1.0	2.0	2.0	2.0
Married	87,258	0.6	0.5	0.0	0.0	1.0	1.0	1.0
Consumption	87,258	1,617.0	946.4	647.0	956.3	1,406.5	2,045.4	2,834.4
Wages	87,258	1,855.9	1,110.8	727.2	1,115.2	1,613.7	2,328.8	3,301.1
Retirement Benefits	20,126	1,079.4	728.8	327.8	530.6	862.1	1,497.0	2,246.6
Social Security Benefits	26,070	171.4	219.5	10.2	28.7	76.8	214.3	501.3
Total Income	87,258	2,171.1	1,278.8	873.1	1,322.8	1,833.8	2,741.4	3,852.9
Net Liquid Assets	87,258	6,686.7	12,987.6	-344.4	527.9	1,927.6	6,689.7	18,566.1
Savings Accounts	58,733	17,878.9	29,210.8	0.0	518.7	6,133.5	21,443.3	50,679.6
Home Mortgage Loans	87,258	73,582.9	52,453.2	17,679.1	34,581.3	62,434.6	100,135.7	141,768.2
Other Banks' Loans	61,613	10,853.1	20,495.7	42.5	344.0	3,321.7	12,420.5	25,857.4
Debt Service-to-Income	87,257	0.14	0.09	0.05	0.08	0.13	0.18	0.26
Civil Servant	87,258	0.5	0.5	0.0	0.0	0.0	1.0	1.0
Panel B: Firms Summary Statistics								
Variable	N	Mean	SD	p10	p25	p50	p75	p90
Total Assets	14,128	11,330.5	32,352.4	140.4	471.7	1,837.8	7,044.3	23,912.3
Cash	14,128	706.2	2,004.7	5.1	22.9	100.0	416.0	1,511.9
Fixed Assets	14,128	2,524.8	7,570.2	3.8	39.0	258.6	1,376.2	5,472.8
Total Liabilities	14,128	6,710.6	20,041.6	83.9	260.5	1,017.8	3,935.9	13,447.6
Total Debt	14,128	2,444.5	8,147.7	0.0	2.9	154.0	1,096.6	4,758.4
Turnover	14,128	9,789.8	24,725.8	162.5	534.9	1,888.4	6,925.1	22,493.4
Interest Paid	14,128	76.6	291.7	0.0	0.1	3.9	27.0	129.3
Net Income	14,128	384.8	1,574.6	-73.2	2.4	36.4	231.6	1,012.5
Industry Volatility	14,128	0.04	0.12	0.01	0.01	0.02	0.04	0.08
Leverage	14,126	0.08	0.34	-0.34	-0.11	0.05	0.29	0.48
Profitability	14,126	0.03	0.16	-0.07	0.00	0.03	0.08	0.16
Tangibility	14,126	0.26	0.24	0.01	0.05	0.19	0.40	0.63
Employee Productivity	13,852	144.9	223.2	20.5	39.4	73.6	149.0	319.7
Average Employee Expenses	13,852	21.8	13.2	10.8	13.7	18.4	25.5	35.9
Number of employees	14,128	75.3	168.8	4.0	9.0	24.0	65.0	164.0

This table lists for each variable its mean, standard deviation, the 10%, 25%, 50%, 75%, and 90% percentiles, and the number of households (Panel A) and firms (Panel B) with non-missing records. In panel A, statistics are computed on household averages over 2019. Income, assets, liabilities, and consumption measures are winsorized at the top and bottom 1% by date. The indicator variable "civil servant" assumes a value of 1 if most of the annual joint salary of the household is paid by a state-owned company or institution and zero otherwise. In Panel B, the statistics correspond to 2018 fiscal year values, to match the lagged structure of the regressions. All variables correspond to book values and are winsorized at the top and bottom 1%. Book assets, cash holdings, fixed assets, total liabilities, turnover, interest paid, and net income are shown in thousand euros. Industry volatility is defined as the standard deviation of sales at the three-digit industry level, normalized by the average industry's total assets. Leverage is defined as total debt financing, net of cash, normalized by total assets; profitability is defined as net income divided by total assets; and tangibility corresponds to the ratio of fixed assets to total assets. Finally, employee productivity is defined as total sales divided by the firm's number of employees.

Table 3.A.2: Marginal Propensity to Consume

	Consumption				
	(1)	(2)	(3)	(4)	(5)
Total Income	0.073***	0.115***	0.112***	0.108***	0.071***
	(0.002)	(0.013)	(0.014)	(0.014)	(0.002)
× Leverage	-0.006*	-0.006***	-0.008***	-0.009***	
	(0.003)	(0.002)	(0.002)	(0.003)	
× Log(Firm's Total Assets)		0.001	0.001	0.002	
		(0.001)	(0.001)	(0.001)	
× Profitability		0.006	0.006	0.004	
		(0.009)	(0.010)	(0.010)	
× Tangibility		0.009*	0.011**	0.013**	
		(0.005)	(0.006)	(0.006)	
× Log(Employees' Productivity)		-0.005***	-0.006***	-0.006***	
		(0.001)	(0.001)	(0.001)	
× Industry's Volatility		-0.057**	-0.059**	-0.059**	
		(0.024)	(0.024)	(0.025)	
× Public Sector					0.007**
					(0.003)
Month × Year FE	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	No	Yes
Industry × Year FE	No	Yes	Yes	Yes	No
Employer FE	No	No	Yes	No	No
Household × Employer FE	No	No	No	Yes	No
R^2	0.550	0.551	0.556	0.560	0.538
Observations	2,356,500	2,336,140	2,335,933	2,334,414	4,428,016

This table presents estimates of the effect of leverage on consumption expenditure. Observations are at the household-month-year level and the panel runs from January 2018 to June 2022. All firm-level variables correspond to the primary employer over the past quarter and are lagged by one year. The dependent variable in all columns is measured as the sum between purchases and payments from either a debit or credit card at this bank. *Total Income* corresponds to the household income deposited at this bank, which includes wages, social security benefits and other pensions. *Leverage* is defined as the ratio of total debt financing, net of cash, to total assets, measured in book value; *Firm's Total Assets* corresponds to book assets; *Profitability* is defined as net income divided by total sales; *Tangibility* is given by fixed assets divided by total assets; *Employees' Productivity* corresponds to total sales divided by the number of employees; and *Industry's Volatility* is computed as the standard deviation of sales at the three-digit industry level, normalized by the industry's total assets. Finally, *Public Sector* is a dummy variable that takes the value of one if the main employer over the last quarter is a state-owned company or institution and zero otherwise. Standard errors in parentheses are computed using two-way clustering (household and employer). *p< 0.1;**$p < 0.05$;***p< 0.01.

TABLE 3.A.3: Marginal Propensity to Consume by Category

	(1) Groc.	(2) Cloth.	(3) House Maint.	(4) Furnit.	(5) Transp.	(6) Health Care	(7) Restau.	(8) Entert. & Educ.	(9) Misc.
Total Income	0.0174***	0.0092***	0.0013	0.0067***	0.0111***	0.0062***	0.0116**	0.0052**	0.0428***
	(0.0025)	(0.0022)	(0.0009)	(0.0016)	(0.0026)	(0.0016)	(0.0055)	(0.0020)	(0.0073)
× Leverage	-0.0007	-0.0017***	-0.0003	-0.0000	-0.0019***	-0.0005	-0.0013**	-0.0002	-0.0056***
	(0.0007)	(0.0004)	(0.0002)	(0.0004)	(0.0006)	(0.0003)	(0.0006)	(0.0005)	(0.0016)
Additional Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.6090	0.4040	0.2500	0.2010	0.3840	0.3270	0.4370	0.3390	0.4250
Observations	1,330,940	1,330,940	1,330,940	1,330,940	1,330,940	1,330,940	1,330,940	1,330,940	1,330,940

This table presents estimates of the effect of leverage on consumption expenditure. Observations are at the household-month-year level and the panel runs from January 2020 to June 2022. All firm-level variables correspond to the primary employer over the past quarter and are lagged by one year. Each column shows a different consumption category as the dependent variable: (1) Groceries; (2) Clothing; (3) Housing Maintenance and Utilities; (4) Furniture; (5) Transport; (6) Health Care; (7) Restaurants; (8) Entertainment and Education; and (9) Miscellaneous Goods and Services. In all regressions, the interaction between income and additional firm-level controls is added. *Total Income* corresponds to the household income deposited at this bank, which includes wages, social security benefits and other pensions. Though omitted from the table, *Leverage* is defined as the ratio of total debt financing, net of cash, to total assets, measured in book value. Additional controls include *Firm's Total Assets*, corresponding to book assets; *Profitability* is defined as net income divided by total sales; *Tangibility* is given by fixed assets divided by total assets; *Employees' Productivity* corresponds to total sales divided by the number of employees; and finally *Industry's Volatility* is computed as the standard deviation of sales at the three-digit industry level, normalized by the industry's total assets. Standard errors in parentheses are computed using two-way clustering (household and employer). *p< 0.1;**p < 0.05;***p< 0.01.

TABLE 3.A.4: Marginal Propensity to Save

	Δ Net Liquid Assets				
	(1)	(2)	(3)	(4)	(5)
Total Income	0.630***	0.435***	0.440***	0.454***	0.616***
	(0.005)	(0.026)	(0.030)	(0.031)	(0.005)
× Leverage	0.014***	0.010*	0.009	0.010	
	(0.005)	(0.005)	(0.006)	(0.006)	
× Log(Firm's Total Assets)		0.003***	0.001	0.001	
		(0.001)	(0.002)	(0.002)	
× Profitability		-0.010	-0.013	-0.013	
		(0.013)	(0.014)	(0.014)	
× Tangibility		-0.009	-0.005	-0.007	
		(0.012)	(0.014)	(0.014)	
× Log(Employees' Productivity)		0.013***	0.016***	0.015***	
		(0.002)	(0.002)	(0.003)	
× Industry's Volatility		0.068	0.080	0.093*	
		(0.051)	(0.053)	(0.053)	
× Public Sector					-0.021***
					(0.006)
Month × Year FE	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	No	Yes
Industry × Year FE	No	Yes	Yes	Yes	No
Employer FE	No	No	Yes	No	No
Household × Employer FE	No	No	No	Yes	No
R^2	0.098	0.098	0.102	0.104	0.094
Observations	2,319,660	2,299,554	2,299,353	2,297,950	4,353,865

This table presents estimates of the effect of leverage on saving. Observations are at the household-month-year level and the panel runs from January 2018 to June 2022. All firm-level variables correspond to the primary employer over the past quarter and are lagged by one year. The dependent variable is measured as changes in checking account balances, net of credit card and overdraft debt payments made by the household. *Total Income* corresponds to the household income deposited at this bank, which includes wages, social security benefits and other pensions. *Leverage* is defined as the ratio of total debt financing, net of cash, to total assets, measured in book value; *Firm's Total Assets* corresponds to book assets; *Profitability* is defined as net income divided by total sales; *Tangibility* is given by fixed assets divided by total assets; *Employees' Productivity* corresponds to total sales divided by the number of employees; and *Industry's Volatility* is computed as the standard deviation of sales at the three-digit industry level, normalized by the industry's total assets. Finally, *Public Sector* is a dummy variable that takes the value of one if the main employer over the last quarter is a state-owned company or institution and zero otherwise. Standard errors in parentheses are computed using two-way clustering (household and employer). *p< 0.1;**$p < 0.05$;***p< 0.01.

Table 3.A.5: Probability of Bankruptcy

	Bankrupt			Bankrupt at t+1		
	(1)	(2)	(3)	(4)	(5)	(6)
High Leverage	1.274***	1.254***	1.319***	0.017**	0.016**	0.018**
	(0.281)	(0.275)	(0.274)	(0.007)	(0.007)	(0.009)
Log(Firm's Total Assets)			-0.036			0.005**
			(0.062)			(0.002)
Profitability			-0.700			-0.053
			(0.437)			(0.042)
Tangibility			-0.823			-0.005
			(0.524)			(0.023)
Log(Employees' Productivity)			-0.205			-0.008
			(0.159)			(0.006)
Industry's Volatility			-1.715			0.000
			(1.678)			(0.015)
Industry FE	No	Yes	Yes	No	No	No
Year FE	No	No	No	Yes	No	No
Industry × Year FE	No	No	No	No	Yes	Yes
R^2	0.002	0.018	0.018	0.000	0.009	0.009
Observations	13,536	13,535	13,114	93,142	93,132	65,578

This table presents estimates for the probability of going bankrupt as a function of firm leverage, according to a linear probability model and considering in-sample firms. The outcome variable in columns (1)–(3) is a dummy variable that takes the value of one if the firm goes bankrupt during the whole sample period (from 2018 to 2022). In these columns, the explanatory variables are measured at the end of the 2017 fiscal year. In columns (4)–(6), the outcome variable is a dummy variable that takes the value of one if the firm goes bankrupt during the following year, and the regression runs at the firm-year level, from 2017 to 2021 (explanatory variables are lagged by one year relative to the dependent variable). Financial firms (CAE codes 64-66) are excluded from the sample. *High Leverage* is a dummy variable that takes the value of one for firms with an above-median leverage ratio, defined as the ratio of total debt financing, net of cash, to total assets, measured in book value; *Firm's Total Assets* corresponds to book assets; *Profitability* is defined as net income divided by total sales; *Tangibility* is given by fixed assets divided by total assets; *Employees' Productivity* corresponds to total sales divided by the number of employees; and finally *Industry's Volatility* is computed as the standard deviation of sales at the three-digit industry level and for the previous 3 years, normalized by the industry's total assets. Robust standard errors are shown in parentheses for columns (1) to (3), while standard errors for the remaining columns are clustered at the firm level. *p< 0.1;**$p<0.05$;***p< 0.01.

Table 3.A.6: Unemployment Risk

	Benefits Recipient$_{t+3}$			Lost Job$_{t+3}$		
	(1)	(2)	(3)	(4)	(5)	(6)
High Leverage	0.0293**	0.0452***	0.0817***	0.1250***	0.1890***	0.1910***
	(0.0131)	(0.0126)	(0.0298)	(0.0436)	(0.0425)	(0.0670)
Age	0.0046***	0.0048***		0.0524***	0.0530***	
	(0.0008)	(0.0008)		(0.0046)	(0.0046)	
Wages	-0.0000	0.0000	0.0001***	-0.0001***	-0.0001***	-0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Additional Controls	No	Yes	Yes	No	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	No	No	Yes	No	No	Yes
R^2	0.0010	0.0020	0.1720	0.0080	0.0090	0.2150
Observations	615,090	609,708	603,282	615,090	609,708	603,282

This table presents estimates of regressions of the probability of becoming unemployed in the following quarter, as a function of the employer's leverage. Observations are at the household-quarter level, measured at the end of each quarter, and the panel runs from January 2018 to December 2021. Only households with a single recorded employer are included in regressions, and all firm-level variables correspond to this employer over the previous quarter. The dependent variable in all columns indicates job loss, defined as a household no longer being employed in the following quarter and not returning to the original employer within one year. In columns (1)–(3), a household must also start receiving social security benefits to be classified as being unemployed. *High Leverage* is a dummy variable that takes the value of one for above-median firms in the leverage ratio, defined as the ratio of total debt financing, net of cash, to total assets, measured in book value. Additional controls include *Firm's Total Assets*, corresponding to book assets; *Profitability*, defined as net income divided by total sales; *Tangibility*, given by fixed assets divided by total assets; *Employees' Productivity*, corresponding to total sales divided by the number of employees; and finally *Industry's Volatility*, computed as the standard deviation of sales at the three-digit industry level, normalized by the industry's total assets. All variables at the firm level are lagged by one year. Standard errors in parentheses are computed using two-way clustering (household and employer). *p< 0.1;**$p < 0.05$;***p< 0.01.

TABLE 3.A.7: Wages

	Log(Earnings)				
	(1)	(2)	(3)	(4)	(5)
Leverage	-0.148	-0.104*	-0.041**	-0.023	
	(0.092)	(0.060)	(0.016)	(0.018)	
Log(Firm's Total Assets)	0.054***	0.055***	0.026***	0.048***	
	(0.017)	(0.011)	(0.004)	(0.013)	
Profitability	-0.637***	-0.107	0.007	0.026	
	(0.127)	(0.069)	(0.029)	(0.032)	
Tangibility	0.052	-0.068	0.038	0.024	
	(0.075)	(0.069)	(0.027)	(0.035)	
Log(Employees' Productivity)	0.127***	0.083***	0.029***	0.025***	
	(0.027)	(0.020)	(0.007)	(0.009)	
Industry's Volatility	-0.970**	1.090***	0.131	0.125	
	(0.467)	(0.418)	(0.098)	(0.098)	
Public Sector					0.244***
					(0.075)
Year FE	Yes	No	No	No	Yes
Industry × Year FE	No	Yes	Yes	Yes	No
Household FE	No	No	Yes	Yes	No
Employer FE	No	No	No	Yes	No
R^2	0.102	0.231	0.813	0.843	0.025
Observations	184,693	184,692	178,398	176,711	344,488

This table presents estimates of regressions of the natural logarithm of wages, defined as annual wages paid by the household's primary employer. Observations are at the household-year level and the panel runs from 2018 to 2021. Financial firms (CAE codes 64-66) are excluded from the sample. *Leverage* is defined as the ratio of total debt financing, net of cash, to total assets, measured in book value; *Firm's Total Assets* corresponds to book assets; *Profitability* is defined as net income divided by total sales; *Tangibility* is given by fixed assets divided by total assets; *Employees' Productivity* corresponds to total sales divided by the number of employees; and finally *Industry's Volatility* is computed as the standard deviation of sales at the three-digit industry level and for the previous 3 years, normalized by the industry's total assets. All variables at the firm level are lagged by one year. Standard errors in parentheses are computed using two-way clustering (household and employer level). *p< 0.1;**$p < 0.05$;***p< 0.01.

Table 3.A.8: Consumption Response to Industry Shock

	Asinh(Consumption)			
	(1)	(2)	(3)	(4)
Industry Shock	-0.006	-0.006		
	(0.007)	(0.007)		
Industry Shock × High Leverage	-0.032***	-0.032***	-0.020***	-0.020***
	(0.008)	(0.008)	(0.007)	(0.007)
High Leverage	-0.006**	0.002	-0.004	-0.000
	(0.003)	(0.003)	(0.003)	(0.003)
Additional Firm Controls	No	Yes	Yes	Yes
Additional Household Controls	Yes	Yes	Yes	Yes
Month × Year FE	Yes	Yes	No	No
Household FE	Yes	Yes	Yes	Yes
Industry × Month × Year FE	No	No	Yes	Yes
Employer FE	No	No	No	Yes
R^2	0.515	0.515	0.520	0.533
Observations	1,178,296	1,169,605	1,169,605	1,169,542

This table presents estimates of regressions of the inverse hyperbolic sine of consumption expenditure on industry-level shocks and main employer's leverage. Observations are at the household-calendar date level and the panel runs from January 2018 to June 2022. The dependent variable, consumption, is defined as the sum between purchases and payments from either a debit or credit card at this bank. All firm-level variables correspond to the primary employer over the past quarter and are lagged by one year. *Industry Shock* is a dummy that takes the value of 1 if the primary employer of the household operates in one of the most affected industry-month pairs in a given year (defined as the bottom 5% of year-on-year monthly change of sales at the two-digit industry level), and 0 otherwise. *High Leverage* is a dummy that takes the value of 1 if the household main employer's leverage is above the sample's median, and 0 otherwise. Additional controls include *Firm's Total Assets*, corresponding to book assets; *Profitability* is defined as net income divided by total sales; and *Tangibility* is given by fixed assets divided by total assets. In all specifications, the inverse hyperbolic sine of income is added as a control. Standard errors in parentheses are clustered at the industry-date level. *p< 0.1;**$p < 0.05$;***p< 0.01.

Table 3.A.9: Parameter Values for the Endogenous Search and Match Model

Parameter	Symbol	Low	High
Relative Risk Aversion	γ	1	2
Debt Payment	b	0	0.1
Risk-free rate	r	0.04	
Household's Discount Factor	β_h	0.996	
Worker's Bargaining Power	δ	0.5	
Elasticity of Matching Technology	η	0.5	
Scaling Factor of Matching Technology	m_0	0.11	
Labor Market Tightness	θ	1.0	
Unemployment Insurance Benefit	ζ	0.62	
Utility from Leisure	l	0.15	
Persistence of Idiosyncratic Productivity	ρ_x	0.98	
Standard Deviation of Idiosyncratic Productivity	σ_x	0.04	

This table reports the household-specific and aggregate parameter values used in the quantitative exercises and simulations. Unless otherwise stated, values are reported for a monthly time interval.

TABLE 3.A.10: Wages: Simulated Data

	Log(Wages)	
	(1)	(2)
Levered	-0.020***	-0.009***
	(0.001)	(0.001)
Household FE	No	Yes
R^2	0.009	0.630
Observations	2,780,800	2,780,798

This table presents estimates of regressions of the natural logarithm of wages, using simulated data. The model is calibrated according to Table 3.A.9, and to ensure a stationary equilibrium, 5,000 periods were simulated but only the last 60 (5 years) are considered. Observations are at the household-month level. *Levered* is a dummy variable that takes the value of one for households working for leveraged employers. Standard errors in parentheses are clustered at the household level. *p< 0.1;**$p < 0.05$;***p< 0.01.

Table 3.A.11: Consumption and Saving: Simulated Data

	Consumption		Saving	
	(1)	(2)	(3)	(4)
Wage	0.462***	0.259***	0.648***	0.741***
	(0.002)	(0.001)	(0.001)	(0.001)
× Levered	-0.037***	-0.026***	0.030***	0.025***
	(0.001)	(0.000)	(0.000)	(0.000)
Household FE	No	Yes	No	Yes
R^2	0.323	0.983	0.778	0.988
Observations	2,780,800	2,780,798	2,733,691	2,733,689

This table presents the effect of leverage on consumption and saving, using simulated data. The model is calibrated according to Table 3.A.9, and to ensure a stationary equilibrium, 5,000 periods were simulated but only the last 60 (5 years) are considered. Observations are at the household-month level. *Levered* is a dummy variable that takes the value of one for households working for leveraged employers. Standard errors in parentheses are clustered at the household level. *p$<$ 0.1;**$p < 0.05$;***p$<$ 0.01.

Internet Appendix of Chapter 3

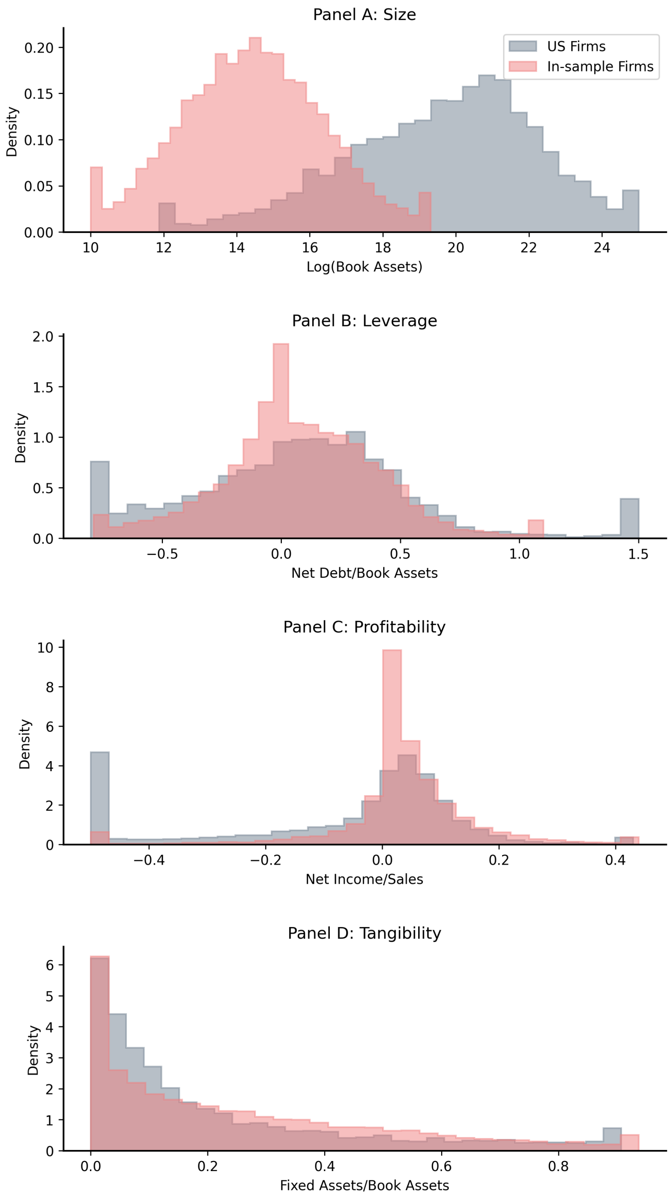
3.B.1 Model Simulation

To solve the model, I start by discretizing the state space. Specifically, I follow the Rouwenhorst (1995) method to approximate the process for the idiosyncratic productivity, x_t. As in Petrosky-Nadeau and Zhang (2017), I do not employ the Tauchen (1986) algorithm given its lower accuracy when dealing with highly persistent processes. I consider 17 grid points to discretize the idiosyncratic process. The state space for savings is bounded, with $a_t \in [-5, 150]$. I solve the model sequentially, starting with a small grid of 10 points. Upon convergence, I expand the grid, until reaching a grid of 81 points.

The aggregate productivity shock is normalized in the steady state as $z_t = 1$. Then, given an initial value of θ_t, normalized in the steady state to $\theta_t = 1$, I approximate the wage schedule, value functions, and associated saving functions. Given $w_t(x_t, b_t, \phi_t, \Phi_t)$, I solve for $W_t(x_t, b_t, \phi_t, \Phi_t)$ and $U_t(\phi_t, \Phi_t)$, as well as the decision rules. In each interaction, I use cubic splines to interpolate the wage schedule, and value and policy functions.

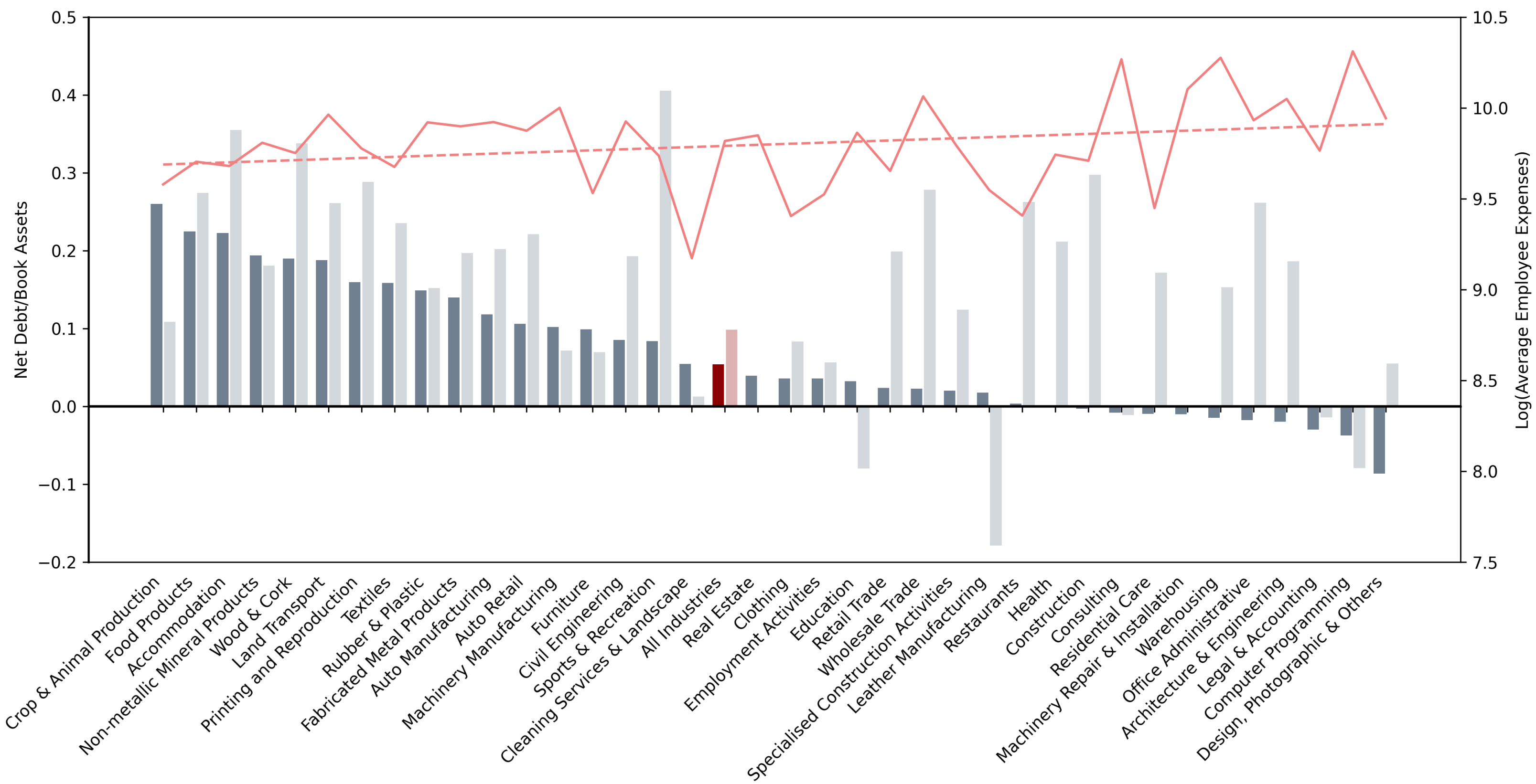
I then find the new wage schedule that solves the problem described in condition (3.8). To do so, I ensure that the first-order condition, given by equation (3.13), and the definition of $J_t(x_t, b, \phi_t, \Phi_t)$, in equation (3.11), are met. These steps are then repeated until these functions converge. The invariant measures are then computed and the fixed cost of posting a vacancy, κ, is found such that the free-entry condition, given by equation (3.12), is satisfied.

FIGURE 3.B.1: Comparison between in-sample firms and US firms



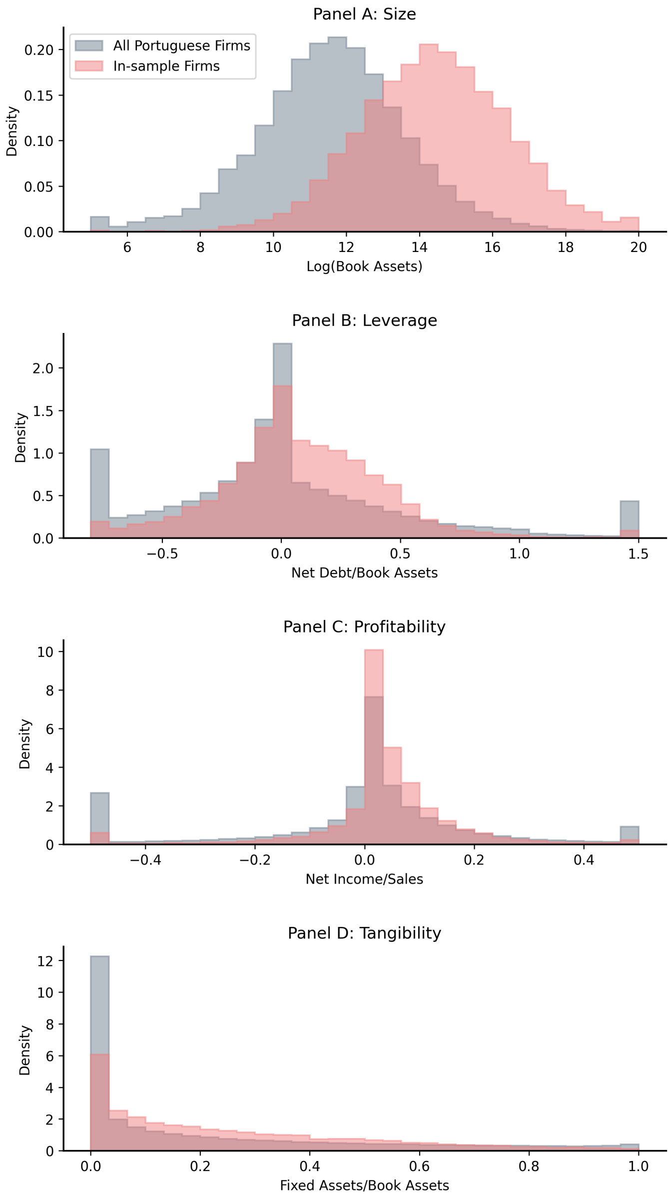
This figure plots the distribution of employers found in the sample of households (in red) and the distribution of US publicly-held firms from Compustat (in blue). Both financial firms (SIC codes 6000-6999) and utilities (SIC codes 4900-4999) are excluded from the Compustat sample, as well as any firm observations with a negative book value of total assets or negative value of sales. In Panel A, size is defined as the natural logarithm of book assets, using an exchange rate USD-EUR of 0.87294 (as of December 31, 2018). Panel B, the leverage ratio is defined as total debt financing minus cash, normalized by book assets. Panel C shows the profitability measure as return-on-assets, computed as net income normalized by book assets. Finally, Panel D plots the tangibility measure, computed as fixed assets divided by book assets.

Figure 3.B.2: Leverage and Average Employee Expenses by Industry



This figure plots the median leverage ratio and median employee expenses per employee for selected industries. Only in-sample firms are considered and only industries for which more than 100 observations exist were considered. Bars represent the average leverage ratio within each industry, computed as total debt financing minus cash, normalized by book assets (left y-axis). For each industry, Portuguese results are compared with U.S. public firms (left/dark blue bar for Portuguese firms and right/light blue bar for U.S. firms). The median leverage ratio for all in-sample firms is shown in red. The figure also plots the median employee expense, computed as the natural logarithm of total employee expenses divided by the number of employees (right y-axis), computed over in-sample firms. The dashed line represents a best-fit line through the right y-axis data points, illustrating the negative correlation (-0.17) between the average employee expenses and leverage ratio at the industry level.

Figure 3.B.3: Comparison between in-sample firms and the full universe of Portuguese firms



This figure plots the distribution of employers found in the sample of households (in red) and the distribution of all firms in Portugal for which non-missing accounting data exists (in blue). Financial firms (CAE codes 64-66) are excluded from the sample. In Panel A, size is defined as the natural logarithm of book assets. Panel B, the leverage ratio is defined as total debt financing minus cash, normalized by book assets. Panel C shows the profitability measure as return-on-assets, computed as net income normalized by book assets. Finally, Panel D plots the tangibility measure, computed as fixed assets divided by book assets.

Table 3.B.1: Summary Statistics of Household Characteristics by Subsample

Variable	Public Sector	Private Sector		
		Low Leverage	Intermediate Leverage	Very High Leverage
HH Average Age	49.2	44.9	44.7	45.3
N. of Mortgagors	1.6	1.7	1.7	1.7
Married	0.6	0.6	0.6	0.7
Consumption	1,699.6	1,605.1	1,548.4	1,512.4
Wages	2,007.9	1,781.2	1,736.2	1,679.5
Retirement Benefits	303.7	215.7	199.8	208.9
Social Security Benefits	33.8	64.7	65.8	65.5
Total Income	2,359.6	2,077.5	2,018.3	1,966.7
Net Liquid Assets	7,275.4	6,628.0	6,182.8	5,971.7
Saving Accounts	13,450.0	12,029.7	10,810.2	10,258.1
Vehicle, Student and Educ. Loans	114.2	78.7	93.0	100.2
Home Mortgage Loans	72,543.6	76,759.5	74,791.8	71,714.3
Other Loans	448.1	416.6	407.9	349.4
Other Banks' Loans	7,667.1	7,543.6	7,755.4	7,439.6
Debt Service-to-Income	0.14	0.15	0.15	0.15
Observations	39,379	6,800	31,223	9,856

This table lists for each variable the corresponding mean within subgroups of households, defined by their employer sector and leverage ratio. Statistics are computed on household averages over 2019. Households are identified as working for the public sector if this is the primary source of income during that particular year. Households whose primary source of income comes from the private sector are further divided depending on their primary employer's leverage. *Low Leverage* corresponds to the bottom quintile of employers' leverage; *High Leverage* corresponds to those in the top quintile of leverage; while the remaining households earn their primary wage from an employer in the second, third or fourth quintile of leverage. Income, assets, liabilities, and consumption measures are winsorized at the top and bottom 1% by date.

Table 3.B.2: Summary Statistics of Firm Characteristics by Subsample

Variable	Low Leverage (Q1)	Intermediate Leverage (Q2:Q4)	Very High Leverage (Q5)	Mean Difference (Q5-Q1)
Total Assets	5,012.3	11,898.4	15,955.3	10,943.0***
Cash	1,396.5	569.8	425.5	-971.0***
Fixed Assets	756.4	2,599.2	4,072.3	3,315.9***
Total Liabilities	2,190.4	6,496.6	11,878.8	9,688.3***
Total Debt	99.5	1,736.9	6,915.0	6,815.6***
Turnover	6,099.0	11,259.9	9,078.5	2,979.5***
Interest Paid	7.4	62.7	187.7	180.3***
Net Income	389.1	455.7	168.2	-220.9***
Industry Volatility	0.0	0.0	0.0	0.0
Number of employees	47.9	83.1	79.1	31.2***
Leverage	-0.4	0.1	0.5	0.9***
Profitability	0.1	0.0	-0.0	-0.1***
Tangibility	0.1	0.2	0.4	0.2***
Employee Productivity	135.3	153.0	129.9	-5.5
Average Employee Expenses	22.8	21.9	20.4	-2.5***
Observations	2,826	8,475	2,825	5,651

This table lists for each variable its mean within subgroups of firms, depending on which quintile of the leverage distribution they belong to. *Low Leverage* corresponds to the bottom quintile of employers' leverage; *High Leverage* corresponds to those in the top quintile of leverage; while the remaining firms belong to the second, third, or fourth quintile of leverage. The statistics correspond to 2018 fiscal year values. All variables correspond to book values and are winsorized at the top and bottom 1%. Book assets, cash holdings, fixed assets, total liabilities, turnover, interest paid, and net income are shown in thousand euros. Industry volatility is defined as the standard deviation of sales at the three-digit industry level, normalized by the average industry's total assets. Leverage is defined as total debt financing, net of cash, normalized by total assets; profitability is defined as net income divided by total assets; and tangibility corresponds to the ratio of fixed assets to total assets. Finally, employee productivity is defined as total sales divided by the firm's number of employees.

Table 3.B.3: Marginal Propensity to Consume - First-Difference Estimates

	ΔConsumption				
	(1)	(2)	(3)	(4)	(5)
ΔTotal Income	0.031***	0.107***	0.107***	0.107***	0.026***
	(0.002)	(0.009)	(0.009)	(0.009)	(0.002)
× Leverage	-0.007***	-0.008***	-0.007***	-0.007***	
	(0.003)	(0.003)	(0.003)	(0.003)	
× Log(Firm's Total Assets)		-0.001*	-0.001*	-0.001*	
		(0.001)	(0.001)	(0.001)	
× Profitability		-0.015	-0.014	-0.014	
		(0.011)	(0.011)	(0.011)	
× Tangibility		0.013**	0.013**	0.013**	
		(0.005)	(0.005)	(0.005)	
× Log(Employees' Productivity)		-0.005***	-0.005***	-0.005***	
		(0.001)	(0.001)	(0.001)	
× Industry's Volatility		-0.018	-0.018	-0.024	
		(0.025)	(0.025)	(0.025)	
× Public Sector					0.007*
					(0.004)
Leverage	0.297	0.424	-1.194	-1.051	
	(0.598)	(0.602)	(2.245)	(2.372)	
Additional Controls	No	Yes	Yes	Yes	No
Month × Year FE	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	No	Yes	Yes	Yes	No
Employer FE	No	No	Yes	No	No
Household × Employer FE	No	No	No	Yes	No
R^2	0.044	0.044	0.045	0.049	0.042
Observations	2,318,932	2,298,824	2,298,545	2,296,713	4,352,161

This table presents estimates of the effect of leverage on consumption expenditure. Observations are at the household-month-year level and the panel runs from January 2018 to June 2022. All firm-level variables correspond to the primary employer over the past quarter and are lagged by one year. The dependent variable in all columns is measured as the first difference of the sum between purchases and payments from either a debit or credit card at this bank. Δ*Total Income* corresponds to the first difference of the monthly household income, which includes wages, social security benefits and other pensions. *Leverage* is defined as the ratio of total debt financing, net of cash, to total assets, measured in book value; *Firm's Total Assets* corresponds to book assets; *Profitability* is defined as net income divided by total sales; *Tangibility* is given by fixed assets divided by total assets; *Employees' Productivity* corresponds to total sales divided by the number of employees; and *Industry's Volatility* is computed as the standard deviation of sales at the three-digit industry level, normalized by the industry's total assets. Finally, *Public Sector* is a dummy variable that takes the value of one if the main employer over the last quarter is a state-owned company or institution and zero otherwise. Standard errors in parentheses are computed using two-way clustering (household and employer). *p< 0.1;**$p < 0.05$;***p< 0.01.

Table 3.B.4: Consumption Response to Leverage

	Asinh(Consumption)				
	(1)	(2)	(3)	(4)	(5)
Asinh(Total Income)	0.033***	0.033***	0.033***	0.016***	0.016***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Leverage	-0.017***	-0.020***	-0.015**	-0.011	-0.007
	(0.006)	(0.007)	(0.007)	(0.011)	(0.013)
Log(Firm's Total Assets)		-0.005**	-0.005***	-0.002	0.010
		(0.002)	(0.002)	(0.002)	(0.009)
Profitability		-0.090***	-0.008	0.006	0.014
		(0.022)	(0.022)	(0.020)	(0.021)
Tangibility		0.013	0.013	-0.030	-0.048*
		(0.015)	(0.016)	(0.019)	(0.029)
Log(Employees' Productivity)		0.011***	0.008**	0.004	-0.004
		(0.004)	(0.004)	(0.004)	(0.006)
Industry's Volatility		-0.168**	-0.138	-0.172*	-0.131
		(0.078)	(0.096)	(0.103)	(0.114)
Month × Year × Group FE	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	No	No	Yes	Yes	Yes
Household FE	No	No	No	Yes	Yes
Employer FE	No	No	No	No	Yes
R^2	0.172	0.172	0.176	0.525	0.540
Observations	2,357,050	2,336,685	2,336,685	2,336,140	2,335,933

This table presents estimates of the effect of leverage on consumption expenditure. Observations are at the household-month-year level and the panel runs from January 2018 to June 2022. All firm-level variables correspond to the primary employer over the past quarter and are lagged by one year. The dependent variable in columns (1) to (3) is measured as the inverse hyperbolic sine of the sum of purchases and payments from either a debit or credit card at this bank. *Total Income* corresponds to the household income deposited at this bank, which includes wages, social security benefits and other pensions. *Leverage* is defined as the ratio of total debt financing, net of cash, to total assets, measured in book value; *Firm's Total Assets* corresponds to book assets; *Profitability* is defined as net income divided by total sales; *Tangibility* is given by fixed assets divided by total assets; *Employees' Productivity* corresponds to total sales divided by the number of employees; and finally *Industry's Volatility* is computed as the standard deviation of sales at the three-digit industry level, normalized by the industry's total assets. All specifications include group-by-month-year fixed effects, with the group referring to terciles of total assets and income in a given year. Standard errors in parentheses are computed using two-way clustering (household and employer). *p< 0.1;**$p < 0.05$;***p< 0.01.

Table 3.B.5: Effect of non-Luxury Sector Leverage on the Luxury Sector

	Log($Turnover_{l}$)		
	(1)	(2)	(3)
High Industry-Adjusted $Leverage_{nl}$	-0.032***	-0.025**	-0.019*
	(0.011)	(0.010)	(0.010)
High Industry-Adjusted $Leverage_{l}$	0.000	0.011	0.005
	(0.011)	(0.011)	(0.011)
Log($Employees_{nl}$)	0.082	0.127	0.111
	(0.124)	(0.116)	(0.110)
Log($Turnover_{nl}$)	-0.012	-0.066	-0.078
	(0.050)	(0.050)	(0.049)
Log(Employee $Expenses_{All}$)	0.317***	0.314***	0.310***
	(0.117)	(0.105)	(0.108)
Additional Controls	No	Yes	Yes
Municipality FE	Yes	Yes	No
Year	Yes	Yes	Yes
District × Year FE	No	No	Yes
R^2	0.989	0.990	0.991
Observations	2,970	2,970	2,970

This table presents estimates of regressions of the effect of leverage on turnover of the luxury goods and services sector. Observations are at the municipality-year level and the panel runs from 2012 to 2022. The outcome variable, *Log($Turnover_l$)*, corresponds to the natural logarithm of total turnover, at the municipality level and considering only firms working for luxury goods and services sectors. Specifically, I define the luxury sector as containing all firms with CAE industry codes 4751, 4771, and 4772 (clothing retailers), 49–51 (transportation), and 55–56 (hotels and restaurants). *High Industry-Adjusted Leverage* is a dummy variable that takes the value of 1 for municipalities whose average leverage ratio, weighted by the number of employees of each firm and adjusted to the two-digit industry average, is above the sample-year median, and 0 otherwise. As before, the leverage ratio is defined as the ratio of total debt financing, net of cash, to total assets, measured in book value. Additional controls include, for each sector, the municipality's average profitability, tangibility, and employee productivity, all weighted by the number of employees of each firm and adjusted to the two-digit industry average. Moreover, *Profitability* is defined as net income divided by total sales; *Tangibility* is given by fixed assets divided by total assets; and *Employees' Productivity* corresponds to total sales divided by the number of employees. Adjusted measures of leverage, profitability, tangibility, and employee productivity are lagged by one year. Standard errors in parentheses are clustered at the municipality level. *p$<$ 0.1;**$p < 0.05$;***p$<$ 0.01.

Table 3.B.6: Sensitivity of Luxury Sector to Regional Productivity Shocks

	Log(Turnover$_{l}$)		Log(Turnover$_{nl}$)	
	(1)	(2)	(3)	(4)
High Regional Industry-Adjusted Leverage$_{All}$	-0.017	-0.021*	-0.024***	-0.021***
	(0.013)	(0.012)	(0.008)	(0.007)
ΔLog(Regional Turnover$_{All}$)	-0.046	-0.041	-0.004	-0.002
	(0.075)	(0.069)	(0.048)	(0.039)
High Regional Industry-Adjusted Leverage$_{All}$ $\times$ ΔLog(Regional Turnover$_{All}$)	0.263***	0.277***	0.096	0.084
	(0.101)	(0.100)	(0.094)	(0.080)
High Industry-Adjusted Leverage$_{l}$	0.000	0.010	0.002	0.007
	(0.011)	(0.011)	(0.008)	(0.007)
High Industry-Adjusted Leverage$_{nl}$	-0.033***	-0.026***	0.015	0.016*
	(0.011)	(0.010)	(0.011)	(0.008)
Log(Employee Expenses$_{All}$)	0.322***	0.321***	0.815***	0.697***
	(0.118)	(0.105)	(0.202)	(0.145)
Additional Controls	No	Yes	No	Yes
Municipality FE	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
R^2	0.989	0.990	0.995	0.996
Observations	2,970	2,970	2,970	2,970

This table presents estimates of regressions of the effect of leverage on turnover of the luxury and non-luxury goods and services sectors. Observations are at the municipality-year level and the panel runs from 2012 to 2022. The outcome variable, *Log(Turnover)* corresponds to the natural logarithm of total turnover, at the municipality level and for each sector. I define the luxury sector (sector l) as containing all firms with CAE industry codes 4751, 4771, and 4772 (clothing retailers), 49–51 (transportation), and 55–56 (hotels and restaurants). Consistently, the non-luxury sector (sector nl) contains all the other firms in the economy. *High Industry-Adjusted Leverage* is a dummy variable that takes the value of 1 for municipalities whose average leverage ratio, weighted by the number of employees of each firm and adjusted to the two-digit industry average, is above the sample-year median, and 0 otherwise. As before, the leverage ratio is defined as the ratio of total debt financing, net of cash, to total assets, measured in book value. Additional controls include, for each sector, the municipality's average profitability, tangibility, and employee productivity, all weighted by the number of employees of each firm and adjusted to the two-digit industry average. Moreover, *Profitability* is defined as net income divided by total sales; *Tangibility* is given by fixed assets divided by total assets; and *Employees' Productivity* corresponds to total sales divided by the number of employees. Adjusted measures of leverage, profitability, tangibility, and employee productivity are lagged by one year. Standard errors in parentheses are clustered at the municipality level. *p$<$ 0.1;**$p < 0.05$;***p$<$ 0.01.

Table 3.B.7: Probability of Bankruptcy (All Portuguese Firms)

	Bankrupt			Bankrupt at t+1		
	(1)	(2)	(3)	(4)	(5)	(6)
High Leverage	0.502***	0.493***	0.498***	0.005***	0.005***	0.005***
	(0.078)	(0.071)	(0.066)	(0.001)	(0.001)	(0.001)
Log(Firm's Total Assets)			0.219***			0.004***
			(0.030)			(0.001)
Profitability			-0.138***			-0.006***
			(0.028)			(0.002)
Tangibility			-0.380***			-0.006**
			(0.075)			(0.003)
Log(Employees' Productivity)			-0.070**			-0.004***
			(0.030)			(0.001)
Industry's Volatility			0.899			0.000
			(0.871)			(0.012)
Industry FE	No	Yes	Yes	No	No	No
Year FE	No	No	No	Yes	No	No
Industry × Year FE	No	No	No	No	Yes	Yes
R^2	0.001	0.008	0.010	0.000	0.001	0.001
Observations	345,492	345,491	264,252	2,459,595	2,459,587	1,374,002

This table presents estimates for the probability of going bankrupt as a function of the firm's leverage, according to a linear probability model and considering all Portuguese firms. The outcome variable in columns (1)–(3) is a dummy variable that takes the value of one if the firm goes bankrupt during the whole sample period (from 2018 to 2022). In these columns, the explanatory variables are measured at the end of the 2017 fiscal year. In columns (4)–(6), the outcome variable is a dummy variable that takes the value of one if the firm goes bankrupt during the following year, and the regression runs at the firm-year level, from 2017 to 2021 (explanatory variables are lagged by one year relative to the dependent variable). *High Leverage* is a dummy variable that takes the value of one for firms with an above-median leverage ratio, defined as the ratio of total debt financing, net of cash, to total assets, measured in book value; *Firm's Total Assets* corresponds to book assets; *Profitability* is defined as net income divided by total sales; *Tangibility* is given by fixed assets divided by total assets; *Employees' Productivity* corresponds to total sales divided by the number of employees; and finally *Industry's Volatility* is computed as the standard deviation of sales at the three-digit industry level and for the previous 3 years, normalized by the industry's total assets. Robust standard errors are shown in parentheses for columns (1) to (3), while standard errors for the remaining columns are clustered at the firm level. *p< 0.1;**$p < 0.05$;***p< 0.01.

Table 3.B.8: Probability of Bankruptcy - Logistic Regression

	In-sample Firms			All Firms		
	(1)	(2)	(3)	(4)	(5)	(6)
High Leverage	0.822***	0.814***	0.864***	1.017***	0.996***	0.867***
	(0.146)	(0.149)	(0.158)	(0.052)	(0.053)	(0.059)
Log(Firm's Total Assets)			-0.017			0.313***
			(0.050)			(0.017)
Profitability			-0.268			-0.217***
			(0.192)			(0.045)
Tangibility			-0.541			-0.517***
			(0.363)			(0.111)
Log(Employees' Productivity)			-0.145*			-0.109***
			(0.087)			(0.026)
Industry FE	No	Yes	Yes	No	Yes	Yes
Likelihood Ratio χ^2	34	32	40	423	1,628	1,815
Observations	13,536	11,893	11,538	345,492	343,141	262,098

This table presents estimates for the probability of going bankrupt as a function of the firm's leverage, according to a logistic regression model. The outcome variable in all specifications is a dummy variable that takes the value of one if the firm goes bankrupt during the whole sample period (from 2018 to 2022). In these columns, the explanatory variables are measured at the end of the 2017 fiscal year. While columns (1)–(3) only consider in-sample firms, columns (4)–(6) extend the analysis to all Portuguese firms. *High Leverage* is a dummy variable that takes the value of one for firms with an above-median leverage ratio, defined as the ratio of total debt financing, net of cash, to total assets, measured in book value; *Firm's Total Assets* corresponds to book assets; *Profitability* is defined as net income divided by total sales; *Tangibility* is given by fixed assets divided by total assets; *Employees' Productivity* corresponds to total sales divided by the number of employees; and finally *Industry's Volatility* is computed as the standard deviation of sales at the three-digit industry level and for the previous 3 years, normalized by the industry's total assets. Standard errors are shown in parentheses. *p$<$ 0.1;**$p < 0.05$;***p$<$ 0.01.

Table 3.B.9: Employee Growth

	$\text{Log(Employees)}_{t+1}$-$\text{Log(Employees)}_t$			$\text{Log(Employees)}_{t+3}$-$\text{Log(Employees)}_t$		
	(1)	(2)	(3)	(4)	(5)	(6)
Leverage	-0.003	-0.001	-0.006	-0.009	-0.008	-0.025
	(0.003)	(0.003)	(0.009)	(0.009)	(0.009)	(0.016)
Log(Firm's Total Assets)	-0.017***	-0.020***	-0.156***	-0.046***	-0.051***	-0.310***
	(0.001)	(0.001)	(0.006)	(0.002)	(0.003)	(0.014)
Profitability	0.035***	0.030***	0.045***	0.043**	0.036**	0.048**
	(0.007)	(0.007)	(0.010)	(0.018)	(0.018)	(0.020)
Tangibility	0.024***	0.042***	0.073***	0.030*	0.078***	0.139***
	(0.005)	(0.006)	(0.018)	(0.015)	(0.016)	(0.038)
Log(Employees' Productivity)	0.022***	0.035***	0.145***	0.059***	0.082***	0.194***
	(0.001)	(0.002)	(0.008)	(0.004)	(0.005)	(0.017)
Industry's Volatility	-0.011	-0.018*	0.009	-0.031	-0.030	0.020
	(0.008)	(0.010)	(0.025)	(0.024)	(0.029)	(0.030)
Year FE	Yes	No	No	Yes	No	No
Industry × Year FE	No	Yes	Yes	No	Yes	Yes
Employer FE	No	No	Yes	No	No	Yes
R^2	0.025	0.053	0.368	0.034	0.070	0.769
Observations	65,330	65,322	64,741	36,679	36,675	35,609

This table presents estimates for the change in number of employees as a function of the firm's leverage, considering in-sample firms. The outcome variable in columns (1)–(3) is the first difference in the number of employees, while columns (4)–(6) consider the same difference over a three-year period (from t to $t + 3$). Financial firms (CAE codes 64-66) are excluded from the sample. *Leverage* is defined as the ratio of total debt financing, net of cash, to total assets, measured in book value; *Firm's Total Assets* corresponds to book assets; *Profitability* is defined as net income divided by total sales; *Tangibility* is given by fixed assets divided by total assets; *Employees' Productivity* corresponds to total sales divided by the number of employees; and finally *Industry's Volatility* is computed as the standard deviation of sales at the three-digit industry level and for the previous 3 years, normalized by the industry's total assets. In all specifications, standard errors are clustered at the firm level. *p< 0.1;**p < 0.05;***p< 0.01.

Table 3.B.10: Employee Growth (All Portuguese Firms)

	$\text{Log(Employees)}_{t+1}$-$\text{Log(Employees)}_t$			$\text{Log(Employees)}_{t+3}$-$\text{Log(Employees)}_t$		
	(1)	(2)	(3)	(4)	(5)	(6)
Leverage	-0.008***	-0.007***	-0.012***	-0.013***	-0.008***	-0.008***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)
Log(Firm's Total Assets)	-0.015***	-0.017***	-0.084***	-0.032***	-0.037***	-0.170***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.002)
Profitability	0.009***	0.008***	0.016***	0.020***	0.015***	0.029***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)
Tangibility	0.037***	0.035***	0.017***	0.057***	0.070***	0.010
	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)	(0.006)
Log(Employees' Productivity)	0.039***	0.045***	0.130***	0.080***	0.093***	0.185***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)
Industry's Volatility	-0.023***	-0.013*	0.107***	-0.204***	-0.010	0.025
	(0.006)	(0.007)	(0.018)	(0.026)	(0.022)	(0.027)
Year FE	Yes	No	No	Yes	No	No
Industry × Year FE	No	Yes	Yes	No	Yes	Yes
Employer FE	No	No	Yes	No	No	Yes
R^2	0.022	0.030	0.283	0.030	0.044	0.706
Observations	1,337,627	1,337,627	1,281,041	681,878	681,878	625,788

This table presents estimates for the change in number of employees as a function of the firm's leverage, considering all Portuguese firms. The outcome variable in columns (1)–(3) is the first difference in the number of employees, while columns (4)–(6) consider the same difference over a three-year period (from t to $t+3$). Financial firms (CAE codes 64-66) are excluded from the sample. *Leverage* is defined as the ratio of total debt financing, net of cash, to total assets, measured in book value; *Firm's Total Assets* corresponds to book assets; *Profitability* is defined as net income divided by total sales; *Tangibility* is given by fixed assets divided by total assets; *Employees' Productivity* corresponds to total sales divided by the number of employees; and finally *Industry's Volatility* is computed as the standard deviation of sales at the three-digit industry level and for the previous 3 years, normalized by the industry's total assets. In all specifications, standard errors are clustered at the firm level. *p< 0.1;**$p < 0.05$;***p< 0.01.

TABLE 3.B.11: Job Transition

	Mover_{y+1}			$\text{Log(Annual Income}_{y+1})$		
	(1)	(2)	(3)	(4)	(5)	(6)
High Leverage	0.938***	1.023***	1.473**	-0.049***	-0.004	0.002
	(0.342)	(0.350)	(0.741)	(0.012)	(0.004)	(0.006)
Mover				-0.076***	0.008	-0.009
				(0.023)	(0.015)	(0.023)
High Leverage × Mover				-0.012	-0.006	-0.018
				(0.030)	(0.021)	(0.027)
Age	-0.104***	-0.106***		0.009***	0.001***	
	(0.013)	(0.012)		(0.001)	(0.000)	
Log(Annual Income)	-1.542***	-1.357***	-0.659		0.802***	0.030***
	(0.229)	(0.214)	(0.911)		(0.007)	(0.010)
Additional Controls	No	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	No	No	Yes	No	No	Yes
R^2	0.050	0.053	0.499	0.193	0.791	0.955
Observations	76,012	75,973	65,502	75,957	75,957	65,486

This table presents estimates of regressions of the probability of switching employers and changes in annual income in the year a transition occurs, as a function of the previous employer's leverage. Observations are at the household-year level, measured at the end of each year, and the panel runs from January 2018 to December 2021. Only households with a single recorded employer are included in all regressions, and all firm-level variables correspond to this employer over the previous year. For the outcome variable in columns (1)–(3) and as a control variable in columns (4)–(6), a household is classified as a *Mover* if no longer working for the main employer in the last quarter of the following year. The outcome variable in columns (4)–(6) corresponds to the natural logarithm of annual income, which considers all wage payments but also social security and retirement benefits. *High Leverage* is a dummy variable that takes the value of one for above-median firms in the leverage ratio, defined as the ratio of total debt financing, net of cash, to total assets, measured in book value. Additional controls include *Firm's Total Assets*, corresponding to book assets; *Profitability*, defined as net income divided by total sales; *Tangibility*, given by fixed assets divided by total assets; *Employees' Productivity*, corresponding to total sales divided by the number of employees; and finally *Industry's Volatility*, computed as the standard deviation of sales at the three-digit industry level, normalized by the industry's total assets. All variables at the firm level are lagged by one year. Standard errors in parentheses are computed using two-way clustering (household and employer). *p< 0.1;**$p < 0.05$;***p< 0.01.

TABLE 3.B.12: Firm Turnover Growth

	Log(Turnover$_{t+1}$)-Log(Turnover$_t$)			Log(Turnover$_{t+3}$)-Log(Turnover$_t$)		
	(1)	(2)	(3)	(4)	(5)	(6)
Leverage	-0.002	-0.013*	0.034*	-0.014	-0.036**	-0.006
	(0.007)	(0.007)	(0.018)	(0.017)	(0.017)	(0.025)
Log(Firm's Total Assets)	-0.006***	-0.006***	-0.194***	-0.037***	-0.038***	-0.403***
	(0.002)	(0.002)	(0.011)	(0.004)	(0.008)	(0.020)
Profitability	-0.079***	-0.074***	0.081***	-0.177***	-0.175***	0.062**
	(0.016)	(0.015)	(0.016)	(0.034)	(0.038)	(0.027)
Tangibility	-0.027***	0.020*	0.028	-0.086***	0.075**	0.118**
	(0.010)	(0.010)	(0.031)	(0.025)	(0.037)	(0.053)
Log(Employees' Productivity)	-0.061***	-0.083***	-0.515***	-0.061***	-0.096***	-0.611***
	(0.004)	(0.004)	(0.012)	(0.008)	(0.025)	(0.019)
Industry's Volatility	0.132***	0.083**	0.020	0.025	0.079	0.032
	(0.028)	(0.034)	(0.035)	(0.064)	(0.092)	(0.050)
Year FE	Yes	No	No	Yes	No	No
Industry × Year FE	No	Yes	Yes	No	Yes	Yes
Employer FE	No	No	Yes	No	No	Yes
R^2	0.075	0.151	0.533	0.041	0.123	0.819
Observations	65,346	65,338	64,761	36,722	36,718	35,652

This table presents estimates for the change in turnover as a function of firm leverage, considering in-sample firms. The outcome variable in columns (1)–(3) is the first difference in turnover, while columns (4)–(6) consider the same difference over a three-year period (from t to $t+3$). Financial firms (CAE codes 64-66) are excluded from the sample. *Leverage* is defined as the ratio of total debt financing, net of cash, to total assets, measured in book value; *Firm's Total Assets* corresponds to book assets; *Profitability* is defined as net income divided by total sales; *Tangibility* is given by fixed assets divided by total assets; *Employees' Productivity* corresponds to total sales divided by the number of employees; and finally *Industry's Volatility* is computed as the standard deviation of sales at the three-digit industry level and for the previous 3 years, normalized by the industry's total assets. Robust standard errors are shown in parentheses for columns (1) to (3), while standard errors for the remaining columns are clustered at the firm level. *p< 0.1;**$p < 0.05$;***p< 0.01.

TABLE 3.B.13: Firm Turnover Growth (All Portuguese Firms)

	$\text{Log}(\text{Turnover}_{t+1})$-$\text{Log}(\text{Turnover}_t)$			$\text{Log}(\text{Turnover}_{t+3})$-$\text{Log}(\text{Turnover}_t)$		
	(1)	(2)	(3)	(4)	(5)	(6)
Leverage	-0.028***	-0.030***	0.006***	-0.044***	-0.041***	-0.004
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)
Log(Firm's Total Assets)	0.031***	0.027***	-0.059***	0.035***	0.022***	-0.182***
	(0.000)	(0.000)	(0.002)	(0.001)	(0.001)	(0.004)
Profitability	-0.024***	-0.025***	0.015***	-0.059***	-0.064***	0.018***
	(0.001)	(0.001)	(0.002)	(0.003)	(0.003)	(0.003)
Tangibility	-0.043***	0.008***	-0.002	-0.074***	0.057***	0.046***
	(0.002)	(0.002)	(0.006)	(0.005)	(0.005)	(0.009)
Log(Employees' Productivity)	-0.170***	-0.183***	-0.655***	-0.195***	-0.215***	-0.710***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.004)
Industry's Volatility	0.614***	0.571***	-0.126***	0.262***	0.937***	0.377***
	(0.031)	(0.045)	(0.029)	(0.042)	(0.109)	(0.064)
Year FE	Yes	No	No	Yes	No	No
Industry $\times$ Year FE	No	Yes	Yes	No	Yes	Yes
Employer FE	No	No	Yes	No	No	Yes
R^2	0.109	0.144	0.555	0.065	0.108	0.790
Observations	1,343,712	1,343,712	1,287,163	690,628	690,628	633,621

This table presents estimates for the change in turnover as a function of firm leverage, considering all Portuguese firms. The outcome variable in columns (1)–(3) is the first difference in turnover, while columns (4)–(6) consider the same difference over a three-year period (from t to $t+3$). Financial firms (CAE codes 64-66) are excluded from the sample. *Leverage* is defined as the ratio of total debt financing, net of cash, to total assets, measured in book value; *Firm's Total Assets* corresponds to book assets; *Profitability* is defined as net income divided by total sales; *Tangibility* is given by fixed assets divided by total assets; *Employees' Productivity* corresponds to total sales divided by the number of employees; and finally *Industry's Volatility* is computed as the standard deviation of sales at the three-digit industry level and for the previous 3 years, normalized by the industry's total assets. Robust standard errors are shown in parentheses for columns (1) to (3), while standard errors for the remaining columns are clustered at the firm level. *p$<$ 0.1;**$p < 0.05$;***p$<$ 0.01.

Table 3.B.14: Leverage and Likelihood of Being in Top-10% of Turnover Distribution

	In-sample Firms		All Firms	
	(1)	(2)	(3)	(4)
Leverage Decile	-0.003**	-0.003***	-0.002	-0.003**
	(0.001)	(0.001)	(0.002)	(0.001)
Turnover Decile	0.050***	0.048***	0.048***	0.045***
	(0.005)	(0.004)	(0.005)	(0.004)
Log(Firm's Total Assets)	0.011	0.013*	0.078***	0.077***
	(0.008)	(0.008)	(0.009)	(0.009)
Profitability	-0.054***	-0.051***	-0.066***	-0.066***
	(0.010)	(0.012)	(0.010)	(0.009)
Tangibility	-0.021	-0.024*	-0.050***	-0.029**
	(0.018)	(0.014)	(0.017)	(0.011)
Log(Employees' Productivity)	0.011	0.014	0.007	0.007
	(0.007)	(0.009)	(0.011)	(0.009)
Industry's Volatility	0.167*	0.287	0.252*	0.358
	(0.100)	(0.299)	(0.138)	(0.289)
Industry FE	No	Yes	No	Yes
R^2	0.267	0.298	0.349	0.363
Observations	10,201	10,201	185,511	185,510

This table presents estimates for the likelihood of being in the top decile of the turnover distribution in 2022, considering a set of 2015 financial variables. Columns (1)–(2) limit the analysis to in-sample firms, while columns (3)–(4) consider all Portuguese firms. In all columns, firms filing for bankruptcy between 2015 and 2022 are excluded, as well as financial firms (CAE codes 64-66). The outcome variable in all columns is a dummy variable that takes the value of one if the firm belongs to the top decile of the turnover distribution in 2022, and zero otherwise. *Leverage Decile* indicates to which decile of the leverage distribution the firm belongs to in 2015; while *Turnover Decile* indicates to which decile of the turnover distribution the firm belongs to in 2015. *Firm's Total Assets* corresponds to book assets; *Profitability* is defined as net income divided by total sales; *Tangibility* is given by fixed assets divided by total assets; *Employees' Productivity* corresponds to total sales divided by the number of employees; and finally *Industry's Volatility* is computed as the standard deviation of sales at the three-digit industry level and for the previous 3 years, normalized by the industry's total assets. Standard errors in parentheses are clustered at the industry level. *p< 0.1;**$p < 0.05$;***p< 0.01.

Table 3.B.15: Wages: Accounting Data

	Log(Average Employee Expenses)			
	(1)	(2)	(3)	(4)
Leverage	-0.071***	-0.073***	-0.061***	-0.001
	(0.009)	(0.009)	(0.008)	(0.007)
Log(Firm's Total Assets)		0.083***	0.081***	0.049***
		(0.002)	(0.002)	(0.005)
Profitability		-0.101***	-0.100***	-0.011
		(0.011)	(0.011)	(0.008)
Tangibility		-0.294***	-0.172***	0.003
		(0.013)	(0.013)	(0.015)
Log(Employees' Productivity)		0.123***	0.123***	0.007
		(0.004)	(0.005)	(0.005)
Industry's Volatility		-0.063*	-0.132***	0.013
		(0.036)	(0.044)	(0.024)
Year FE	Yes	Yes	No	No
Industry $\times$ Year FE	No	No	Yes	Yes
Employer FE	No	No	No	Yes
R^2	0.021	0.284	0.419	0.871
Observations	91,619	65,260	65,252	64,668

This table presents estimates of regressions of the effect of leverage on the average annual wage bill, considering in-sample firms. Observations are at the firm-year level and the panel runs from 2015 to 2022. Financial firms (CAE codes 64-66) are excluded from the sample. *Leverage* is defined as the ratio of total debt financing, net of cash, to total assets, measured in book value; *Firm's Total Assets* corresponds to book assets; *Profitability* is defined as net income divided by total sales; *Tangibility* is given by fixed assets divided by total assets; *Employees' Productivity* corresponds to total sales divided by the number of employees; and finally *Industry's Volatility* is computed as the standard deviation of sales at the three-digit industry level, normalized by the industry's total assets. All independent variables are lagged by one year. Standard errors in parentheses are clustered at the firm level. *p< 0.1;**$p < 0.05$;***p< 0.01.

Table 3.B.16: Wages: Accounting Data (All Portuguese Firms)

	Log(Average Employee Expenses)			
	(1)	(2)	(3)	(4)
Leverage	-0.060***	-0.046***	-0.030***	-0.016***
	(0.001)	(0.001)	(0.001)	(0.002)
Log(Firm's Total Assets)		0.100***	0.104***	0.071***
		(0.001)	(0.001)	(0.002)
Profitability		-0.042***	-0.053***	-0.006***
		(0.001)	(0.001)	(0.001)
Tangibility		-0.124***	-0.080***	-0.012**
		(0.004)	(0.004)	(0.005)
Log(Employees' Productivity)		0.126***	0.135***	0.018***
		(0.001)	(0.001)	(0.001)
Industry's Volatility		-0.416***	-0.553***	-0.141***
		(0.032)	(0.051)	(0.026)
Year FE	Yes	Yes	No	No
Industry $\times$ Year FE	No	No	Yes	Yes
Employer FE	No	No	No	Yes
R^2	0.017	0.167	0.200	0.773
Observations	1,878,765	1,297,091	1,297,091	1,242,972

This table presents estimates of regressions of the effect of leverage on the average annual wage bill, considering all Portuguese Firms. Observations are at the firm-year level and the panel runs from 2015 to 2022. *Leverage* is defined as the ratio of total debt financing, net of cash, to total assets, measured in book value; *Firm's Total Assets* corresponds to book assets; *Profitability* is defined as net income divided by total sales; *Tangibility* is given by fixed assets divided by total assets; *Employees' Productivity* corresponds to total sales divided by the number of employees; and finally *Industry's Volatility* is computed as the standard deviation of sales at the three-digit industry level, normalized by the industry's total assets. All independent variables are lagged by one year. Standard errors in parentheses are clustered at the firm level. *p$<$ 0.1;**$p < 0.05$;***p$<$ 0.01.

Table 3.B.17: Wages Response to Industry Shock

	Asinh(Wages)			
	(1)	(2)	(3)	(4)
Industry Shock	-0.040	-0.037		
	(0.025)	(0.025)		
Industry Shock × High Leverage	-0.014	-0.016	-0.011	-0.017
	(0.032)	(0.032)	(0.032)	(0.033)
High Leverage	-0.043***	-0.045***	-0.038***	-0.023
	(0.012)	(0.013)	(0.012)	(0.015)
Additional Firm Controls	No	Yes	Yes	Yes
Month × Year FE	Yes	Yes	No	No
Household FE	Yes	Yes	Yes	Yes
Industry × Month × Year FE	No	No	Yes	Yes
Employer FE	No	No	No	Yes
R^2	0.401	0.402	0.424	0.433
Observations	1,178,296	1,169,605	1,169,605	1,169,542

This table presents estimates of regressions of the inverse hyperbolic sine of wages on industry-level shocks and the main employer's leverage. Observations are at the household-calendar date level and the panel runs from January 2018 to June 2022. Wages are defined as total wages received by the household, irrespective of the source and considering all employers in a given household. All firm-level variables correspond to the primary employer over the past quarter, lagged by one year. *Industry Shock* is a dummy that takes the value of 1 if the primary employer of the household operates in one of the most affected industry-month pairs in a given year (defined as the bottom 5% of year-on-year monthly change of sales at the two-digit industry level), and 0 otherwise. *High Leverage* is a dummy that takes the value of 1 if the household main employer's leverage is above the sample's median, and 0 otherwise. Additional controls include *Firm's Total Assets*, corresponding to book assets; *Profitability* is defined as net income divided by total sales; and *Tangibility* is given by fixed assets divided by total assets. Standard errors in parentheses are clustered at the industry-date level. *p< 0.1;**$p < 0.05$;***p< 0.01.

Table 3.B.18: Industry Shock Impact on Wages: Intensive versus Extensive Margin

	Log(Wages)		No Wage	
	(1)	(2)	(3)	(4)
Industry Shock	-0.026***		0.001	
	(0.009)		(0.003)	
Industry Shock × High Leverage	-0.015	-0.005	0.001	0.001
	(0.014)	(0.009)	(0.004)	(0.004)
High Leverage	-0.000	-0.000	0.006***	0.005***
	(0.003)	(0.003)	(0.002)	(0.002)
Additional Controls	Yes	Yes	Yes	Yes
Month × Year FE	Yes	No	Yes	No
Household FE	Yes	Yes	Yes	Yes
Industry × Month × Year FE	No	Yes	No	Yes
R^2	0.729	0.745	0.300	0.323
Observations	1,104,704	1,104,703	1,169,605	1,169,605

This table presents estimates for the effect of industry-level shocks and the main employer's leverage on wages, decomposing the effect between the intensive and extensive margins. Observations are at the household-calendar date level and the panel runs from January 2018 to June 2022. Wages are defined as total wages received by the household, irrespective of the source and considering all employers in a given household. Columns (1) and (2) consider as dependent variable the natural logarithm of wages, while columns (3) and (4) consider a dummy variable that takes the value of 1 if no wage payment is recorded, and 0 otherwise. All firm-level variables correspond to the primary employer over the past quarter, lagged by one year. *Industry Shock* is a dummy that takes the value of 1 if the primary employer of the household operates in one of the most affected industry-month pairs in a given year (defined as the bottom 5% of year-on-year monthly change of sales at the two-digit industry level), and 0 otherwise. *High Leverage* is a dummy that takes the value of 1 if the household main employer's leverage is above the sample's median, and 0 otherwise. Additional controls include *Firm's Total Assets*, corresponding to book assets; *Profitability* is defined as net income divided by total sales; and *Tangibility* is given by fixed assets divided by total assets. Standard errors in parentheses are clustered at the industry-date level. *p< 0.1;**$p < 0.05$;***p< 0.01.

Table 3.B.19: Wages Response to Industry Shock: 2018-2019 Subsample

	Asinh(Wages)			
	(1)	(2)	(3)	(4)
Industry Shock	-0.026	-0.022		
	(0.040)	(0.040)		
Industry Shock × High Leverage	-0.095*	-0.088*	-0.032	-0.039
	(0.052)	(0.054)	(0.051)	(0.052)
High Leverage	-0.036	-0.041*	-0.044*	-0.012
	(0.022)	(0.024)	(0.024)	(0.030)
Additional Firm Controls	No	Yes	Yes	Yes
Month × Year FE	Yes	Yes	No	No
Household FE	Yes	Yes	Yes	Yes
Industry × Month × Year FE	No	No	Yes	Yes
Employer FE	No	No	No	Yes
R^2	0.476	0.477	0.507	0.513
Observations	568,977	564,072	564,072	564,007

This table presents estimates of regressions of the inverse hyperbolic sine of wages on industry-level shocks and the main employer's leverage. Observations are at the household-calendar date level and the panel runs from January 2018 to December 2019. Wages are defined as total wages received by the household, irrespective of the source and considering all employers in a given household. All firm-level variables correspond to the primary employer over the past quarter, lagged by one year. *Industry Shock* is a dummy that takes the value of 1 if the primary employer of the household operates in one of the most affected industry-month pairs in a given year (defined as the bottom 5% of year-on-year monthly change of sales at the two-digit industry level), and 0 otherwise. *High Leverage* is a dummy that takes the value of 1 if the household main employer's leverage is above the sample's median, and 0 otherwise. Additional controls include *Firm's Total Assets*, corresponding to book assets; *Profitability* is defined as net income divided by total sales; and *Tangibility* is given by fixed assets divided by total assets. Standard errors in parentheses are clustered at the industry-date level. *p< 0.1;**p < 0.05;***p< 0.01.

Table 3.B.20: Consumption Response to Industry Shock: 2018-2019 Subsample

	Asinh(Consumption)			
	(1)	(2)	(3)	(4)
Industry Shock	0.006	0.005		
	(0.009)	(0.009)		
Industry Shock × High Leverage	-0.027***	-0.024***	-0.018**	-0.018**
	(0.009)	(0.009)	(0.009)	(0.009)
High Leverage	-0.006	-0.004	-0.003	-0.001
	(0.006)	(0.006)	(0.006)	(0.007)
Additional Firm Controls	No	Yes	Yes	Yes
Additional Household Controls	Yes	Yes	Yes	Yes
Month × Year FE	Yes	Yes	No	No
Household FE	Yes	Yes	Yes	Yes
Industry × Month × Year FE	No	No	Yes	Yes
Employer FE	No	No	No	Yes
R^2	0.645	0.645	0.647	0.655
Observations	568,977	564,072	564,072	564,007

This table presents estimates of regressions of the inverse hyperbolic sine of monthly consumption expenditure on industry-level shocks and main employer's leverage. Observations are at the household-calendar date level and the panel runs from January 2018 to December 2019. The dependent variable, consumption, is defined as the sum between purchases and payments from either a debit or credit card at this bank. All firm-level variables correspond to the primary employer over the past quarter and are lagged by one year. *Industry Shock* is a dummy that takes the value of 1 if the primary employer of the household operates in one of the most affected industry-month pairs in a given year (defined as the bottom 5% of year-on-year monthly change of sales at the two-digit industry level), and 0 otherwise. *High Leverage* is a dummy that takes the value of 1 if the household main employer's leverage is above the sample's median, and 0 otherwise. Additional controls include *Firm's Total Assets*, corresponding to book assets; *Profitability* is defined as net income divided by total sales; and *Tangibility* is given by fixed assets divided by total assets. In all specifications, the inverse hyperbolic sine of income is added as a control. Standard errors in parentheses are clustered at the industry-date level. *p< 0.1;**p < 0.05;***p< 0.01.

Table 3.B.21: Firm's Probability of Default Following an Industry Shock

	Bankrupt Dummy			
	(1)	(2)	(3)	(4)
High Leverage	1.819***	0.760**	1.587***	0.773**
	(0.321)	(0.307)	(0.317)	(0.300)
Industry Shock	0.631	0.530		
	(0.387)	(0.328)		
Industry Shock × High Leverage	1.513**	1.592**	1.400**	1.413**
	(0.695)	(0.729)	(0.671)	(0.679)
Additional Firm Controls	No	Yes	No	Yes
Industry FE	No	No	Yes	Yes
R^2	0.003	0.007	0.013	0.016
Observations	114,338	109,059	114,338	109,059

This table presents a cross-sectional analysis of the probability of going bankrupt as a function of the firm's leverage, according to a linear probability model and considering in-sample firms. The outcome variable in columns (1)–(4) is a dummy variable that takes the value of one if the firm goes bankrupt from 2019 to 2022. In all columns, the explanatory variables are measured at the end of the 2018 fiscal year. Financial firms (CAE codes 64-66) are excluded from the sample. *High Leverage* is a dummy variable that takes the value of one for firms with an above-median leverage ratio, defined as the ratio of total debt financing, net of cash, to total assets, measured in book value. Moreover, *Industry Shock* is a dummy variable that takes the value of one for firms working in one of the bottom 5% performing industries during 2018, measured in terms of year-on-year turnover change, and zero otherwise. Though unreported, additional firm controls are included in columns (2) and (4), namely, *Firm's Total Assets* corresponding to book assets; *Profitability*, defined as net income divided by total sales; *Tangibility*, given by fixed assets divided by total assets; *Employees' Productivity*, corresponding to total sales divided by the number of employees; and finally *Industry's Volatility*, computed as the standard deviation of sales at the three-digit industry level and for the previous 3 years, normalized by the industry's total assets. Standard errors in parentheses are clustered at the industry-date level. *p$<$ 0.1;**$p < 0.05$;***p$<$ 0.01.

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