Employer Leverage and Household Consumption*

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ABSTRACT

Exploiting a rich dataset of matched households and employers, I present novel evidence on the impact of employer capital structure on employee consumption and saving decisions. Despite earning lower wages, households employed by highly leveraged employers exhibit lower marginal propensities to consume. The effect is primarily driven by cutting in "luxury" goods and services. Thus, these results suggest a novel channel through which financial distress costs spill over to other—potentially unrelated—firms: the "employee-spending channel". To establish causality, I analyze employees' responses to negative industry-wide shocks, and find that only those employed by highly leveraged firms cut consumption, with no differential effect on wages. I interpret these findings through a Diamond-Mortensen-Pissarides matching model, where heterogeneous risk-averse employees bargain with heterogeneous employers to determine wages. Consistent with the model, the consumption response is strongest among low-wealth households, for whom unemployment is more painful. Overall, evidence suggests that financial distress costs are being partially shifted to employees.

JEL classification: E21, E62, G28, H31, G50
Keywords: Household finance, Financial distress, Firm leverage, Consumption, Savings, Income

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1 Introduction

Financial leverage imposes significant costs on employees through the increased 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 the non-pecuniary distress costs endured through unemployment spells (Oswald, 1997; Helliwell, 2003). Moreover, the costs of corporate bankruptcy for employees far exceed those endured in unemployment, as the destruction of firm-specific human capital results in persistent income losses for the displaced workers.[1]

However, the existing literature studying the effect of financial leverage on wages is inconclusive with respect to the fundamental question of whether or not employees care about leverage and firm risk. The key problem with existing analyses of this question is that at least two opposing effects operate: while leverage increases the risk borne by employees, it also increases the bargaining power of the firm when setting wages. The dominant force then depends on the specific model and/or empirical setting.[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's leverage depresses wages; while Graham, Kim, Li, and Qiu (2023) find a wage premium. I begin by providing further evidence to this ongoing discussion and find that both in a household-level panel and in aggregate income statement data from Portuguese firms, there is a negative relationship between wages and employer indebtedness.

My main contribution, however, is to show how company leverage affects consumption and saving, where theory is less ambiguous about the null hypothesis: employees working for riskier firms should engage in more precautionary savings. I tackle this question using a dataset built from high-frequency transaction data from a large Portuguese bank and merged

[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 men lose an average of 1.4 years of pre-layoff earnings in normal times, increasing to 2.8 years during recessions.

[2] Additionally, selection effects hamper the analysis. For example, 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).

with employers' accounting variables, enabling me to observe about 87 thousand Portuguese households, who are employed by about 15 thousand companies. My key finding is that workers recognize this risk *ex ante*: those employed by highly leveraged firms exhibit lower marginal propensities to consume (MPC), although in my sample they earn *less* (which would predict higher MPC out of income). Taken together, the evidence suggests that financial distress costs are partially borne by employees, who optimally cut consumption to manage firm risk. These results hold even *within* employment-spell, where two-side selection bias is less of a concern.

Using these fine-grained data about firm risk, employer-employee matching, and employee consumption patterns, I begin by documenting how households employed in the public sector–where employment risk is low–exhibit higher marginal propensities to consume, as measured by debit and credit card payments at the transaction level. This behavior consistently leads employees to leverage up by decreasing liquid saving. Consistent with this channel and within the private sector, higher employer leverage ratios are associated with lower marginal propensities to consume. While this result holds across households, I also show it holds *within* household. To further mitigate concerns about omitted variables, I show that these results are robust to the inclusion of industry-by-year, employer, and employment-spell fixed effects. At the interquartile range of the leverage ratio, these results suggest that marginal propensities to consume fall by about 3% (7% between the top and bottom deciles). Given that pay has been found to be 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), my results suggest that the use of debt may lead to lower employee motivation, arguably imposing an additional cost on the firm.

The overall average effect in consumption also conceals an important degree of heterogeneity. By splitting the sample on household and employer characteristics, I find that the consumption response is substantially greater for poorer households. Moreover, 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 in more volatile industries and in "slack" labor markets. These findings suggest that households are particularly sensitive to their employer's indebtedness when the consequences of unemployment are more severe, or the expected separation rate is higher. Although I do not propose specific channels through which financing decisions information flows from employers to households, I document that the sensitivity of consumption to leverage is much stronger for households working in publicly listed companies, where information asymmetries are likely lower due to financial disclosure requirements. As such, informational frictions may impose further costs on uninformed households, who are unable to optimally readjust for firm risk.

Leveraging the richness of the data, I further decompose the overall average effect by examining how leverage influences the household consumption basket. Interestingly, the effect is driven by non-necessity, or "luxury", goods and services. 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 in previous empirical works.[3] On the other hand, the effect is negligible in groceries, health care and housing maintenance or utility expenditures. 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 insure themselves against employer risk, employees might help propagate financial distress shocks across the economy. Namely, through these employee-consumer networks, a financing decision made by a firm in sector A, can potentially lead to a demand shock for a company in sector B, even if they do not share the same supply chain or financial network. In an external validity exercise using Portuguese data aggregated at the municipality level, I provide evidence that the turnover of the "luxury" goods and services sector is correlated with leverage at the non-"luxury" sector within municipalities. Additionally, evidence suggests that leverage helps to propagate regional shocks: whenever nearby municipalities experience a productivity shock, the

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

"luxury" sector suffers, but only if companies in nearby municipalities are highly leveraged.

While these results suggest that leverage and firm risk are associated with lower consumption, the endogeneity of leverage remains a potential concern in this baseline result, 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 and measure the contemporaneous wage and consumption changes. I find that following such industry-wide shocks only households working for high-leverage firms cut consumption, though there is no differential effect in wage payments. These results would then be consistent with the hypothesis that, when facing such shocks, firms will on average experience economic distress, but only highly leveraged companies are subject to financial distress costs. Relative to other households working in low-leverage firms within the same industry, the effect in consumption is both statistically and economically significant, implying a 3-percentage-point larger cut in consumption during troubled times. Furthermore, households' concern about their employer's financial strength also appears to be warranted: highly leveraged firms are twice as likely to default in my sample and increasingly do so after these shocks.

Additionally, I find that the impact of imperfect risk-sharing between firms and employees is not limited to consumption or saving decisions, but also to employment choices. Specifically, I provide evidence 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 observe directly the underlying motive for job termination, the future income and unemployment benefits pattern is consistent with both higher voluntary and involuntary termination rates.

To help understand the economic mechanisms that determine these empirical findings, I propose a matching model with two-sided heterogeneity, where wages are determined in a Nash bargaining procedure, in the spirit of Bils, Chang, and Kim (2011). 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). Insofar as leverage increases the probability of firm failure, employees would then 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] Using the state-level adoption of right-to-work laws and unemployment insurance system changes in the United States as exogenous variation in union bargaining power, Matsa (2010) finds a positive relation between union power and financial leverage; and in 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. While focusing on public firms operating in the United States, 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, as well as different levels of savings 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 levered firms. Job-match quality is then subject to exogenous shocks, which might lead to either the firm or the employee terminating the match. Part of this risk is treated as idiosyncratic and as such workers cannot insure against it, apart from 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

[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); or, more recently, Matsa (2010) and Michaels, Beau Page, and Whited (2019).

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. For a calibration of the model's parameters that attempts to replicate stylized facts of the Portuguese economy, these bargaining frictions introduce a wage discount from the use of leverage. Interestingly, even though high-leverage firms' workers 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 poorer households, which resonates my own empirical findings.

This paper relates to several strands of the literature. First, it complements the emerging literature on the impact of capital structure impact on employees and the labor market.[5] While opposing evidence has been found for the effect of leverage on wage determination (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 both for outsiders, who are able to reasonably perceive a future employer's financial strength (Brown and Matsa, 2016); but also for insiders, who react to their employer's credit deterioration by increasing networking activity (Gortmaker, Jeffers, and Lee, 2022). 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. This paper contributes to this literature by showing that employees react to employment risk by cutting spending and insuring themselves through precautionary saving.

In addition, I complement the literature on income risk and households' precautionary saving. Kantor and Fishback (1996) examine how the introduction of workers' compensation

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

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,[6] Fuchs-Schündeln and Schündeln (2005) suggest that self-selection of risk-averse workers into low-risk jobs may result in underestimating its relevance. In a related paper using matched employee-employer data, Alfaro and Park (2020) measure the impact of employer-level stock return volatility on employee spending. While their results suggest a strong link between employer stock-level volatility and labor income risk, I complement their working by describing how capital structure may magnify this channel.

Though the main focus of the paper is on the employee response to capital structure, this paper is also related to the literature on the indirect costs of financial distress (Titman, 1984). Due to their nature, indirect costs are difficult to measure. However, evidence suggests they are much more significant than direct ones, working 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), as well as through fire sales of firm's assets (Pulvino, 1998). Additionally, there is evidence that the loss of human capital and its impact in employee pay might be important in quantifying 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 at least partially shifted to employees, who are paid less and have to restrain 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 "luxury" goods. 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), these 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.

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

The paper is laid out as follows. Section 2 describes the matched worker-firm sample. Section 3 describes the empirical strategy, with the results being presented in Section 4. Section 5 presents and analyzes a consumption-saving model in which heterogeneous risk-averse employees match with firms with varying levels of leverage. Finally, Section 6 concludes. The appendix contains all proofs, as well as additional empirical findings supporting the paper's main results.

2 Data

The dataset consists of household-employer pairs, covering clients with an outstanding mortgage loan at a large Portuguese bank, from January 2018 to June 2022. However, the sample is restricted to only include households who i) regularly use this bank's accounts, through either credit or debit card, for making purchases and payments (requiring a minimum average of 10 payments per month); and ii) choose direct deposit of wages, which is crucial in identifying the household's employers. While in a previous paper (Adelino, Ferreira, and Oliveira, 2024) the final sample includes retired individuals and unemployed, in this work a subset of the former is used, considering only households in which at least one element is employed, either in the private or the public sector, at least once throughout 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-the-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 either a credit or a debit card at this bank. By using the bank's internal information about the households' liabilities, which includes outstanding debt, interest rate, date of origination, maturity, and monthly installments, and merging this data with the Portuguese Credit Register, managed by Bank of Portugal, it is also possible to fully characterize the liability side of the households' balance sheet.

Apart from payments and purchases, the data also track 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 by requesting direct deposit of the wage 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 am able to match each transfer to the universe of companies operating in Portugal. To achieve this, I apply the Levenshtein Distance string metric over the name of the entity, relative to the names of all companies operating in Portugal, with its accuracy being validated by multiple random manual checks.

Having identified the name and thus the unique tax identifier of each employer, I then exploit the firm-level database SABI INFORMA (Sistema de Análisis de Balances Ibéricos), made available by Bureau van Dijk. The database uses detailed accounting data from IES (*Informação Empresarial Simplificada*), allowing me to construct a set of employer-level measures reflecting its financial strength.

2.1 Household Statistics

Panel A of Table 1 presents a summary of the main variables at the household level for the final sample, which includes about 87 thousand households. This sample considers all households for which a valid employer match is found during the sample period, either in the public or the 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, including cash withdrawals, from either a credit or a debit card from this bank. Table 2 shows that households whose main wage payment comes from 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 less, at about 90 euros, when compared to those households working for firms in the top quintile of the leverage distribution.

The average total 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 monthly income, at the national level, which in 2019 amounted to 1,800 euros. This sample of borrowers differs from the average Portuguese household, as I am focusing on homeowners with mortgage, a group that represented in aggregate around 30% of all Portuguese households in 2021,[7] and earn on average higher wages than the remaining Portuguese population (Xerez, Pereira, and Cardoso, 2019). Households in the public sector earn significantly higher wages, at about 270 euros per month, and about 490 euros more in total income, as shown in Table 2. Within the private sector, once again those working for the most leveraged firms earn lower wages on average, at about 100 euros per month, compared to households working for the least leveraged firms (a similar figure is found when considering the total income of the household).

While I am able to capture a significant fraction of monthly household income and consumption, I do not observe outbound SEPA transfers, nor 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, which considers their checking account balance net of their outstanding credit card and overdraft balances. A fraction of these households, approximately 59 thousand households, has a savings account at this bank, holding about 17.9 thousand euros in such accounts. Looking at liabilities, households had on average a mortgage balance of 73.6 thousand euros. Only a small fraction of households hold auto or student loans (about 1%), or other types of loans, such as personal loans (about 7%). Conditional on having the former, these households have an outstanding balance of about 7 thousand euros; and conditional on having personal and other types of loans, their outstanding balance is about 6.4 thousand euros. Nonetheless, around 71% of households have loans with other banks, showing an outstanding balance of about 10.7 thousand euros (though 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.

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

Notably, they have a lower outstanding mortgage balance, partially explained by their age (such households are on average 4 years older than households working for the private sector). Furthermore, those working for more leveraged firms carry lower net liquid assets (around 650 euros less, when compared to the households working for firms in the bottom quintile), and have a lower outstanding mortgage balance, at around 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.[8]

2.2 Firm Statistics

Table 3 reports a few characteristics of in-sample firms. In particular, 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 3-digit national industry code given by the standard deviation of sales at the 3-digit industry level in the 3 previous 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, while average employee expenses correspond to total wage bills divided by the number of employees.

Since I include lagged variables as a control in my empirical design, the sample of firms runs from 2015 to 2022,[9] though summary statistics for firms are computed for the 2018

[8]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.

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

fiscal year only. Financial firms are excluded from the sample (CAE codes 64 to 66), as well as any firm observations with 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 firm, employing about 75 workers in 2019, while the median firm would be a small firm, employing about 24 workers. Total debt is about 2.4 million euros on average (6.7 million euros in total liabilities), costing 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.

As most of the comparable studies focus on US publicly-held firms, it is also instructive to compare in-sample firms with the standard dataset for such US-focused studies. Figure IA.1 presents the distribution of in-sample firms, *vis-à-vis* the distribution of Compustat firms.[10] As expected, measured by book assets these households' employers are much smaller than most Compustat firms (the average US public firm has book assets of about 4.2 billion euros, as opposed to about 11.3 million euros for firms in-sample). Companies in-sample also use less leverage, as defined above (average of 11% for firms in-sample versus 33%).[11] 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 more levered, more profitable, and have higher tangibility of assets.

ending in 2022.

[10]To construct this sample, all firms from the Compustat Fundamentals dataset 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 6000-6999) and utilities (SIC codes 4900-4999).

[11]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.

3 Empirical Methodology

The first test conducted in this paper addresses whether households working for relatively more levered firms receive higher wages. To do so, I begin by identifying the primary employer for each household in each sample year. Having identified the primary employer, the annual wage paid by this firm is computed, and this measure is used as the outcome variable in the following baseline specification:

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

where the observation level is at the household-year level, with household h, working for employer e at year y. The main explanatory variable is the lagged leverage ratio, computed as total financing, net of cash, to book assets, thus capturing the sensitivity of employee wages to the employer's financial leverage. $Z_{e,y-1}$ is a set of employer-level controls which 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, and 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 employees' productivity, to account for the possibility that more productive workers are paid more; and the industry's volatility measured in the three previous years, which by being correlated to the worker's willingness to bear risk may determine wages.

While I do not observe education levels in the data, in some specifications I include household fixed effects, to absorb time-invariant characteristics of the household. I also account for year (ν_y) fixed effects, to control for common shocks affecting all households. Finally, in more stringent specifications, I also include industry-year and employer fixed effects, to further mitigate concerns about omitted industry or employer-level variables.

I then proceed by testing whether households working for more levered firms adjust their consumption and saving decisions. I consider the 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, measured as the sum of purchases and payments from either a debit or a credit card at this bank; and the change in net liquid assets, which considers changes in checking account balances, net of credit card and overdraft payments made. In particular, to describe household behavior, I estimate marginal propensities to consume and save, using the following baseline specification:

$$\begin{aligned} Y_{h,e,t} &= \beta_0 Income_{h,t} + \beta_1 Income_{h,t} \times Z_{e,t-12} \\ &\quad + \lambda Income_{h,t} \times Leverage_{e,t-12} + \mu_h + \nu_t + \varepsilon_{h,e,t}, \end{aligned} \tag{2}$$

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 levered firm, an effect measured by coefficient λ. I also include in this specification the interaction between income and the set of additional controls for the employer described above, denoted by $Z_{e,t}$: size, profitability, tangibility, average employees' productivity, and industry's volatility.

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

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

I classify an industry as being treated if the year-on-year change in industry sales (at the 2-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. Given the design, I consider, in all specifications, household and industry-by-month-year fixed effects. These findings are then shown as percentage changes, as the outcome variable is either the inverse hyperbolic sine of wages, consumption of net liquid savings (to allow for changes in both the intensive and extensive margin).

4 Effects of Capital Structure on Employees

4.1 Risk and Wages

Before presenting the results for the effect of leverage on wages and household behavior, it is worthwhile to consider first if there is any evidence that households *should* receive any compensating differential, i.e., whether they face higher unemployment or income risk by working for levered employers.

Table 4 shows the estimates for a linear probability model, where the outcome variable is a dummy variable taking the value of one if the firm goes bankrupt. First, I consider the probability of a sample firm going bankrupt, during the whole sample period, i.e., from 2018 to 2022, as a function of the explanatory variables described above (values at the end of the 2017 fiscal year). In this case, I use a dummy variable, *High Leverage*, which takes the value of one for firms with above-median leverage ratio, as my main explanatory variable.[12] Estimates for this model are presented in columns (1)-(3). Column (1) shows that firms with above-median leverage ratios are much 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 2-digit level, and column (3) adds all the additional firm-level controls. Across all columns the coefficient relative to the leverage ratio is statistically and economically significant, suggesting that employees working for above-median firms are exposed to higher unemployment risk.[13]

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

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

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.[14]

However, when excluding from the analysis bankrupted firms, I find no evidence that levered firms are more likely to exhibit worse employee growth in the future. These results are presented in Table 5. This result holds across all specifications for in-sample firms in the short-run (after one year), as shown in columns (1)-(3), and in the long-run (after three years), in columns (4)-(5). Interestingly, this effect does not hold when considering all Portuguese firms, as show in Table IA.3 in the Internet Appendix. While the magnitude in columns (1)-(3) is significantly higher, columns (4) and (5) show comparable magnitudes to Table 5 (and even lower point estimates in column (6)). While across all specifications, results are statistically significant, the effect is driven by out-of-sample firms, which are substantially different (as shown in Figure IA.3). Consequently, evidence suggest that for larger and more profitable Portuguese firms, highly leveraged firms are not more likely to shed employees outside of bankruptcy, neither in the immediate nor in the long-run periods.[15]

Unfortunately, the data used only allow weak evidence on whether job terminations are more likely to be employee or employer-driven. In contrast to most US states, where firms are not obliged to provide a reason for dismissal, unilateral termination of regular employees in Portugal implies 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. And though structural reforms were made within the scope of the international bailout in 2011, Portuguese employment protection is still very high. For example, in 2019 the Organisation for Economic Co-operation and Development (OECD)

[14]Table IA.1 shows comparable results even if using the overall universe of Portuguese firms, and Table IA.2 shows consistent results by running a logistic regression model.

[15]For example, most collective dismissals between 2017 and 2022 were applied by micro, small and medium 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 total), with the non-renewal of temporary contracts being the main source of registered unemployment (about 50% of total).

ranked Portugal as having the third-strictest employment regulation for regular workers (while being in the top 10 countries in relation to temporary workers). This rigidity might explain the absence of differential employee growth, as firms avoid incurring in such costs and complexity outside of bankruptcy.

Regardless of the exact mechanism used by firms to fire its employees, Table 6 provides evidence that in-sample households are more likely to become unemployed if working for a highly leveraged company. Columns (1)-(3) show that households employed by high-leverage employers are more likely to have no recorded wage payment during the following quarter while being the recipient of social security payments.[16] This result suggests that these households are more likely to lose their job,[17] an increase of about 60% relative to the unconditional average (which stands at about 0.13% per quarter), in the most stringent specification. In columns (4)-(6) I introduce a less strict definition of unemployment, identifying households who being currently employed and show no recorded wage payments in the following quarter, irrespective of receiving social security benefits. Households may opt to receive unemployment benefits through a different bank or by mail, but 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 the current job, an increase in column (6) of about 25% relative to the unconditional mean of about 0.72% per quarter.

Moreover, columns (1)-(3) of Table 7 show that households working primarily for highly leveraged firms (above-median firms in leverage ratio) 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, at about 1.5 percentage points in the most stringent specification. I also examine the income behavior of movers and the differential effect for those previously working in a highly leveraged firm, in columns (4)-(6).[18] I fail to find evidence that

[16]Which include–but may not be limited to–unemployment insurance benefits

[17]To exclude alternative explanations, such as short-term leaves (e.g., either due to sickness or maternity leaves), households who return to the original employer within one year are not classified as being unemployed.

[18]To rule out alternative explanations, such as members of the household switching jobs following a positive

households switching employers suffer a negative impact on their annual total income, which might suggest those departures are either anticipated or voluntary. Additionally, I find no differential effect for those previously working for highly leveraged firms.

Could higher leverage also signal worse managerial quality or firm prospects? Table 8 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 in the long run in columns (1) and (4), respectively, a negative and statistically significant effect is found after adding industry-by-year fixed effects (columns (2) and (5), for the short- and long-run effect, respectively). Finally, adding employer fixed effect flips the direction of the effect in the short-run, and turns the magnitude over the long run statistically insignificant. However, by considering all Portuguese firms, Table IA.4 suggests that indeed more levered 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.

Taken together, these findings suggest that levered firms impose indeed higher unemployment risk over households. Levered firms are more likely to see their employer go bankrupt, and households working for such firms face higher likelihood of *involuntary* termination of their job. Simultaneously, 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 (1) to understand how wages are determined and, in particular, how they are affected by the use of leverage. Table 9 shows the estimates for the effect of the firm-level variables on wage determination, using the net wage receipts recorded in this bank. In column (1) I show that households whose main employer operates in the public sector earn, on average, a 24% premium.[19] More importantly,

shock to other household members, I only consider those households with a single employer. However, in unreported results, adding this restriction does not change the conclusions.

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

columns (2) to (5), 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 (a 4.1% wage *discount*) and statistically significant. Consequently, I find, if anything, a penalty being applied over employees in levered firms.

Finally, in Table 10 I support these findings by running a firm-year level regression 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. While in this case I use aggregate accounting data, as opposed to the transaction-level data used before, results are broadly consistent with the previous findings, since more levered employers pay lower wages on average. Columns (1) and (2), which include only year fixed effects, show that the average wage discount is about 7% and is invariant to other firm-level controls. In column (3), industry-by-year fixed effects are included, showing that this result is still economically and statistically significant when accounting for overall industry trends. However, I fail to find evidence that leverage exerts a negative pressure on wages *within* the firm, as the coefficient of interest in column (4) is statistically insignificant. Table IA.5 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 from 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, evidence is suggestive that workers should receive compensation for the use of leverage, but in equilibrium employers are able to 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 *within* employer.

4.2 Effect on the Marginal Propensities to Consume and Save

I now estimate the effect of leverage on household consumption and saving by looking at marginal propensities to consume and save liquid assets, as per equation (2).

Table 11 reports the estimate for the marginal propensity to consume, showing that income risk is an important driver of this sensibility. Column (1) first 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. Notice, however, how this is true even if they earn *higher* wages on average.[20] While being only tangentially connected to the theoretical framework present before, this result is consistent with the main hypothesis developed in this paper: households recognize income and employment risk and act on these through the consumption decision (and consequently, exhibiting precautionary saving behavior). Starting in column (2) I report the marginal propensity to consume only for households whose main employer is a private sector firm, thus focusing on the effect of leverage.[21] Column (2) shows a marginally significant and negative effect of leverage, which becomes larger in absolute value and highly significant by including industry-by-year fixed effects, as shown in column (3). Finally, I show that the results are robust to the inclusion of employer and employment-spell fixed effects, and imply that a household working for an employer in the top 10% of the leverage ratio distribution reduces their marginal propensity to consume by about 7% when compared to a household working for a bottom 10% firm. Interestingly, I also find a negative and statistically significant effect from increased industry volatility. Additionally, households working for more labor-intensive companies, measured by their tangibility ratio and employee productivity, exhibit lower marginal propensities to consume.

A caveat is however 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 issue and retire debt, and as such capital structure may be capturing time-varying, firm-specific omitted variables. However, the main contribution of the paper is *not* about capital structure determinants,[22] but whether capital structure is perceived as a potential source for income and

[20]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.

[21]Table IA.6 considers an alternative specification using the inverse hyperbolic sine of wages. 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.

[22]Though of course in equilibrium firms would respond to the imperfect insurance provided to workers 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 12 decomposes the overall result on consumption according to different spending categories. Due to data limitations, this panel runs only from January 2020 to June 2022. Moreover, I consider a single specification which 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 levered 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 restaurants expenditure, as seen in columns (2), (5), and (7), respectively.[23] These findings are then consistent with households exhibiting lower propensities to consume in categories what the literature as described before as "luxury" goods and services, i.e., those with an income elasticity greater than one.[24]

Mechanically, I observe that households employed by highly leveraged firms increase the propensity to save in liquid assets, as shown in Table 13. Column (1) shows that households employed by the public sector exhibit lower precautionary saving. Consistently, columns (2)-(5) show that leverage is correlated with higher propensities to save, though the result becomes insignificant in columns (4) and (5). 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.

Interestingly, aggregate behavior shows identical patterns. In Tables IA.7 and IA.8 in the Internet Appendix I examine whether 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,

adjust their leverage ratio accordingly.

[23] And in miscellaneous goods and services, which considers undefined spending (for example, cash withdrawals or purchases at large online retailers) and transactions which do not fit in the remaining categories.

[24] Though the consumption categories change between studies, see for example Clements, Wu, and Zhang (2006), where clothing and transportation exhibit an income elasticity well above one.

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 12; while all other firms in the economy 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.[25]

Table IA.7 in the Internet Appendix reports that total turnover of the "luxury" sector is lower in municipalities where the non-"luxury" sector is more levered. Columns (1)-(2) show that even after controlling for other financial ratios by sector, turnover in the "luxury" sector is about 2% lower in municipalities where the rest of the companies exhibit high leverage ratios. As shown in both columns, this effect is robust to controlling for changes in the employment level and total employee pay, ameliorating concerns that results are driven by higher unemployment or pay cuts in municipalities with higher leverage levels. Finally, column (3) includes district-by-year fixed effects to ensure that common regional shocks are not driving these findings.

Finally, Table IA.8 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 over 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; but 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

[25]More specifically, for the latter variables, an industry-adjusted measure is first computed, by subtracting the corresponding 2-digit industry mean in each sample-year. All measures are then computed as a weighted average by the number of employees of each firm.

in nearby municipalities are highly-levered. Nonetheless, no amplification effect occurs in relation to 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 financing decisions of a given employer and then transmitted through a employee-consumer network.

4.3 Heterogeneous Effects

To further characterize how households perceive this source of risk, I re-estimate the model in equation (2) and interact the effect of leverage on the propensity to consume with various sample splits (including the interaction effect between income and the group indicator). Figure 1 plots the λ coefficient of equation (2) for different groups of households, splitting the sample according to household characteristics.

Panel A shows that the effect of leverage over 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, 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 section 5. Thus, one possible explanation is that when the possibility of unemployment is particularly painful, because households are in a low-liquidity state, the precautionary savings motive become 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 behaviour, it is challenging to pin down specific channels through which households acquire information about the employer's financial strength. However, Panel A of Figure 1 shows the household sensitivity to employer debt is much stronger when working for a publicly listed company.[26] Whatever the specific channel through which they consume this information, i.e., 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. Nonetheless, expected costs are also affected by the "loss given default". To capture the latter, I consider the vacancies-to-unemployment ratio at the regional level,[27] and find that households working in "slack" labor markets exhibit lower propensities to consume, with this effect being marginally significant as well.

4.4 Responses to Exogenous Shock

In this section, I provide further evidence that leverage and financial distress are an important concern of households, when making consumption and saving decisions, by looking at an arguable exogenous industry shock. I consider industry-wide revenue shocks as an exogenous instrument for financial distress. To construct a monthly measure of industry-wide shocks I match the employer's data with year-on-year monthly changes in the industry's calendar unadjusted turnover, from the Eurostat's Short-term business statistics, at the 2-digit NACE Rev.2 code.[28] However, these data are only available for a subset of my sample, focusing on

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

[27]Data are retrieved from *Instituto do Emprego e Formação Profissional*, providing data on new vacancies and unemployment stock by the 2-digit industry code and region (NUTS II), for each month. In particular, this measure is computed by considering new vacancies over the previous quarter, normalized by the total unemployment stock.

[28]NACE (*Nomenclature statistique des Activités économiques dans la Communauté Européenne*) corresponds to the Statistical Classification of Economic Activities in the European Community. CAE (*Classificação de Actividades Económicas*) Rev.3, which I consider for industry classification of all employers at the 5-digit level, is integrated under the former.

manufacturing and service activities.

I proceed by ranking all the industry-by-month combinations and then selecting the worst performing 5%.[29] The rationale for selecting this shock is that while on average firms experience economic distress, the highly leveraged companies additionally experience financial distress.

Before characterizing the consumption response, in Table 14 I check whether there is any differential effect on wages. If these firms are experiencing economic distress, it might be the case that wage payments are delayed, and so the pass-through of the shock is felt by households at the extensive margin. As such, in the following tests I consider the inverse hyperbolic sine of wages as the dependent variable.[30] However, columns (1) and (2) show that the wage drop following such shock is statistically insignificant. Moreover, all specifications show that there is no differential effect for households working in above-median leverage firms.

Interestingly, Table 15 then shows that while low-leverage employers do not induce any consumption response by their employees, households working for highly leveraged firms cut consumption when experiencing this industry-wide shock. This consumption drop is economically and statistically significant, at about 2% in the most stringent specification. To alleviate concerns that the COVID-19 pandemic response might be partially driving these results, in the Internet Appendix, I report identical wage and consumption responses even when considering just 2018-2019 (Tables IA.9 and IA.10, respectively). Finally, Table 16 reports estimated coefficients for the effect of this industry shock on the probability of going bankrupt within the sample period. In all specifications, high leverage firms are more likely to go bankrupt, but do so increasingly so if exposed to such industry shock, increasing the probability of bankruptcy by about 1.5 percentage points.

[29] Due to the concern that the COVID-19 pandemic would 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 find similar results.

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

5 Theory

In this section I introduce a matching model of endogenous job creation and destruction, building on previous work from Bils, Chang, and Kim (2011). In contrast to their work, I calibrate the model to match some stylized facts of the Portuguese economy, as well as adding two important sources of heterogeneity: in the model I propose here, workers have different sensitivities to risk, with varying levels in the coefficient of relative risk aversion; while firms are different depending on their use of leverage.

The goal of the model is to understand whether bargaining frictions could help match empirical findings while trying to further understand how endogenous matching between workers and firms might drive heterogeneity in these findings. Unemployed individuals search for a job and, by assumption, they have perfect knowledge about the exogenously determined amount of debt that the potential employer holds.[31] On the other hand, entrepreneurs have perfect knowledge about workers' characteristics, namely how risk-averse they are and how much wealth they hold.[32] Workers are risk averse and can save to partially insure themselves against job-match idiosyncratic shocks, and they can also borrow, subject to an exogenous borrowing constraint. Moreover, I assume they are also additionally 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 bargain for a higher wage as compensation, in the spirit of Berk, Stanton, and Zechner (2010); however, while increasing unemployment risk, leverage reduces the available surplus to be shared with the employee, which even though modeled very differently, resembles the intuition behind Michaels, Beau Page, and Whited (2019).

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

[32] One could think about previous job experience and age as proxies for these two variables. How information flows between parties is, however, outside the scope of this paper.

5.1 Model Setting

Consider a given 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 for being employed is denoted by $\mathbb{1}_e$, and as such unemployed households derive utility from l, the exogenous value of leisure.[33] In each period consumption must be nonnegative and households are subject to a traditional budget constraint, as follows

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

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

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 riskless bond. On the other hand, households are also allowed to borrow, subject to an exogenous borrowing constraint, such that

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

[33] Allowing the value of leisure to depend on employment status is helpful in calibrating the model to match real moments.

Entrepreneurs and Firms

Entrepreneurs maximize the discounted present value of match surplus, represented 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 changes over time according to two Markov processes, which govern aggregate productivity, denoted by z_t, and idiosyncratic job-match quality, denoted by x_t. Moreover, I assume a standard autoregressive process of order one for both variables: the persistence of the aggregate process is represented by ρ_z, and the corresponding innovations are normally distributed, with $\varepsilon_z \in \mathcal{N}(0, \sigma_z^2)$; while ρ_x denotes the persistence of the idiosyncratic process and σ_x represents the standard deviation of idiosyncratic shocks.

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

Labor Market

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

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

with m_0 representing the efficiency of the matching technology, u_t representing the number of unemployed workers, v_t the number of posted vacancies, and η the elasticity of job matchings with respect to vacancies (with $0 \leq \eta \leq 1$). As such, 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; while the job-finding rate, the rate at which unemployed workers finds 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 and both idiosyncratic and systematic shocks are realized. Following a match, households and entrepreneurs decide whether to continue or separate. If they decide to continue, production is realized and the agreed wage, which depends on the household type and wealth, job-match quality, and employer's leverage, is paid. Otherwise, by deciding to not continue the current match, households join the measure of unemployed workers who search for a new match. Finally, assume that the distribution of employed and unemployed households is characterized 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. Also, denote by $\phi_t = (\gamma, a_t)$ the vector of household-specific states for households, while $\Phi = (z_t, \lambda_e, \lambda_u)$ corresponds to 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 introduced 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 the following problem

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

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 $t = t + 1$. Notice that the last term relates to the household 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

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

Finally, from the perspective of the entrepreneur who is matched with a household, the value of a match 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. In turn, 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 represents the fixed cost of posting the vacancy and λ'_u corresponds to 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, and as such 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, corresponding 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 corresponds to 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 17. 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 steady state and model parameters are chosen with a model period of one month in mind. I begin by normalizing the unconditional mean of the aggregate productivity, assuming that in the steady state $z = 1$. Additionally, I normalize the job market tightness $\theta = 1$. The annual risk-free rate is set to 4% and the household's monthly discount factor, β_h, to 0.996. The latter is set for the model to generate a realistic level of average financial holdings to average household income, at about 13 for Portugal in 2017.[34] I assume two values for the coefficient of relative risk aversion, $\gamma \in \{1, 2\}$, both within the usual calibration of this literature. As also traditional in this literature, I choose a symmetric bargaining power for sharing the job-match surplus, thus equal to the elasticity of the matching technology, i.e., $\delta = \eta = 0.5$. For the idiosyncratic process, I choose $\rho_x = 0.98$, to match the high persistence of observed earnings, and a standard deviation of innovations of about 0.035, both comparable with the calibration of Fujita and Moscarini (2017). I then choose a debt cost, b, of 0.1 for levered firms, with the objective of making the model's wage leverage gap to be comparable in size to the empirical counterpart, presented in section 4.

Compared to the US economy, Portugal is characterized by significantly longer unemployment, even if unemployment rates are comparable at times. Therefore, consistent with Blanchard and Portugal (2001), I set the matching technology parameter m_0 to be equal to 0.11, generating an average unemployment spell duration of about 9 months. The utility from leisure, l is 0.15, as per 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, relative to the US.[35] In particular, the unemployment benefit is then chosen to target an unemployment rate of 6.5% (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 the Internet Appendix.

[34] 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.

[35] For the 2000-2022 period, the average unemployment benefit after 2 months of unemployment, as a share of previous income, was about 76% in Portugal and 61% for the US (data retrieved from the OECD).

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. However, 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 split for households working in unlevered and levered firms.

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

An equivalent exercise is made in Panel B, but splitting the wage schedule according to the employer's leverage. For this numerical example, there is an unambiguous effect of leverage, which depresses wages. Everything else constant, increasing the entrepreneur's debt payments has a direct effect on the value of match, which feeds back into the bargaining game and lowers wages. What is less obvious is that an offsetting force to this direct channel exists. By increasing debt payments and reducing the surplus generated by a match, leverage also makes employment riskier and decreases the value of employment to the household, as the probability of reaching a separating threshold is now greater. Thus, through this channel, wages would actually increase.

Distribution of Wealth

Figure 3 plots, for the same calibrated parameters, wealth distribution, first by splitting households according to their risk aversion coefficient (Panel A), and then to the employer's leverage (Panel B). As expected, there are significant differences in Panel A, since more risk-averse individuals increase savings to insure themselves against income risk. However, the interplay between wages and income risk, both varying according to the use of leverage by the employer, makes differences in the wealth distribution by employer's leverage less striking, as seen in Panel B. As such, this motivates an empirical approach based not on levels but on flows and in particular on *propensities* to consume and save.

Simulated Panel

In this section, I generate a panel of households in a stationary equilibrium. In particular, 250 thousand household paths are simulated, and by randomly keeping 50 thousand households, I create an artificial panel of consumption, saving, and employment decisions. To ensure stationarity, I simulate 5,000 periods, while keeping only the last 60 periods (thus comparable to the sample period). I then conduct a series of empirical tests that are comparable in design to tests performed on the empirical data.

Table 18 shows that in the simulated panel households working for levered employers receive lower wages, consistent with the wage schedule and the channels discussed above. However, even if they receive lower wages on average, the need for insurance dominates and households working for levered employers significantly decrease their propensities to consume, as shown in columns (1)-(2) of Table 19. Consistently, this consumption response is accompanied by an increase in households' propensity to save earned wages, as reported in columns (3)-(4).

6 Conclusion

Using a rich dataset I bring novel evidence on the spillover effects of capital structure on the firm's employees. In particular, these data allow us to study an unexplored connection between leverage and employees: how the latter, further exposed to income and unemployment risk by the employer's use of leverage, readjust their consumption and saving decisions.

To explore the suggested channels through which leverage could affect household decisions, I propose a Diamond-Mortensen-Pissarides model with a precautionary saving motive, which 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, but on the other hand, leverage depresses job-match surplus and reduces wages. Calibrating the model for the Portuguese economy leverage results in a negative effect on wages, and through the increase in unemployment risk leads to households decreasing (increasing) their propensity to consume (save).

As in the model, while analyzing the matched employer-employee dataset I find that leverage is associated with lower pay; even so, households working for highly leveraged firms exhibit a lower marginal propensity to consume. The effect is particularly strong when unemployment is painful due to low wealth, or when working for employers in highly volatile industries, where separation is more likely. I complement these findings by showing that when exposed to a contemporaneous industry-wide shock, households working for highly leveraged employers immediately cut consumption, though facing no differential effect on wages. Taken together, these results are consistent with the proposed model, to the extent that leverage increases separation rates and imposes a cost on households, who are forced to cut back consumption and boost savings.

Moreover, empirically this response is also highly heterogeneous with respect to the consumption basket: while being statistically insignificant for goods and services traditionally identified as "necessities", the effect is mostly driven by reductions in the consumption of "luxury goods", i.e., those with an income elasticity greater than unity. As such, through changes in the consumption basket of employees, this paper further contributes to the literature on the spillover effects of capital structure by implying an indirect effect over other firms. Interestingly, these affected firms might not be competitors, nor belong to the same supply chain as the levered firm, and may be concentrated in specific industries. Though outside the scope of this paper, these results suggest that "employee-consumer" networks might be important in explaining aggregate movements, as opposed to the traditional supply and financial networks previously explored in the literature. Additionally, though no formal test is conducted, these results suggest that a shock of a given type (e.g., a shock to financial distress costs) in a given sector can propagate to unrelated sectors while manifesting itself in different forms (e.g., as a productivity shock). Interestingly, there might exist situations where then no meaningful productivity shock feeds back into the initial sector.

More generally, these results also imply broader questions about the firms' financing decision and society. In recent times, concerns about the high levels of indebtedness in the private sector led to restrictions on the tax deductibility of interest, and additional efforts are being made to further limit the equity-debt tax bias. By providing evidence that capital structure can shift costs of financial distress to employees and distort employee behavior, while mostly imposing such costs on poorer households, these findings can raise additional questions on the optimality of the interest tax deductibility from a social perspective. Overall, I believe that the evidence presented here can lead to further questions on the important but understudied interaction between labor and finance.

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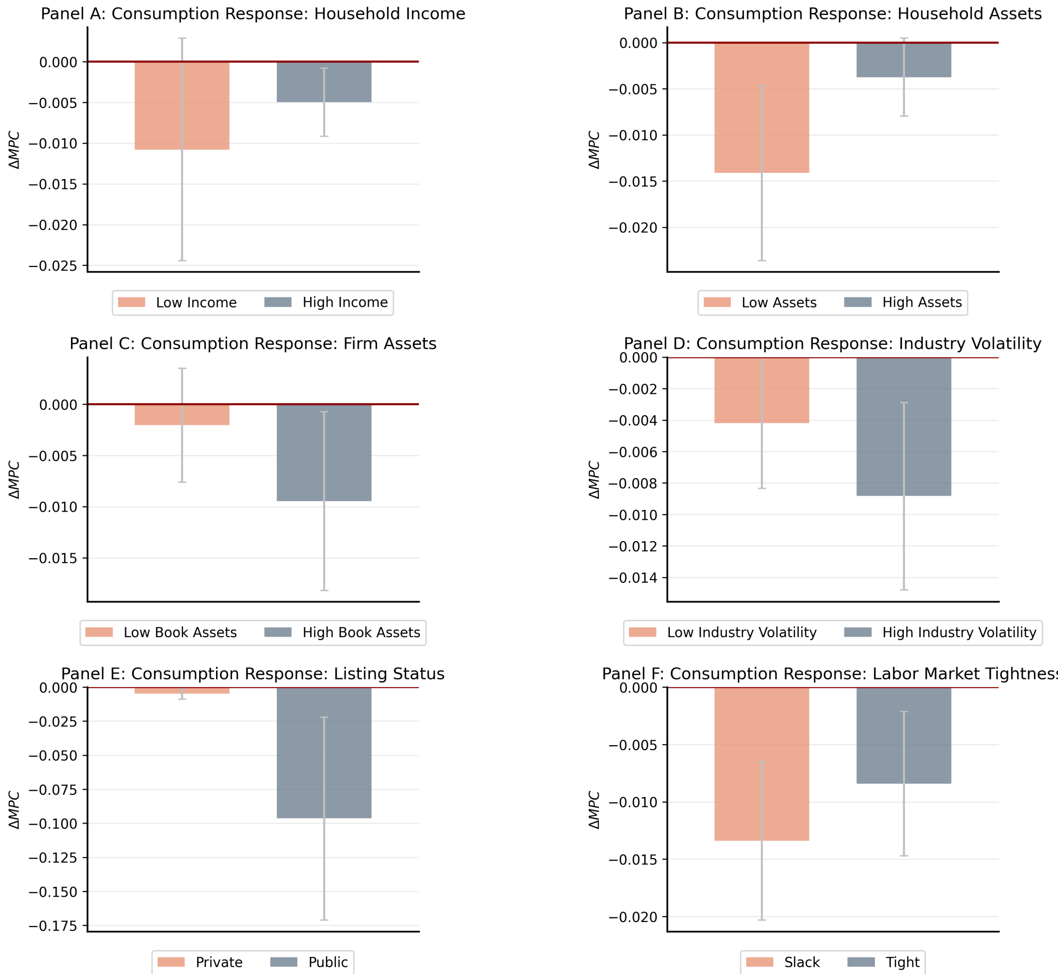
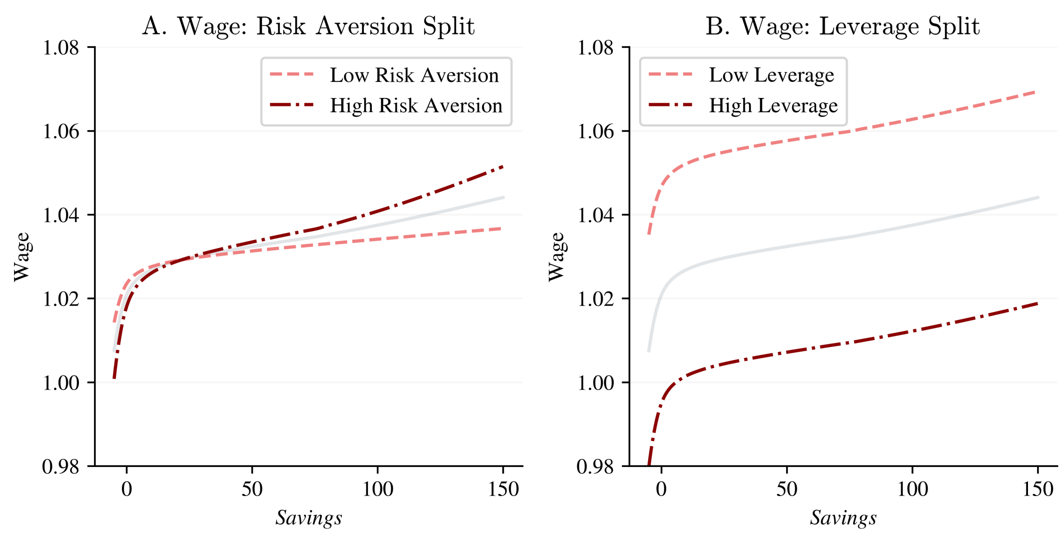
Figure 1: Heterogeneity in the Consumption Response



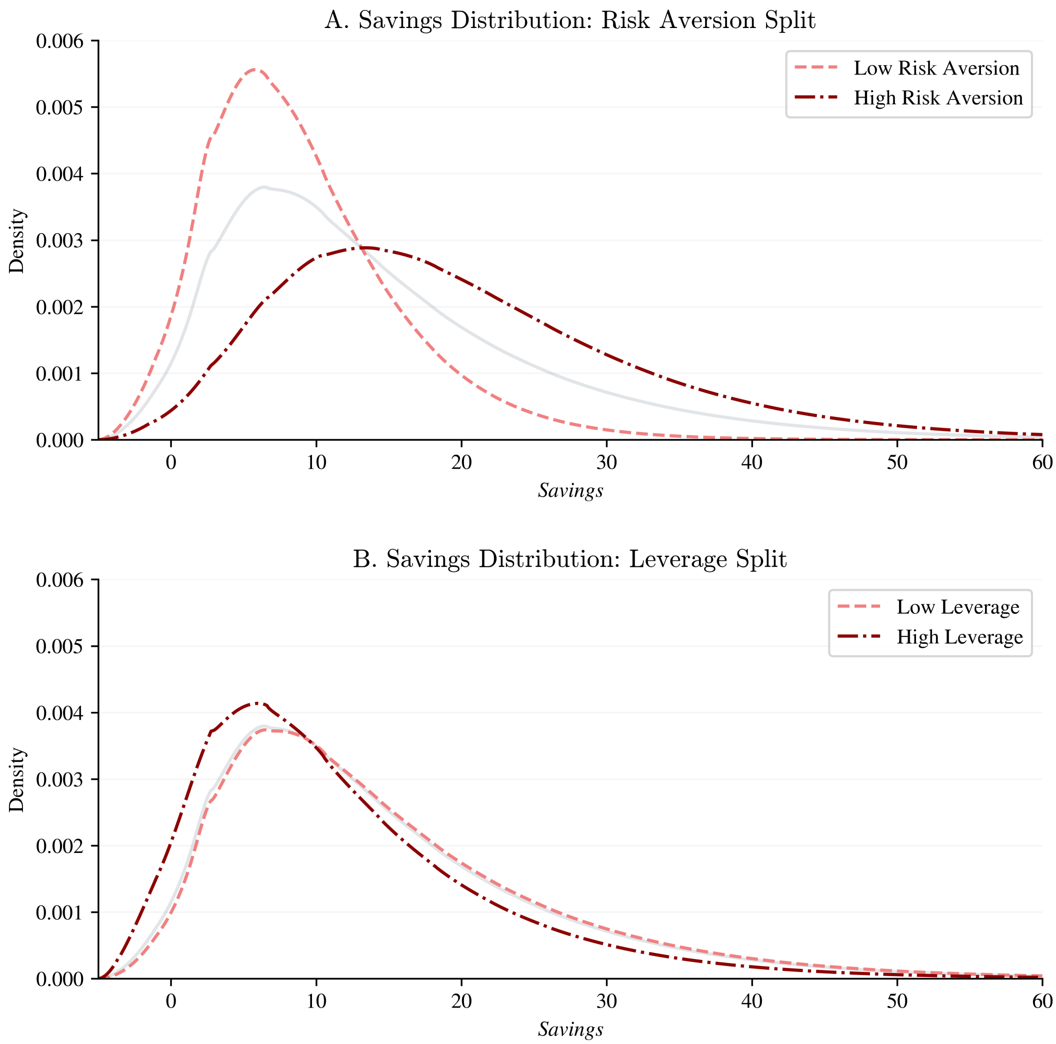
This figure plots the regression coefficients and 95% confidence intervals effect of leverage on consumption, according to different splits of household characteristics. The regression is based on equation (2), where the main explanatory variable corresponds to the interaction between income and *Leverage*, 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 belongs to. The dependent variable on 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 which takes the value of one if the household belongs to the bottom quartile in the income distribution and zero other. For 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 taking the value of one for firms in the bottom quartile in the ROA distribution, and zero otherwise. Finally, Panel D splits the sample by considering households whose employer operates in a highly volatile industry (defined as being in the top quartile, and according to the industry volatility measure described in Table 3). Panel E consider a dummy variable which takes the value of one if the household's employer is publicly listed, and zero otherwise. 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's 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



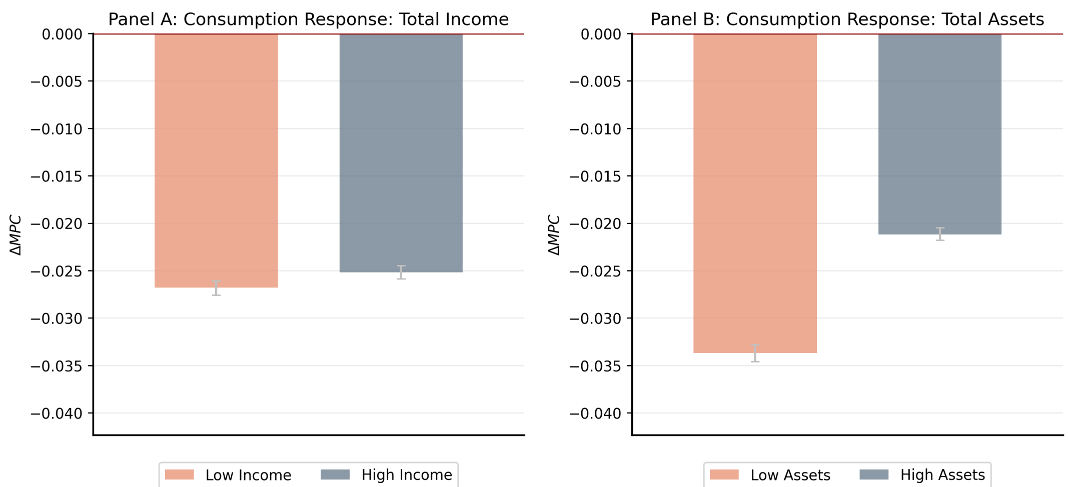
This figure plots the wage schedule as a function of household savings, based on the calibration reported in Table 17. In both panels the average wage for different types of households and firms, assuming a job-match quality equal to the unconditional mean of x, is represented in grey (solid line). Keeping 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 unlevered firm ($b = 0$), and in red (dash-dotted line) the same function for a levered 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 17. In both panels, the density for each wealth level, across all levels of productivity, risk aversion, and leverage, is represented in grey (solid line). Panel A then shows 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 plots in orange (dashed line) the wealth distribution for an unlevered firm ($b = 0$), and in red (dash-dotted line) for a levered 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 (2). The main explanatory variable, the interaction between wages and *Levered*, a dummy variable which takes the value of one for levered 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: Household Summary Statistics

Variable	N	Mean	SD	p10	p25	p50	p75	p90
HH 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
Saving Accounts	58,733	17,878.9	29,210.8	0.0	518.7	6,133.5	21,443.3	50,679.6
Vehicle, Student and Educ. Loans	1,275	6,999.0	5,353.2	1,056.1	2,792.9	5,853.9	9,941.1	14,901.1
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 Loans	5,767	6,356.3	6,426.5	525.6	1,919.4	4,334.1	8,794.8	14,898.1
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	0.45	0.50	0.00	0.00	0.00	1.00	1.00

This table lists for each variable its mean, standard deviation, the 10%, 25%, 50%, 75%, and 90% percentiles, and the number of households for which non-missing records exist. 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. In Panel B, all variables correspond to book values and are winsorized at the top and bottom 1%.

Table 2: 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 its mean within subgroups of households, defined by their employer. Households are identified as working for the public sector if this is the primary source of income during that particular year. Households whose primary source of income comes from the private sector are further divided depending on their primary employer's leverage. *Low Leverage* corresponds to the bottom quintile of employers' leverage; *High Leverage* corresponds to those in the top quintile of leverage; while the remaining households earn their primary wage from an employer in the second, third or fourth quintile of leverage. Income, assets, liabilities, and consumption measures are winsorized at the top and bottom 1% by date.

Table 3: Firm 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
Number of Employees	14,128	75.3	168.8	4.0	9.0	24.0	65.0	164.0
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

This table lists for each variable its mean, standard deviation, the 10%, 25%, 50%, 75%, and 90% percentiles, and the number of firms for which non-missing records exist. The statistics presented here correspond to 2018 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 3-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 4: 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 $\times$ 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 the firm's 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 3-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 5: 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 3-year period ($t = t$ to $t = t + 3$). 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 3-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	0.029**	0.045***	0.082***	0.125***	0.189***	0.191***
	(0.013)	(0.013)	(0.030)	(0.044)	(0.043)	(0.067)
Age	0.005***	0.005***		0.052***	0.053***	
	(0.001)	(0.001)		(0.005)	(0.005)	
Wages	-0.000	0.000	0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
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	0.001	0.002	0.172	0.008	0.009	0.215
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 all regressions, and all firm-level variables correspond to this employer over the previous quarter. For the outcome variable in all columns, a household is classified as having lost a job if no longer working for the main employer in the following quarter and do not return to the original employer after one year However, columns (1)-(3) further imposes that the household starts to receive 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 values. 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 3-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: 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 values. 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 3-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 8: 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 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 3-year period ($t = t$ to $t = t + 3$). Financial firms (CAE codes 64-66) are excluded from the sample. *Public Sector* is a dummy variable which takes the value of one if the main household employer over the last quarter is a state-owned company or institution. *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 3-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 9: Wages and Employer's Leverage

	Log(Annual Earnings)				
	(1)	(2)	(3)	(4)	(5)
Public Sector	0.244***				
	(0.075)				
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)
Year FE	Yes	Yes	No	No	No
Industry $\times$ Year FE	No	No	Yes	Yes	Yes
Household FE	No	No	No	Yes	Yes
Employer FE	No	No	No	No	Yes
R^2	0.025	0.102	0.231	0.813	0.843
Observations	344,488	184,693	184,692	178,398	176,711

This table presents estimates of regressions of the natural logarithm of wages, defined as the mean monthly wage paid by the household's primary employer. Observations are at the household-year level and the panel runs from January 2018 to December 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 3-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 10: 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 be employee, considering in-sample firms. Observations are at the household-year level and the panel runs from January 2018 to December 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 3-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 level). *p< 0.1;**$p < 0.05$;***p< 0.01.

Table 11: Marginal Propensity to Consume

	Consumption				
	(1)	(2)	(3)	(4)	(5)
Total Income	0.071***	0.073***	0.115***	0.112***	0.108***
	(0.002)	(0.002)	(0.013)	(0.014)	(0.014)
× Public Sector	0.007**				
	(0.003)				
× 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)
Month × Year FE	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	No
Industry × Year FE	No	No	Yes	Yes	Yes
Employer FE	No	No	No	Yes	No
Household × Employer FE	No	No	No	No	Yes
R^2	0.538	0.550	0.551	0.556	0.560
Observations	4,428,016	2,356,500	2,336,140	2,335,933	2,334,414

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 sum between purchases and payments from either a debit or credit card at this bank. *Public Sector* is a dummy variable which takes the value of one if the main household employer over the last quarter is a state-owned company or institution. *Leverage* is defined as the ratio of total debt financing, net of cash, to total assets, measured in book values; *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 3-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 12: 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. *Leverage* is defined as the ratio of total debt financing, net of cash, to total assets, measured in book values. 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 3-digit industry level, normalized by the industry's total assets. In all specifications, social security and retirement benefits are added as controls. Standard errors in parentheses are computed using two-way clustering (household and employer). *p< 0.1;**$p<0.05$;***p< 0.01.

Table 13: Marginal Propensity to Save

	Δ Net Liquid Assets				
	(1)	(2)	(3)	(4)	(5)
Total Income	0.616***	0.630***	0.435***	0.440***	0.454***
	(0.005)	(0.005)	(0.026)	(0.030)	(0.031)
× Public Sector	-0.021***				
	(0.006)				
× 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)
Month × Year FE	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	No
Industry × Year FE	No	No	Yes	Yes	Yes
Employer FE	No	No	No	Yes	No
Household × Employer FE	No	No	No	No	Yes
R^2	0.094	0.098	0.098	0.102	0.104
Observations	4,353,865	2,319,660	2,299,554	2,299,353	2,297,950

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 the sum between end-of-the-month checking and saving accounts' balances, net of debt payments made by the household. *Public Sector* is a dummy variable which takes the value of one if the main household employer over the last quarter is a state-owned company or institution. *Leverage* is defined as the ratio of total debt financing, net of cash, to total assets, measured in book values; *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 3-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 14: 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 2-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 15: 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 2-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 16: 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 on 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 3-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.

Table 17: 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 18: Wages and Employer's Leverage: Simulated Data

	Log(Annual Earnings)	
	(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 annual wages, using simulated data. The model is calibrated according to Table 17, 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 levered employers. Standard errors in parentheses are clustered at the household level. *p$<$ 0.1;**$p < 0.05$;***p$<$ 0.01.

Table 19: Consumption, Saving, and Employer's Leverage: Simulated Data

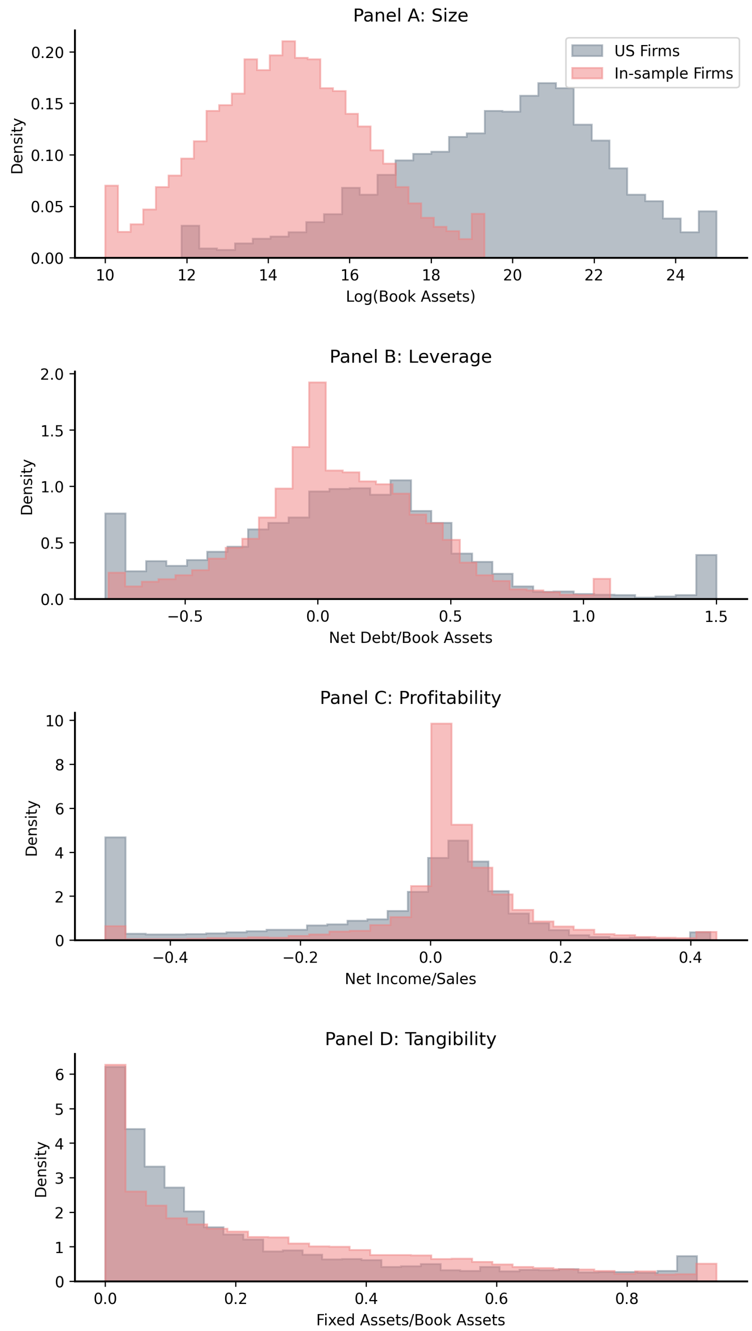
	Consumption		Saving	
	(1)	(2)	(3)	(4)
Wage	0.462***	0.259***	0.648***	0.741***
	(0.002)	(0.001)	(0.001)	(0.001)
× Levered	-0.037***	-0.026***	0.030***	0.025***
	(0.001)	(0.000)	(0.000)	(0.000)
Household FE	No	Yes	No	Yes
R^2	0.323	0.983	0.778	0.988
Observations	2,780,800	2,780,798	2,733,691	2,733,689

This table presents the effect of leverage on consumption and saving, using simulated data. The model is calibrated according to Table 17, 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 levered employers. Standard errors in parentheses are clustered at the household level. *p< 0.1;**$p < 0.05$;***p< 0.01.

Internet Appendix for

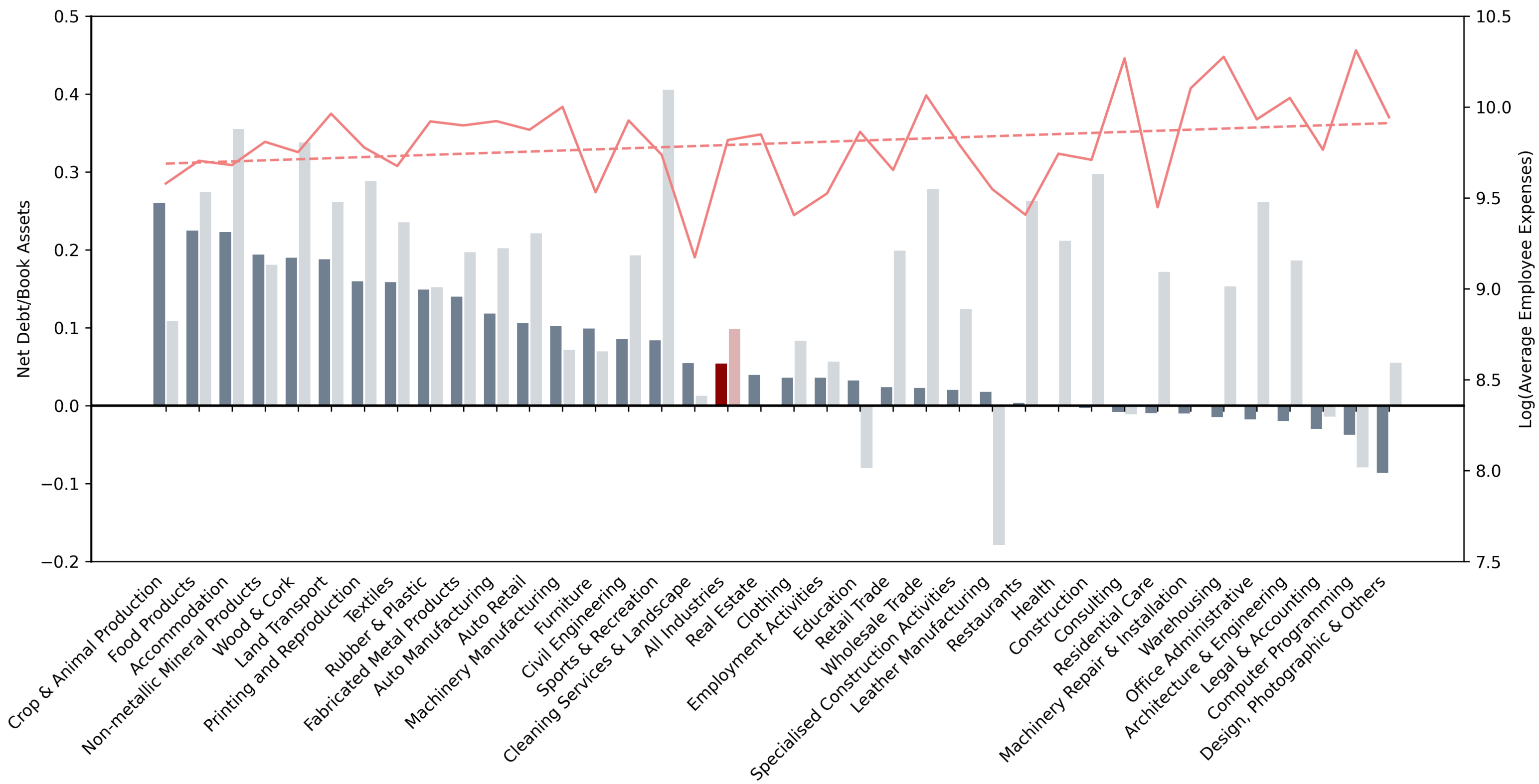
"Homemade Unleverage: Do Households Care About Employers' Leverage?"

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



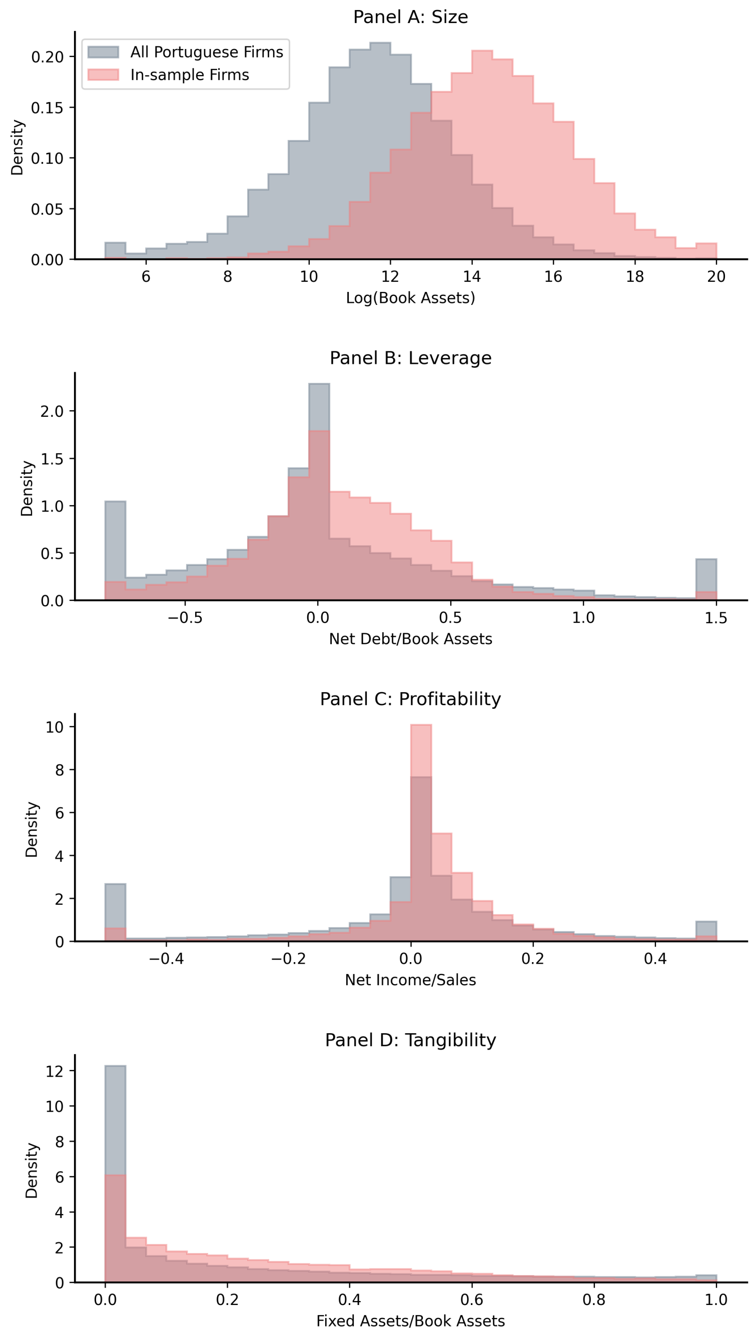
This figure plots the distribution of employers found in the sample of households (in red) and the distribution of US publicly-held firms from Compustat (in blue). Both financial firms (SIC codes 6000-6999) and utilities (SIC codes 4900-4999) are excluded from the Compustat sample, as well as any firm 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). 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: 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 3-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.2: 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 and considering all Portuguese firms. 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 3-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.3: 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 × 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 3-year period ($t = t$ to $t = t + 3$). 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 3-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.4: 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 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 3-year period ($t = t$ to $t = t + 3$). 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 3-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.5: 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 $\times$ Year FE	No	No	Yes	Yes
Employer FE	No	No	No	Yes
R^2	0.017	0.167	0.200	0.773
Observations	1,878,765	1,297,091	1,297,091	1,242,972

This table presents estimates of regressions of the effect of leverage on the average annual wage bill be employee, considering all Portuguese Firms. Observations are at the household-year level and the panel runs from January 2018 to December 2021. *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 3-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 year level). *p$<$ 0.1;**$p < 0.05$;***p$<$ 0.01.

Table IA.6: 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 hpyerbolic 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 values; *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 3-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.7: Effect of non-"Luxury" Sector Leverage on the "Luxury" Sector

	Log(Turnover$_{\text{l}}$)		
	(1)	(2)	(3)
High Industry-Adjusted Leverage$_{\text{nl}}$	-0.032***	-0.025**	-0.019*
	(0.011)	(0.010)	(0.010)
High Industry-Adjusted Leverage$_{\text{l}}$	0.000	0.011	0.005
	(0.011)	(0.011)	(0.011)
Log(Employees$_{\text{nl}}$)	0.082	0.127	0.111
	(0.124)	(0.116)	(0.110)
Log(Turnover$_{\text{nl}}$)	-0.012	-0.066	-0.078
	(0.050)	(0.050)	(0.049)
Log(Employee Expenses$_{\text{All}}$)	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. *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 2-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 2-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 employees' productivity are lagged by one year. Standard errors in clustered at the municipality level. *p< 0.1;**$p < 0.05$;***p< 0.01.

Table IA.8: Sensitivity of "Luxury" Sector to Regional Productivity Shocks

	Log($\text{Turnover}_{\text{l}}$)		Log($\text{Turnover}_{\text{nl}}$)	
	(1)	(2)	(3)	(4)
High Regional Industry-Adjusted $\text{Leverage}_{\text{All}}$	-0.017	-0.021*	-0.024***	-0.021***
	(0.013)	(0.012)	(0.008)	(0.007)
ΔLog(Regional $\text{Turnover}_{\text{All}}$)	-0.046	-0.041	-0.004	-0.002
	(0.075)	(0.069)	(0.048)	(0.039)
High Regional Industry-Adjusted $\text{Leverage}_{\text{All}}$ $\times$ ΔLog(Regional $\text{Turnover}_{\text{All}}$)	0.263***	0.277***	0.096	0.084
	(0.101)	(0.100)	(0.094)	(0.080)
High Industry-Adjusted $\text{Leverage}_{\text{l}}$	0.000	0.010	0.002	0.007
	(0.011)	(0.011)	(0.008)	(0.007)
High Industry-Adjusted $\text{Leverage}_{\text{nl}}$	-0.033***	-0.026***	0.015	0.016*
	(0.011)	(0.010)	(0.011)	(0.008)
Log(Employee $\text{Expenses}_{\text{All}}$)	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. *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 2-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 2-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 employees' productivity are lagged by one year. Standard errors in clustered at the municipality level. *p< 0.1;**$p < 0.05$;***p< 0.01.

Table IA.9: 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 2-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.10: 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 2-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 controls. Standard errors in parentheses are clustered at the industry-date level. *p$<$ 0.1;**$p < 0.05$;***p$<$ 0.01.