Capital Structure and Employee Consumption*

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ABSTRACT

I show that firm capital structure can affect employee consumption and saving decisions using a new matched employer-employee data set from Portugal. Specifically, employees of highly leveraged firms exhibit lower marginal propensities to consume, particularly in non-essential goods and services. This effect cannot be attributed to a wage premium in these firms. I identify these effects by exploiting negative industry-wide shocks. I rationalize the findings using a Diamond-Mortensen-Pissarides matching model, where heterogeneous risk-averse employees bargain with heterogeneous employers to determine wages. Consistent with the model, low-wealth individuals are most affected due to their relatively higher unemployment costs. My results suggest that financial distress costs are partially shifted to employees.

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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, 1994), 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 leveraged 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, Ren, Shu, and Yang, 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

[1] Graham, Kim, Li, and Qiu (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, while Graham, Kim, Li, and Qiu (2023) find a wage premium for highly leveraged firms.

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 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 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

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

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

[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);

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 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

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.

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, Kim, Li, and Qiu, 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, Silva, Thell, and Vig (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 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

[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).

[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.

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, Matvos, Syverson, and Venkataraman, 2013; Custodio, 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, Kim, Li, and Qiu, 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, Carvalho, Ozdaglar, and Tahbaz-Salehi, 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.

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.

2.1 Household Statistics

Panel A of Table 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 IA.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 IA.1. Within the private sector, those 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

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

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]

2.2 Firm Statistics

Panel B of Table 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, Kim, Li, and Qiu (2023)). I compute a measure of industry volatility at the three-digit industry code level, given by the standard

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

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

Table IA.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

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

compare in-sample firms with the standard data set for such U.S.-focused studies. Figure IA.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 IA.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 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 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:

$$\begin{aligned} Y_{h,e,t} &= \beta_0 Income_{h,t} + \lambda Income_{h,t} \times Leverage_{e,t-12} \\ &\quad + \beta_1 Income_{h,t} \times Z_{e,t-12} + \mu_h + \nu_t + \varepsilon_{h,e,t}, \end{aligned} \tag{1}$$

[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 IA.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.

where Y 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 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

[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.

year and use this measure as the outcome variable in the following baseline specification:

$$Log(Earnings)_{h,e,y} = \lambda Leverage_{e,y-1} + Z_{e,y-1} + \nu_y + \varepsilon_{h,e,y}, \tag{2}$$

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:

$$\begin{aligned} Y_{h,e,i,t} &= \lambda High\ Leverage_{e,t-12} \times Industry\ Shock_{i,t} + \beta_0 High\ Leverage_{e,t-12} \\ &\quad + \beta_1 Industry\ Shock_{i,t} + Z_{e,t-12} + \mu_h + \nu_{i,t} + \varepsilon_{h,e,i,t}. \end{aligned} \tag{3}$$

where Y 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.

4 Effects of Capital Structure on Employees

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 (1).

Table 2 reports the estimates for the marginal propensity to consume, showing that income and unemployment risk are important drivers of this sensitivity. 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.[14] 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.[15] Finally, higher employee productivity is associated with lower propensities to consume, which may capture the positive correlation between productivity and wages, as shown in section 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,

[14] Table IA.3 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.

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

as shown in section 4.3.[16] 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,[17] 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 4.4 I try to ameliorate these concerns by exploring an arguably exogenous shock.

Table 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 maintenance 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.[18] 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.[19]

[16]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.

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

[18]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.

[19]Though the decomposition of consumption into spending categories varies between studies, see for example

Mechanically, I observe that households employed by highly leveraged firms increase their propensity to save in liquid assets, as shown in Table 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 IA.4 and IA.5 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–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.[20]

Table IA.4 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

Clements, Wu, and Zhang (2006), where clothing and transportation exhibit an income elasticity well above one.

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

(3) includes district-by-year fixed effects to ensure that common regional shocks are not driving these findings.

Finally, Table IA.5 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.

4.2 Heterogeneous Effects

To characterize how different households perceive this source of risk, I re-estimate the model in equation (1), decomposing the effect of leverage on the propensity to consume by interacting it with group indicators. [21] Figure 1 plots the λ coefficient in equation (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

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

(introduced in section 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 1 shows that the household sensitivity to employer debt is much stronger when working for a publicly listed company.[22] 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 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.[23] In Panel F, I find that households working in slack labor markets exhibit lower

[22]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.

[23]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.

propensities to consume, with this effect being marginally significant as well.

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 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.[24] Column (1) shows that firms with above-median leverage ratios are more 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.[25]

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.[26]

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

[25] 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.

[26] Table IA.6 shows comparable results even when using the overall universe of Portuguese firms, and Table IA.7 shows consistent results by running a logistic regression model.

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 IA.8 presents the results. Interestingly, this null result does not hold when considering all Portuguese firms, as shown in Table IA.9 in the Internet Appendix. While the magnitudes in columns (1)–(3) are significantly higher, columns (4) and (5) show comparable magnitudes to Table IA.8, 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.[27]

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). Moreover, 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 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

[27] 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).

are more likely to have no recorded wage payment during the following quarter while being the recipient of social security payments.[28] 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 rates. Columns (1)–(3) of Table IA.10 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.[29] 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?

[28] 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.

[29] 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.

Table IA.11 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 IA.12 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.[30]

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 *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 (2) to understand how wages are determined and, in particular, how they are affected by the use of leverage. Table 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

[30]Consistently, Table IA.13 shows that, in the long run, highly leveraged firms are no more likely to end up in the top decile of the turnover distribution.

operates in the public sector earn, on average, a 24% premium.[31]

Finally, in Table IA.14 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 insignificant after controlling for firm fixed effects. Table IA.15 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.

[31] 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.

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.[32] 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.[33] 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.

Before characterizing the consumption response, I first examine whether there is any differential effect on wages, as shown in Table IA.16 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.[34] 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 8 shows that while low-leverage employers do not induce any consumption response by their employees, households working for highly leveraged firms

[32]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.

[33]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.

[34]Alternative specifications, such as the natural logarithm of $y + 1$, yield similar results.

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. 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 IA.17 and IA.18, respectively). Finally, Table IA.19 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.

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.[35] On the other hand, entrepreneurs have perfect knowledge about workers' characteristics, including risk-aversion and wealth levels.[36] Workers are risk averse and can save to partially insure themselves against idiosyncratic job-match shocks, and they

[35] 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.

[36] 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.

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).

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.[37] In each period, consumption must be nonnegative, and households are subject to a traditional budget

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

constraint, as follows

$$c_t \leq (1+r)a_t + (1-\mathbb{1}_e)\zeta + \mathbb{1}_e w_t - a_{t+1}, \quad \forall t \in [0,\infty)\,, \tag{4}$$

$$c_t \geq 0, \quad \forall t \in [0,\infty)\,. \tag{5}$$

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

$$a_t \geq \underline{a}, \quad \forall t \in [0,\infty)\,. \tag{6}$$

Entrepreneurs and Firms

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

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta_f^t \left(z_t x_t - b\right), \tag{7}$$

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

$$\arg\max_{w_t} \left\{ \left[W_t(x_t, b_t, \phi_t, \Phi_t) - U_t(\phi_t, \Phi_t)\right]^{\delta} \left[J_t(x_t, b, \phi_t, \Phi_t) - V_t(b, \Phi_t)\right]^{1-\delta} \right\}, \tag{8}$$

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 (4) to (5), can be summarized as follows

$$W_t(x_t, b_t, \phi_t, \Phi_t) = \max_{\{c_t, a_{t+1}\}} \left\{ \frac{c_t^{1-\gamma} - 1}{1-\gamma} + \beta_h \mathbb{E}_t \max\left[W_{t+1}, U_{t+1}\right] \right\}, \tag{9}$$

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 (4) to (5), is given by

$$U_t(\phi_t, \Phi_t) = \max_{\{c_t, a_{t+1}\}} \left\{ \frac{c_t^{1-\gamma} - 1}{1-\gamma} + l + \beta_h \left\{ \left(1 - \theta_t q(\theta_t)\right) \mathbb{E}_t\left[U_{t+1}\right] + \theta_t q(\theta_t) \mathbb{E}_t\left[W_{t+1}\right] \right\} \right\}. \tag{10}$$

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

$$J_t(x_t, b, \phi_t, \Phi_t) = z_t x_t - b - w(x_t, b, \phi_t, \Phi_t) + \beta_f \mathbb{E}_t \left[\max\left\{J_{t+1}, V_{t+1}\right\}\right], \tag{11}$$

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

$$V_t(b, \Phi_t) = -\kappa + \beta_f q(\theta_t) \int \mathbb{E}_t \left[J_{t+1}\right] \mathrm{d}\lambda'_u(\phi_{t+1}) + \beta_f (1 - q(\theta_t)) \mathbb{E}_t \left[V_{t+1}\right], \tag{12}$$

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 (8):

$$J_t(x_t, b, \phi_t, \Phi_t) = \frac{1-\delta}{\delta} \left[W_t(x_t, b_t, \phi_t, \Phi_t) - U_t(\phi_t, \Phi_t)\right] c_t^{\gamma}. \tag{13}$$

Therefore, a stationary equilibrium consists of a set of value functions, as described in equations (9) to (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 (9) to (10) are met;

2. Given the wage schedule and optimal saving decision rules, condition (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 (13).

5.2 Quantitative Analysis

This section presents some numerical examples based on the baseline calibration reported in Table 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.[38] 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 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

[38] 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.

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 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.[39] 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 A of the Internet Appendix

Wage Schedule

Figure 2 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

[39]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).

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 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 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 10 shows that, in the simulated panel, households working for leveraged employers receive lower wages, consistent with the wage schedule and the channels discussed 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 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 4 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.

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 analysis of the matched employer-employee data set 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, as opposed to 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–and primarily imposing these costs on more fragile households–my findings raise further questions on the optimality of the interest tax deductibility from a societal perspective.

References

Abowd, John M, and Orley C Ashenfelter, 1981, Anticipated unemployment, temporary layoffs, and compensating wage differentials, in *Studies in labor markets* . pp. 141–170 (University of Chicago Press).

Acemoglu, Daron, Vasco M Carvalho, Asuman Ozdaglar, and Alireza Tahbaz-Salehi, 2012, The network origins of aggregate fluctuations, *Econometrica* 80, 1977–2016.

Acemoglu, Daron, Asuman Ozdaglar, and Alireza Tahbaz-Salehi, 2015, Systemic risk and stability in financial networks, *American Economic Review* 105, 564–608.

Acemoglu, Daron, and Robert Shimer, 1999, Efficient unemployment insurance, *Journal of political Economy* 107, 893–928.

Adelino, Manuel, Miguel A Ferreira, and Miguel Oliveira, 2024, The heterogeneous effects of household debt relief, *Available at SSRN*.

Agrawal, Ashwini K, and David A Matsa, 2013, Labor unemployment risk and corporate financing decisions, *Journal of Financial Economics* 108, 449–470.

Akyol, Ali C, and Patrick Verwijmeren, 2013, Human capital costs, firm leverage, and unemployment rates, *Journal of Financial Intermediation* 22, 464–481.

Alfaro, Iván, and Hoonsuk Park, 2020, Firm uncertainty and household spending, *Available at SSRN 3669359*.

Allen, Franklin, and Douglas Gale, 2000, Financial contagion, *Journal of political economy* 108, 1–33.

Azariadis, Costas, 1975, Implicit contracts and underemployment equilibria, *Journal of political economy* 83, 1183–1202.

Baghai, Ramin P, Rui C Silva, Viktor Thell, and Vikrant Vig, 2021, Talent in distressed firms: Investigating the labor costs of financial distress, *The Journal of Finance* 76, 2907–2961.

Baily, Martin Neil, 1974, Wages and employment under uncertain demand, *The Review of Economic Studies* 41, 37–50.

Baldwin, Carliss Y, 1983, Productivity and labor unions: An application of the theory of self-enforcing contracts, *Journal of Business* pp. 155–185.

Barrot, Jean-Noël, and Julien Sauvagnat, 2016, Input specificity and the propagation of idiosyncratic shocks in production networks, *The Quarterly Journal of Economics* 131, 1543–1592.

Berk, Jonathan B, Richard Stanton, and Josef Zechner, 2010, Human capital, bankruptcy, and capital structure, *The Journal of Finance* 65, 891–926.

Bils, Mark, Yongsung Chang, and Sun-Bin Kim, 2011, Worker heterogeneity and endogenous separations in a matching model of unemployment fluctuations, *American Economic Journal: Macroeconomics* 3, 128–154.

Blanchard, Olivier, and Pedro Portugal, 2001, What hides behind an unemployment rate: Comparing portuguese and us labor markets, *American Economic Review* 91, 187–207.

Brown, Jennifer, and David A Matsa, 2016, Boarding a sinking ship? an investigation of job applications to distressed firms, *The Journal of Finance* 71, 507–550.

Carroll, Christopher D, and Andrew A Samwick, 1997, The nature of precautionary wealth, *Journal of monetary Economics* 40, 41–71.

——— , 1998, How important is precautionary saving?, *Review of Economics and statistics* 80, 410–419.

Chemmanur, Thomas J, Yingmei Cheng, and Tianming Zhang, 2013, Human capital, capital structure, and employee pay: An empirical analysis, *Journal of Financial Economics* 110, 478–502.

Clark, Andrew E, 2001, What really matters in a job? hedonic measurement using quit data, *Labour economics* 8, 223–242.

Clements, Kenneth W, Jiawei Si, Eliyathamby A Selvanathan, and Saroja Selvanathan, 2020, Demand elasticities for 9 goods in 37 countries, *Applied Economics* 52, 2636–2655.

Clements, Kenneth W, Yanrui Wu, and Jing Zhang, 2006, Comparing international consumption patterns, *Empirical Economics* 31, 1–30.

Cohn, Jonathan B, and Malcolm I Wardlaw, 2016, Financing constraints and workplace safety, *The Journal of Finance* 71, 2017–2058.

Custodio, Claudia, Miguel A Ferreira, and Emilia Garcia-Appendini, 2023, Indirect costs of financial distress, *Review of Finance* 27, 2233–2270.

Dasgupta, Sudipto, and Kunal Sengupta, 1993, Sunk investment, bargaining and choice of capital structure, *International Economic Review* pp. 203–220.

Davis, Steven J, and Till M Von Wachter, 2011, Recessions and the cost of job loss, Discussion paper National Bureau of Economic Research.

Dore, Timothy E, and Rebecca Zarutskie, 2023, When does higher firm leverage lead to higher employee pay?, *The Review of Corporate Finance Studies* 12, 36–77.

Dynan, Karen E, 1993, How prudent are consumers?, *Journal of Political Economy* 101, 1104–1113.

Ellul, Andrew, and Marco Pagano, 2019, Corporate leverage and employees' rights in bankruptcy, *Journal of Financial Economics* 133, 685–707.

Fuchs-Schündeln, Nicola, and Matthias Schündeln, 2005, Precautionary savings and self-selection: evidence from the german reunification "experiment", *The Quarterly Journal of Economics* 120, 1085–1120.

Fujita, Shigeru, and Giuseppe Moscarini, 2017, Recall and unemployment, *American Economic Review* 107, 3875–3916.

Gill, Balbinder Singh, Jongmoo Jay Choi, and Kose John, 2024, Firm leverage and employee pay: The moderating role of ceo leadership style, *International Review of Financial Analysis* p. 103382.

Gortmaker, Jeff, Jessica Jeffers, and Michael Lee, 2022, Labor reactions to credit deterioration: Evidence from linkedin activity, *Available at SSRN 3456285*.

Graham, John R, Hyunseob Kim, Si Li, and Jiaping Qiu, 2023, Employee costs of corporate bankruptcy, *The Journal of Finance* 78, 2087–2137.

Gruber, Jonathan, 1994, The consumption smoothing benefits of unemployment insurance, .

Hamermesh, Daniel S, and John R Wolfe, 1990, Compensating wage differentials and the duration of wage loss, *Journal of Labor Economics* 8, S175–S197.

He, Jie, Xiao Ren, Tao Shu, and Huan Yang, 2022, The employee clientele of corporate leverage: Evidence from family labor income diversification, *Available at SSRN 2880187*.

Helliwell, John F, 2003, How's life? combining individual and national variables to explain subjective well-being, *Economic modelling* 20, 331–360.

Hortaçsu, Ali, Gregor Matvos, Chad Syverson, and Sriram Venkataraman, 2013, Indirect costs of financial distress in durable goods industries: The case of auto manufacturers, *The Review of Financial Studies* 26, 1248–1290.

Kantor, Shawn Everett, and Price V Fishback, 1996, Precautionary saving, insurance, and the origins of workers' compensation, *Journal of Political Economy* 104, 419–442.

Krusell, Per, Toshihiko Mukoyama, and Ayşegül Şahin, 2010, Labour-market matching with precautionary savings and aggregate fluctuations, *The Review of Economic Studies* 77, 1477–1507.

Liu, Ping, 2019, A model of capital structure under labor market search, *Available at SSRN 3038469*.

Matsa, David A, 2010, Capital structure as a strategic variable: Evidence from collective bargaining, *The Journal of Finance* 65, 1197–1232.

Michaels, Ryan, T Beau Page, and Toni M Whited, 2019, Labor and capital dynamics under financing frictions, *Review of Finance* 23, 279–323.

OECD, 2020, *Recent trends in employment protection legislation*.

Opler, Tim C, and Sheridan Titman, 1994, Financial distress and corporate performance, *The Journal of finance* 49, 1015–1040.

Oswald, Andrew J, 1997, Happiness and economic performance, *The economic journal* 107, 1815–1831.

Palacios, Miguel, 2013, Labor intensity, risk and return, *Vanderbilt Owen Graduate School of Management Research Paper*.

Perotti, Enrico C, and Kathryn E Spier, 1993, Capital structure as a bargaining tool: The role of leverage in contract renegotiation, *The American Economic Review* pp. 1131–1141.

Petrosky-Nadeau, Nicolas, and Lu Zhang, 2017, Solving the diamond–mortensen–pissarides model accurately, *Quantitative Economics* 8, 611–650.

Pulvino, Todd C, 1998, Do asset fire sales exist? an empirical investigation of commercial aircraft transactions, *The Journal of Finance* 53, 939–978.

Qian, Yiming, 2003, Human-capital-intensive firms: Incentives and capital structure, *Available at SSRN 423540*.

Rouwenhorst, K Geert, 1995, Asset pricing implications of equilibrium business cycle models, *Frontiers of business cycle research* 1, 294–330.

Rynes, Sara L, Barry Gerhart, and Kathleen A Minette, 2004, The importance of pay in employee motivation: Discrepancies between what people say and what they do, *Human Resource Management: Published in Cooperation with the School of Business Administration, The University of Michigan and in alliance with the Society of Human Resources Management* 43, 381–394.

Sautner, Zacharias, and Vladimir Vladimirov, 2017, Indirect Costs of Financial Distress and Bankruptcy Law: Evidence from Trade Credit and Sales*, *Review of Finance* 22, 1667–1704.

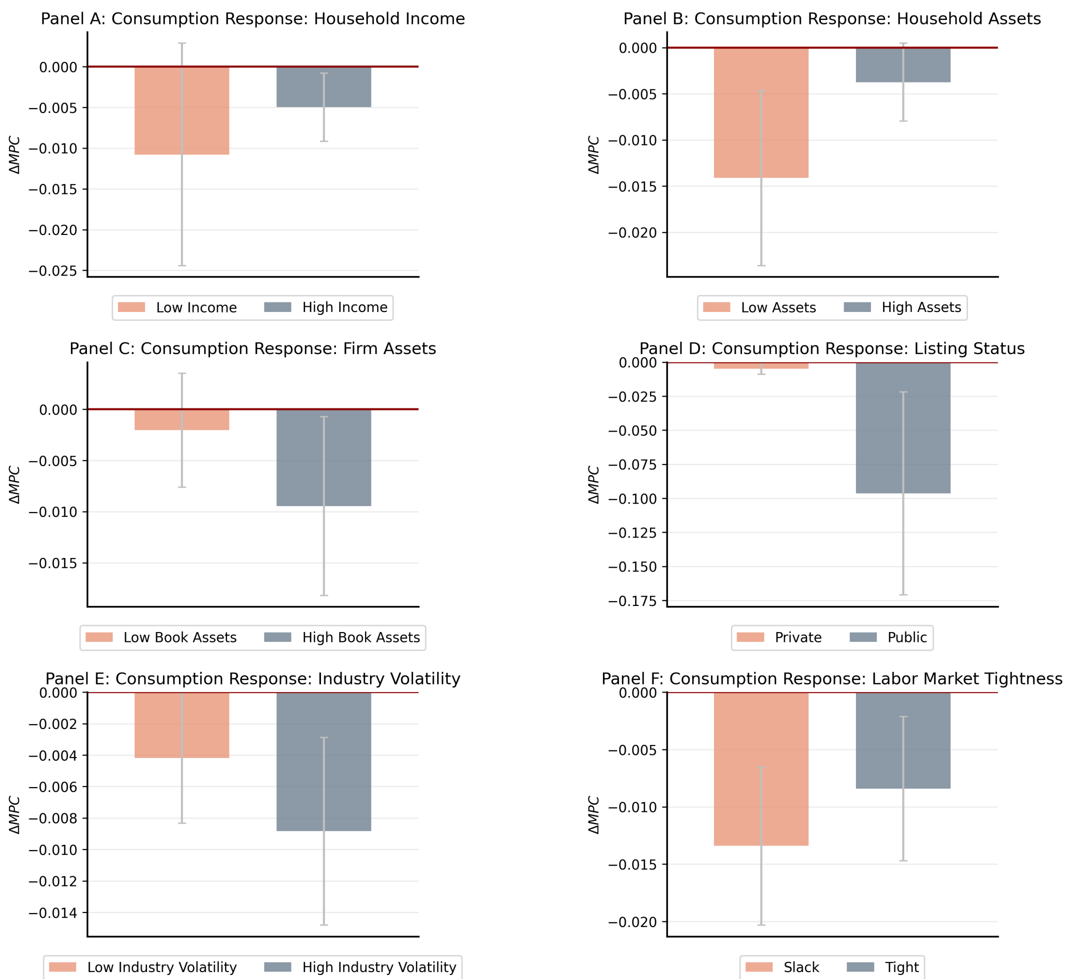
Tauchen, George, 1986, Finite state markov-chain approximations to univariate and vector autoregressions, *Economics letters* 20, 177–181.

Titman, Sheridan, 1984, The effect of capital structure on a firm's liquidation decision, *Journal of financial economics* 13, 137–151.

Topel, Robert H, 1984, Equilibrium earnings, turnover, and unemployment: New evidence, *Journal of Labor Economics* 2, 500–522.

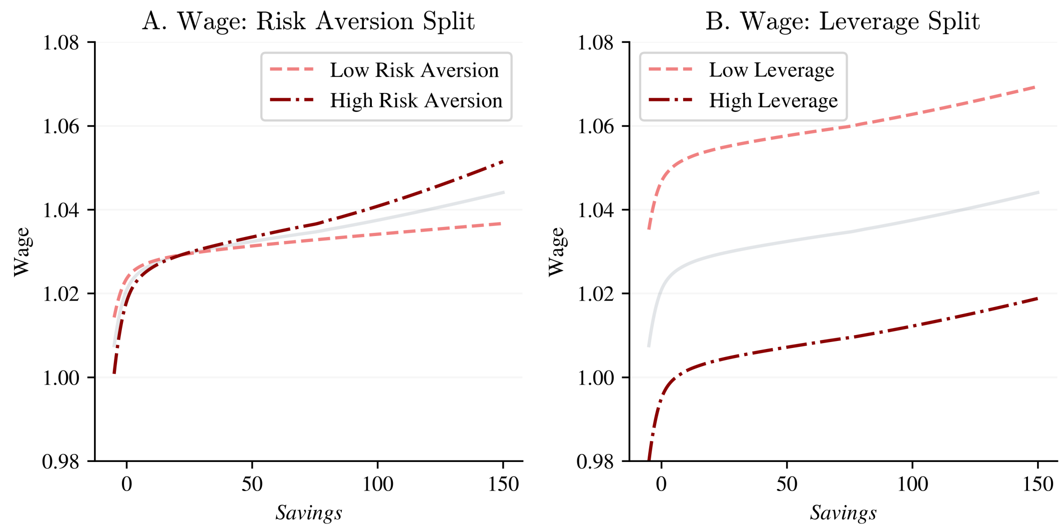
Xerez, Romana, Elvira Pereira, and Francielli Dalprá Cardoso, 2019, Habitação própria em portugal numa perspetiva intergeracional, *Lisboa: Fundação Calouste Gulbenkian.*

Figure 1: Heterogeneity in the Consumption Response



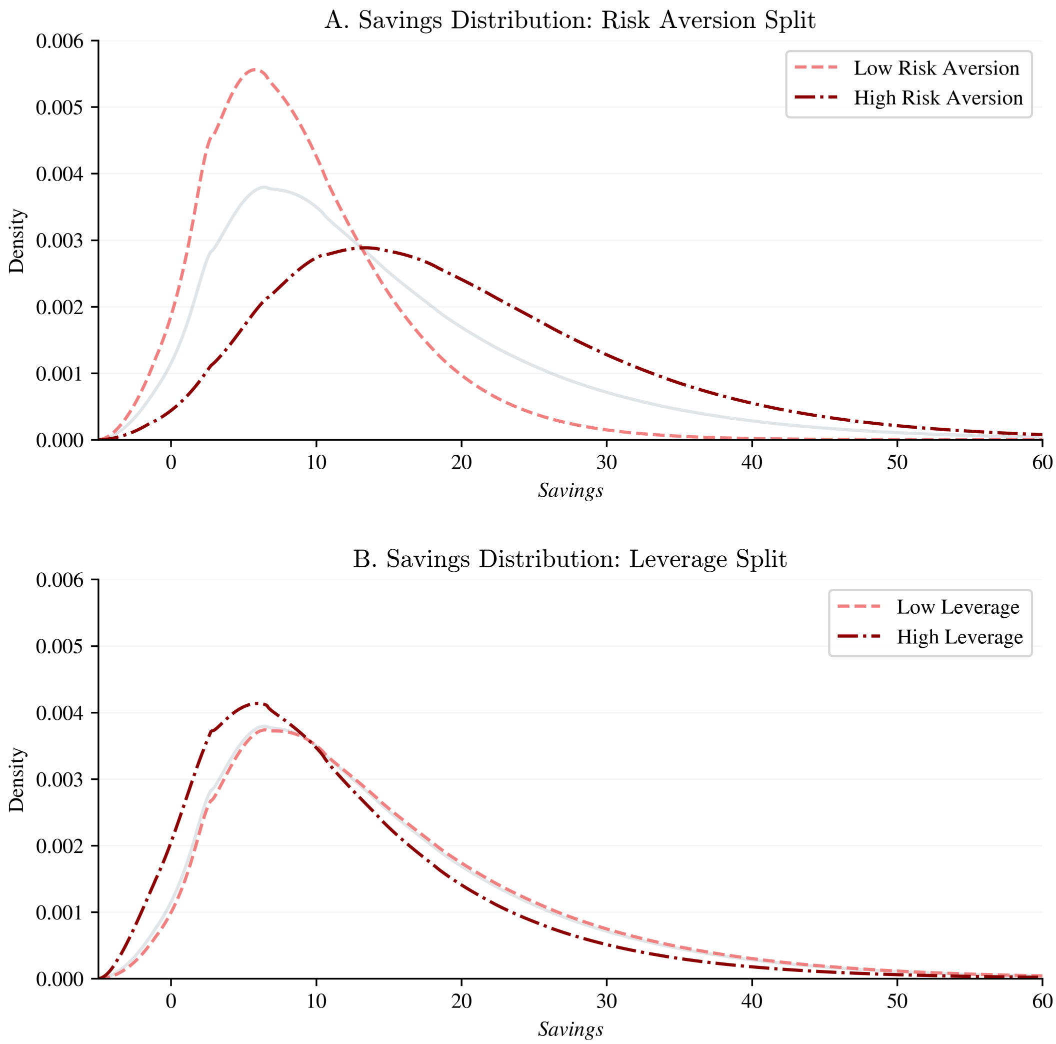
This figure plots the regression coefficients and 95% confidence intervals effect of leverage on consumption, based on different household and firm characteristics. The regression is based on equation (1), where the main explanatory variable is the interaction between income and *Leverage*, defined as 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 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 2: Wages as a Function of Savings: Risk Aversion and Employer's Leverage Splits



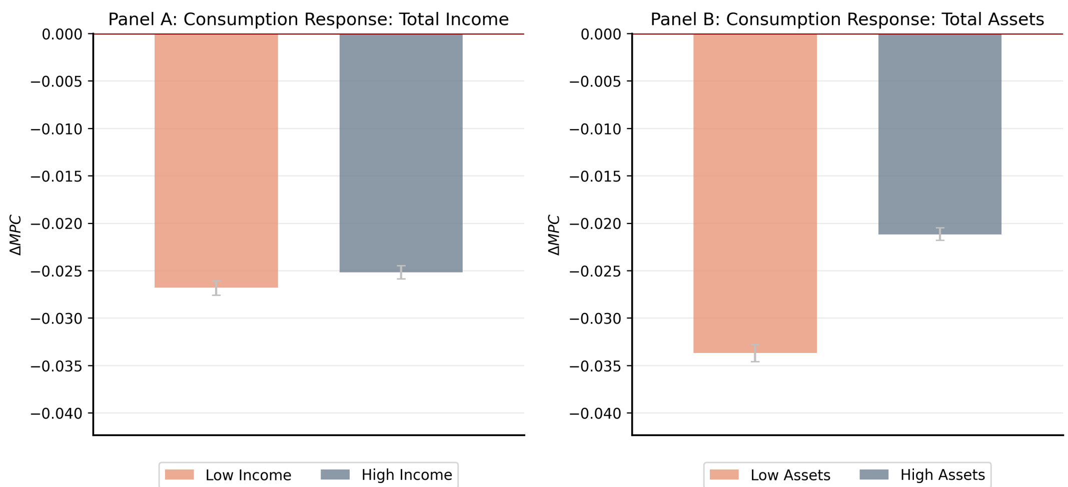
This figure shows the wage schedule as a function of household savings, based on the calibration reported in Table 9. In both panels, the average wage for different types of households and firms, assuming a job-match quality equal to the unconditional mean of x, is represented in gray (solid line). Keeping 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: Wealth Distribution: Risk Aversion and Employer's Leverage Splits



This figure plots the wealth distribution, based on the calibration reported in Table 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 4: 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 5.2. The empirical methodology is comparable to the real data analysis and is based on the model defined in equation (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 1: Summary Statistics

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 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. *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: 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	0.017***	0.009***	0.001	0.007***	0.011***	0.006***	0.012**	0.005**	0.043***
	(0.003)	(0.002)	(0.001)	(0.002)	(0.003)	(0.002)	(0.005)	(0.002)	(0.007)
× Leverage	-0.001	-0.002***	-0.000	-0.000	-0.002***	-0.000	-0.001**	-0.000	-0.006***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.002)
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	0.609	0.404	0.250	0.201	0.384	0.327	0.437	0.339	0.425
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. 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 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. *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 5: Probability of Bankruptcy

	Bankrupted			Bankrupted 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 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 7: Wages and Employer's Leverage

	Log(Annual 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 8: Household's Reaction to Industry Shock - Consumption

	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 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 10: Wages and Employer's Leverage: 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 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 11: Consumption, Saving, and Employer's Leverage: 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 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 for
"Capital Structure and Employee Consumption"

This internet appendix describes the computational methodology employed in solving and simulating the model (section A), and contains supplementary figures and tables, providing various robustness checks (section B).

A Model Simulation

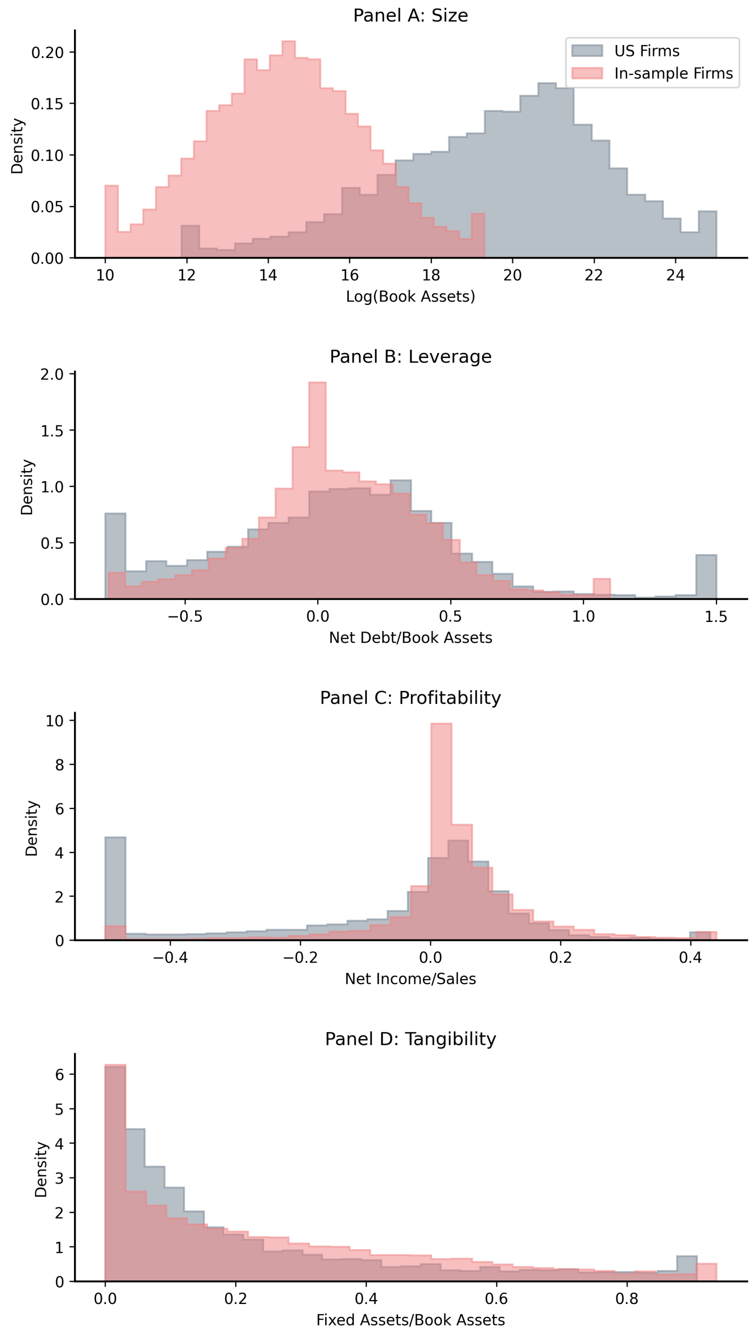
To solve the model, I start by discretizing the state space. Specifically, I follow the Rouwenhorst (1995) method to approximate the process for the idiosyncratic productivity, x_t. As in Petrosky-Nadeau and Zhang (2017), I do not employ the Tauchen (1986) algorithm given its lower accuracy when dealing 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 $theta_t$, 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 (8). To do so, I ensure that the first-order condition, given by equation (13), and the definition of $J_t(x_t, b, \phi_t, \Phi_t)$, in equation (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 (12), is satisfied.

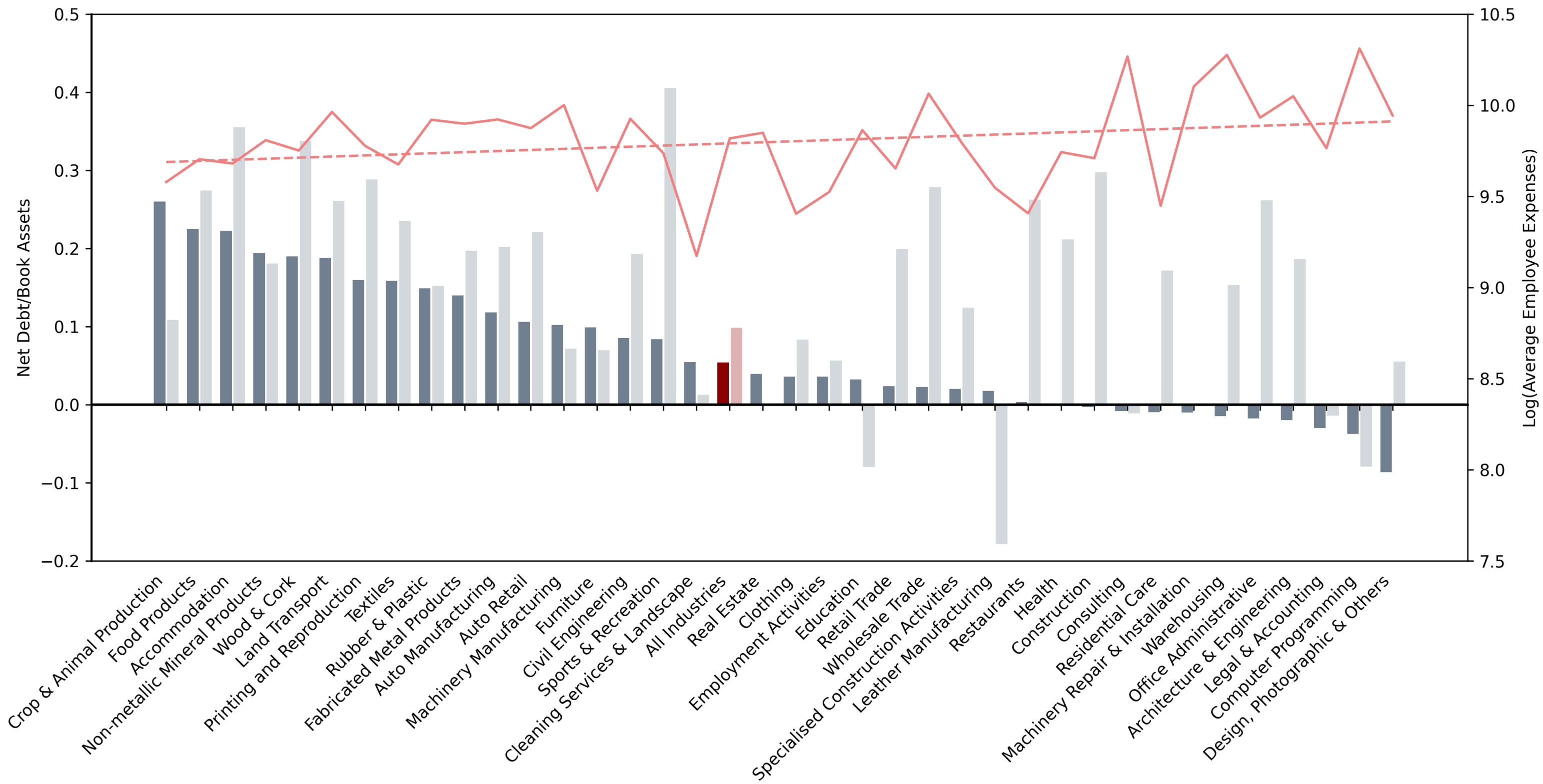
B Robustness

Figure IA.1: Comparison between in-sample firms and US firms



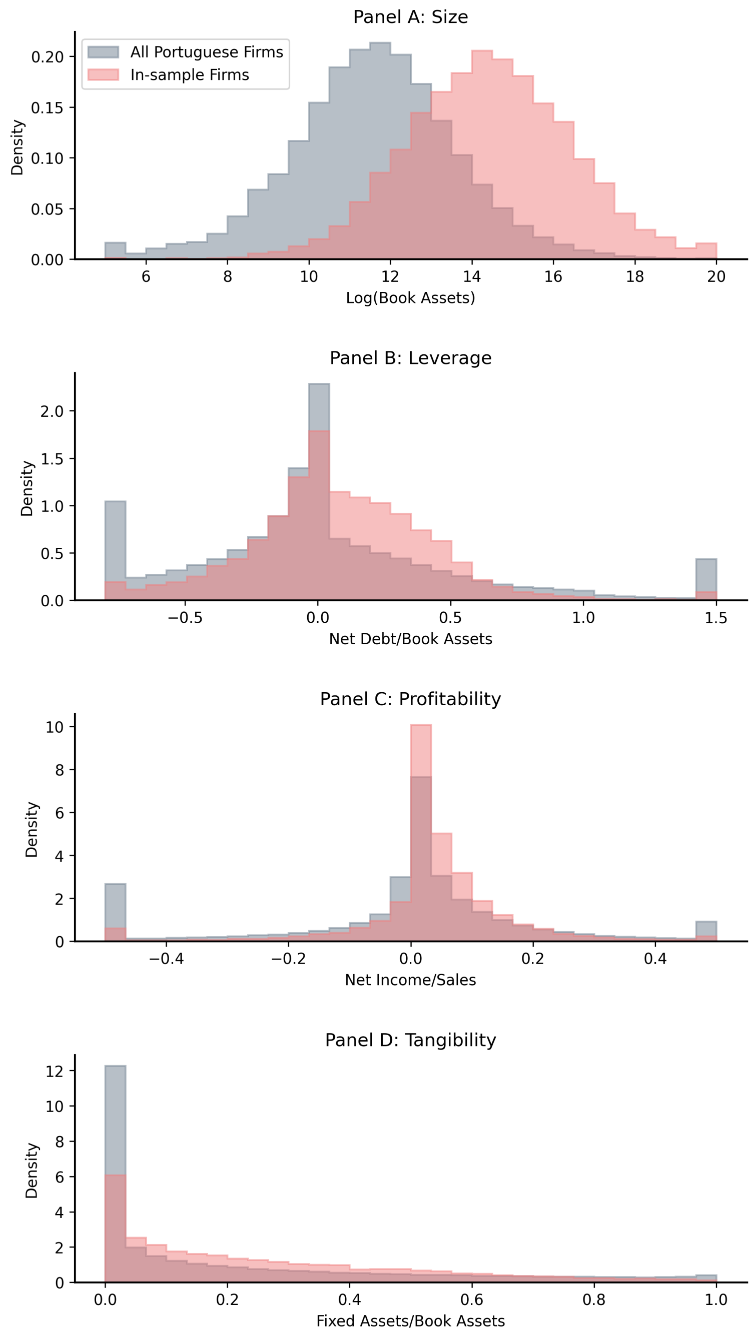
This figure plots the distribution of employers found in the sample of households (in red) and the distribution of US publicly-held firms from Compustat (in blue). Both financial firms (SIC codes 6000-6999) and utilities (SIC codes 4900-4999) are excluded from the Compustat sample, as well as any firm 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 IA.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 bar/dark blue for Portuguese firms and right bar/light blue 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 IA.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 IA.1: Household Summary Statistics 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 IA.2: Firm Summary Statistics 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 IA.3: 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. *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 IA.4: 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 IA.5: 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 goods and services sector. 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 IA.6: Probability of Bankruptcy (All Portuguese Firms)

	Bankrupted			Bankrupted 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 IA.7: 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 IA.8: Number of Employees

	$\text{Log(Employees)}_{t+1}$-$\text{Log(Employees)}_t$			$\text{Log(Employees)}_{t+3}$-$\text{Log(Employees)}_t$		
	(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 IA.9: Number of Employees (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 $\times$ 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 IA.10: 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 IA.11: Turnover

	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 IA.12: Turnover (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 × 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 IA.13: 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 IA.14: Wages and Employer's Leverage - 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 × 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 IA.15: Wages and Employer's Leverage: 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 × 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 IA.16: Household's Reaction to Industry Shock - Wages

	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 IA.17: Household's Reaction to Industry Shock - Wages (Excluding Pandemic)

	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 natural logarithm 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 IA.18: Household's Reaction to Industry Shock - Consumption (Excluding Pandemic)

	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 natural logarithm 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 IA.19: Firm's Probability of Default Following an Industry Shock

	Bankrupted 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.