Household Debt Overhang and Human Capital Investment

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Abstract

Unlike labor income, human capital is inseparable from individuals and does not completely accrue to creditors, even at default. As a result, human capital investment should be more resilient to "debt overhang" than labor supply. We develop a dynamic model displaying this important difference. We find that while both labor supply and human capital investment are hump-shaped in household indebtedness, human capital investment tails off less aggressively as indebtedness builds up. This is especially the case when human capital depreciation rates are lower. Importantly, because skills acquisition is only valuable when households expect to supply labor in the future, the anticipated greater reduction in labor supply due to debt overhang back-propagates into a reduction in skills acquisition ex ante. Using longitudinal data, we provide empirical support for the model.

Keywords: Household indebtedness, Human capital investment, Labor skills acquisition, Debt overhang, Household default.

JEL: G20, G21, G30, G32, G50, G51, L10, L20.

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1 Introduction

The rising U.S. household debt has renewed interest among scholars and policymakers in understanding the real effects of household balance sheet.[1] Recent studies find that household leverage induces a "debt overhang" effect on individuals' labor supply, particularly when default is expected. Households in the U.S. are often protected by limited liability. Therefore, any incremental income earned from labor supply is partially used to fulfill debt obligations (via liability repayment), postponing the discharge of debt through bankruptcy. As such, households bear the full cost of supplying labor while part of the benefits accrues to creditors. Such wealth transfer discourages households from exerting effort ex ante (e.g., Bernstein, 2021; Donaldson, Piacentino, and Thakor, 2018). Less well understood, however, is an equally important aspect of household decisions – human capital investment.

Human capital is *inalienable* from the household (Hart and Moore, 1994) because attained knowledge can not be transferred from individuals to creditors. Therefore, different from labor supply, human capital investment allows households to generate future incremental income (even after default) by continuing to utilize their acquired skills. This preserved value of human capital investment mitigates the wealth transfer from households onto creditors, and thus, makes it more resilient to debt overhang compared with labor supply. In addition, labor supply and human capital investment are inter-temporally linked. Because engaging in costly human capital investment is only valuable if households anticipate supplying labor in the future and thereby benefit from the market premium for skilled labor (Autor, Katz, and Kearney, 2006), the response of labor supply to debt overhang can feedback into human capital investment decisions.

In this paper, we examine how household debt differentially affects the incentives in acquiring skills versus labor supply, and how the two actions are interconnected. We focus on one type of human capital investment – households' labor skills acquisition after they start

[1] According to the Federal Reserve Bank of New York, U.S. household debt jumped by its largest amount in 14 years and passed $15 trillion for the first time as of the second quarter of 2021. See https://www.newyorkfed.org/microeconomics/hhdc. See also Gomes, Haliassos, and Ramadorai (2021) for a survey of the recent literature studying households' choice and management of debt, including mortgages, credit cards, and payday loans.

their career – because as shown in Acemoglu (1997), a large proportion of human capital investment in modern economics takes place within firms, and because this is the type for which we have compelling empirical identification. Given the indisputable role of human capital in delivering sustained economic growth and the economic importance of mitigating human capital depreciation (e.g., Goldin and Katz, 2010; Dinerstein, Megalokonomou, and Yannelis, 2020), this study provides relevant implications for public policies that can enhance social welfare.

We develop a dynamic model featuring inseparability of human capital and an intertemporal link between human capital and labor supply. We start by showing that individual incentives to acquire labor skills is hump-shaped with respect to the level of household leverage. Such behavior can be explained by the interplay of two opposing forces. The first force emerges directly from the conventional diminishing marginal utility of consumption implied by risk aversion. As household indebtedness increases, a larger fraction of its income accrues to creditors via debt repayment and the household's overall level of consumption declines. In this case, the higher marginal utility of consumption incentivizes the household to acquire human capital and raise consumption. Under this *diminishing marginal utility* force, effort in skills acquisition is increasing in household indebtedness.

This first force interplays with the *debt overhang* force stating that households do not fully internalize the benefits of acquiring labor skills, because such effort allows households to increase their earnings and hence continue to fulfill debt obligations, instead of discharging them by filing for bankruptcy (e.g., He, 2011; Diamond and He, 2014). Thus, debt overhang constitutes a transfer of wealth from households to lenders, rendering effort in skills acquisition a decreasing function of indebtedness. This second force becomes dominant when household indebtedness surpasses a threshold and default becomes more probable. The two forces together yield a hump-shaped relation between indebtedness and skills acquisition.

Labor supply exhibits a similar hump-shape with respect to household indebtedness – reflecting the interplay of *diminishing marginal utility* and *debt overhang*, yet with notable differences. Because labor supply generates transitory income, no additional benefits accrue to the household once it is used to pay creditors. Thus, compared to skills acquisition, labor supply faces greater wealth transfer from households to lenders, making it more susceptible to debt overhang. This distinction results in an earlier and more pronounced decline in the supply of labor as households approach default – that is, labor supply begins to drop at a lower level of household indebtedness, and it drops at a faster rate than skills acquisition. Compared to a benchmark case that mutes the presence of default (and thus debt overhang), households' labor supply decision exhibits a greater distortion than skills acquisition, attributable to the inalienability of human capital.

Importantly, the sharp decay of labor supply feeds back into households' skills acquisition decisions ex ante. Because skills acquisition effort increases households' marginal productivity, this effort is only valuable if households anticipate to supply labor in the future. As such, we find that when labor supply is expected to collapse at high levels of indebtedness, it suppresses households' incentive to acquire labor skills in the first place – a "back-propagation" effect. This is particularly the case when the cost of these two actions features high substitutability, i.e., when households are forced to choose one over the other. In such a case, households optimally choose skills acquisition over labor supply near bankruptcy (due to human capital's preserved value), and this *anticipated* reduction in labor supply discourages human capital investment ex ante. This finding suggests that studying the balance sheet effects on household policies needs to account for the fact that household skills acquisition and labor supply decisions are deeply intertwined. Public policies intended to incentivize the supply of labor through balance sheet interventions (e.g., limiting household debt) should also factor in their impact on skills acquisition due to the dynamic complementarity between these two decisions. We provide more discussion on such policies in relation to the existing literature below.

The nuances between skills acquisition and labor supply are further illustrated by comparative statics analyses. For example, when skills depreciate quickly, that is, when the payoffs of skills acquisition are concentrated in the shorter term – leaving little value in the future and much like the case of transitory income from labor supply, the relation between skills acquisition and household indebtedness converges to that of labor supply. In such a case, the two actions resemble each other in terms of their low resilience to debt overhang. In addition, we find that when hourly wages become more volatile, risk-averse households not only boost their effort in acquiring labor skills – reflecting a "precautionary" motive to hedge against uncertainty, but also increase labor supply accordingly to materialize the premium for skilled labor.

In the next part of our study, we take the theoretical predictions to data. Testing these predictions necessitates information on individuals' labor skills acquisition and on household balance sheets. The 1979 National Longitudinal Surveys (hereafter, NLSY79) provide such information. NLSY79 is a longitudinal project conducted by the U.S. Bureau of Labor Statistics. It surveys a representative sample of American residents since their teen ages, and tracks various financial and professional information into the late stages of their lives. We construct household indebtedness based on the itemized balance sheet.

Importantly, NLSY79 contains information about individuals' participation in training programs after they start their careers. On-career training allows individuals to advance their human capital value, and thus represents well-defined labor skills acquisition (Acemoglu, 1997; Clifford and Gerken, 2021). By observing whether an individual participates in training and the duration of the participation, we can qualify and quantify skills acquisition.

Several features of the training data are critical to fitting our theoretical framework. First, NLSY79 allows us to observe whether the training is initiated by an individual or requested by her employer. Therefore, we can differentiate the individual's voluntary decision – corresponding to the modeled skills acquisition incentive – from obligatory behavior to fulfill employers' requirements. Second, for each training program, we observe which party pays for the training cost. By focusing on training programs not paid by individuals themselves (and instead by e.g., employers or the government), we can mute the effect of financial constraints (affordability) in explaining human capital investment (e.g., Chakrabarti, Fos, Liberman, and Yannelis, 2023; Lochner and Monge-Naranjo, 2012). In this case, we isolate how household indebtedness affects labor skills acquisition by shaping individuals' incentives – instead of their financial limitations. Lastly, the NLSY79 provides each household's week-by-week labor records, allowing us to measure labor supply and contrast it with skills acquisition.

We construct a sample of 6,729 individuals surveyed by NLSY79 between 1991 and 2014. We find that our theoretical predictions are born in the data. We first document a hump-shaped relation between household indebtedness and labor skills acquisition. Training participation initially increases with indebtedness; it peaks around 80% of household debt-to-asset ratio before switching to declining with indebtedness. Labor supply shows a similar hump shape. However, it begins to decline at a lower level of household indebtedness (an earlier manifestation of debt overhang), and the speed of decline is more rapid than that of skills acquisition (a sharper manifestation of debt overhang) – both matching the model prediction.

In addition, this hump shape exhibits significant variation with respect to skills depreciation rates and income uncertainty, as predicted by the model comparative statics. First, we capture skills depreciation based on their exposure to technology in the spirit of Kogan, Papanikolaou, Schmidt, and Seegmiller (2022), as well as changes in an individual's wage path around the completion of skills acquisition. As expected, skills with high depreciation rates – resembling the case of transitory income from labor supply – exhibit a pattern similar to that of labor supply. In such a case, skills acquisition begins to drop at a much lower level of household indebtedness, and it drops at a faster rate. This result reinforces the role of human capital's inalienability in driving our results. Second, we use the volatility of households' earnings to proxy for the uncertainty of income, and again observe patterns that closely match the model predictions. Higher volatility of individuals' earnings induces households to increase both skills acquisition and labor supply to counter the reduced utility due to greater uncertainty.

We next exploit the rich records in NLSY79 to differentiate several alternative theories proposed in existing studies – such as "housing lock", "mental distress", and "inattentiveness" – that may explain the relation between household indebtedness and skills acquisition. These records include whether a household owns or rents a residential property, their mental health history, and their household composition (e.g., whether they have children). We do not find support for these alternatives and thus, the hump-shaped relation most likely reflects the interplay between *diminishing marginal utility* and *debt overhang*, as the model posits.

Our empirical results are obtained after we include a host of control variables including individuals' gender, ethnicity, education level, marital status, employment status, employer characteristics, and life-cycle related factors. The inclusion of fixed effects for individuals' work industry, occupation, county-by-year, and industry-by-occupation further rules out industrial and occupational shocks, or county-level economic conditions that might affect both household indebtedness and skills acquisition. In addition, for any unobservable confounding factors to explain our results, they must correlate with household indebtedness in such a way as to differently affect training participation depending on the level of indebtedness: If certain characteristics encourage households to enroll in training at a lower household indebtedness, then the effect of these characteristics must reverse when indebtedness becomes higher. Nevertheless, to further filter out such possibilities, we perform an instrumental variable analysis, in the spirit of Bernstein (2021), based on plausibly exogenous variation on individuals' mortgage-loan-to-value ratio due to the dynamics of housing market conditions. We confirm our main findings.

The effect of household debt on individual decisions has received growing attention in recent literature. Using a labor-search model, Donaldson, Piacentino, and Thakor (2018) study labor supply decisions of indebted households protected by limited liability. They show that a debt overhang problem makes households reluctant to work because they must use their wages to make debt repayments. This behavior is similar to indebted firms in corporate finance. Consequently, employers pay higher wages to attract workers and, in equilibrium, post fewer vacancies due to heightened labor costs, leading to low employment. The labor skills acquisition that we study generates intangible returns, which are largely inalienable from individuals. This feature in turn renders different responses between skills acquisition and labor supply to household indebtedness. Our results thus complement the previous study.

Importantly, Donaldson, Piacentino, and Thakor (2018) posit that policies intended to limit household debt can mitigate debt overhang, restore labor supply incentives, and ultimately increase employment (an extensive margin effect). Our finding that labor supply has a "back-propagation" effect suggests the restored labor supply can further increase households' effort in acquiring labor skills ex ante, thereby raising the productivity of employment (an intensive margin effect).[2]

Hart and Moore (1994) highlights the role of the inalienability of human capital in corporate finance settings. They focus on the human capital of entrepreneurs and characterize the associated optimal financial contracts between the entrepreneur and external financiers. Our paper builds on this key insight about human capital to rationalize the relationship between household indebtedness and human capital investment.

More broadly, our paper is related to the theoretical literature studying household work incentives. Lazear (2000) provides a framework to study on the job incentives. Lazear, Shaw, and Stanton (2016) rationalize the finding that worker productivity increases during recessions thereby "making do with less." Their key mechanism hinges upon the greater incentives to exert effort in workplaces since unemployment goes up in recessions, increasing the opportunity cost of shirking. Chetty and Szeidl (2007) explain high short-term elasticity of labor supply as a result of high risk-aversion induced by consumption commitment with respect to small and short-lived shocks. Our paper abstracts away from the impact of macroeconomic conditions and consumption commitments on household work incentives, and instead focuses on the relationship between household balance sheets and skills acquisition.[3]

[2]In a similar vein, the Earned Income Tax Credit (EITC) – designed to encourage low income households to increase their labor supply (Meyer and Rosenbaum, 2001; Eissa and Liebman, 1996), will deliver the additional benefit of encouraging household skills acquisition ex ante, according to our model.

[3]Our work is also related to the public finance literature analyzing financial constraints and human capital acquisition. Boldrin and Montes (2005) study the role of the welfare state in financing human capital acquisition in an intergenerational model with exogenous borrowing constraints, while Andolfatto and Gervais (2006) provide additional insights when borrowing constraints are endogenous. Relatedly, Livshits, MacGee, and Tertilt (2003, 2007) explore the impact of bankruptcy rules on household debt overhang and emphasizes the importance of persistent versus transitory shocks. Chen and Zhao (2017) study the interaction of labor market and bankruptcy decisions and find that Chapter 7 filings lead to a higher labor supply compared to counterfactual repayment or Chapter 13 filings. In a model without defaultable debt, Griffy (2021) shows that poorer households choose to increase labor supply at the expense of human capital acquisition, due to

Our paper also borrows insights from the large corporate finance literature exploring the impact of debt financing on firms' investment decisions. Myers (1977) seminal contribution shows the distortionary effect of debt overhang on firm investment in a static setting. Hennessy (2004) develops the first dynamic setting in which debt overhang can be directly linked to Tobin's Q and characterizes the magnitude of debt overhang throughout the life of the firm. Chen and Manso (2017) quantify debt overhang costs within a dynamic capital structure model endowed with systematic macro-economic risks.[4] More recently, multiple papers have studied various mechanisms to mitigate debt overhang. For example, Hackbarth and Mauer (2012) explores debt priority, Diamond and He (2014) explores debt maturity, and Bensoussan, Chevalier-Roignant, and Rivera (2021) explores performance sensitive debt in the spirit of Manso, Strulovici, and Tchistyi (2010), amongst others. Our paper contributes to this literature by developing the first dynamic household finance model characterizing the distortionary impact of debt overhang on human capital investment. Unlike canonical models of corporate finance – in which the firm "ceases to exist" or is transferred to creditors after bankruptcy, households carry on with their lives post bankruptcy, offering them opportunities to materialize the continuation value of acquired human capital. To this end, our implications can apply to an extended corporate model, in which the existing intangible assets (e.g., supplier or bank relationships) can be redeployed, after bankruptcy, by the same set of prior shareholders for a new venture.

On the empirical side, existing literature finds both a negative and positive effect of household indebtedness on individual decisions. Regarding negative effects, studies find that rising household debt reduces labor supply or income (Dobbie and Song, 2015; Bernstein, 2021; Di Maggio, Kalda, and Yao, 2019), consistent with the prediction of Donaldson, Piacentino, and Thakor (2018). It also reduces labor mobility (Ferreira, Gyourko, and Tracy, 2010, 2011; Di Maggio, Kalda, and Yao, 2019; Bernstein and Struyven, 2022; Brown and

a high marginal utility of consumption.

[4] Other papers studying firms' dynamic investment and financing decisions include Mello and Parsons (1992); Mauer and Triantis (1994); Mauer and Ott (2000); Titman, Tompaidis, and Tsyplakov (2004); Ju and Ou-Yang (2006); Moyen (2007); Sundaresan and Wang (2007); Tserlukevich (2008); Strebulaev and Whited (2012); and Hackbarth, Rivera, and Wong (2022).

Matsa, 2020; Gopalan, Hamilton, Kalda, and Sovich, 2021), residential home improvement (Melzer, 2017), and inventors' productivity (Bernstein, McQuade, and Townsend, 2021). Regarding positive effects, Zator (2020) shows that higher mortgage interest rates make households work and earn more in order to cover increased mortgage payments. Studying lottery settings, Imbens, Rubin, and Sacerdote (2001) and Cesarini, Lindqvist, Notowidigdo, and Östling (2017) find that increases in household wealth (ceteris paribus a reduction in household indebtedness) reduce labor supply. On the other hand, Rizzo and Zeckhauser (2003) find that wealth shortfalls from a reference point incentivize households to boost earnings.

Our main contribution to this literature is to document, in a unified theoretical framework, that household indebtedness's positive and negative effects co-exist in the context of human capital investment. Their presence depends on the regimes of indebtedness and stems from the interplay of the two forces that respectively encourage and discourage households to exert effort. As such, our work depicts a fuller picture of the relationship between household indebtedness and decisions.

2 Model

2.1 Model setup

An infinitely lived household derives utility from consumption C_t, and dis-utility from exerting effort in acquiring labor skills a_t. Labor skills increase the household's productivity and hourly wage it receives. The household is free to choose how many hours to work – the amount of labor supply (l_t) – at a given hourly wage. Thus, the household's total wages are the product of hourly income and number of working hours. Similar to skills acquisition, labor supply is costly and generates dis-utility for the household.

Different from risk-neutral corporations (thanks to diversification), a typical household is assumed to be risk-averse. For tractability, we assume logarithmic consumption preferences and quadratic cost of skills acquisition and labor supply such that per-period utility is given by:

$$u(C,a,l) = \log C - g(a,l), \qquad \text{where} \qquad g(a,l) = \theta_a \frac{a^2}{2} + \theta_l \frac{l^2}{2} + \theta_{al} a l. \tag{1}$$

θ_a and θ_l denote the marginal cost of skills acquisition and labor supply, respectively. θ_{al} captures the relative complementarity between exerting effort in skills acquisition and supplying labor. A negative θ_{al} indicates that the cost of skills acquisition partially offsets the cost of labor supply (or vice versa), yielding a high level of complementarity. Conversely, a positive θ_{al} indicates a low level of complementarity (or a high level of substitution). In the baseline model, we focus on the case in which skills acquisition and labor supply costs are independent from each other (i.e., $\theta_{al} = 0$). We then explore the rich nuances of the model when θ_{al} varies.

A household's life-time utility from consumption, skills acquisition, and labor supply, $\{C_t, a_t, l_t\}_{t \geq 0}$, is given by

$$\mathbb{E}\left[\int_0^\infty e^{-\delta t} u(C_t, a_t, l_t) dt\right], \tag{2}$$

where $\delta > 0$ is the household's subjective discount rate.

Denote $K_t \geq 0$ as the hourly labor income per-period. The dynamics of K are given by the (controlled) geometric Brownian motion (GBM) process:

$$dK_t = K_t[(a_t - \rho)dt + \sigma dB_t], \tag{3}$$

where B_t is a standard brownian motion, and $\sigma > 0$ is a proxy for labor income uncertainty, which we assume to be purely idiosyncratic. Equation (3) implies that exerting effort $a_t \geq 0$ in acquiring labor skills makes the household more productive, thereby increasing the future hourly wages. However, the value of acquiring labor skills declines over time, captured by a depreciation rate $\rho > 0$. The depreciation reflects that in reality, acquired skills (or more broadly human capital) do not always retain the initial value as time goes by. Naturally, the depreciation rate varies across different skills, and in later analyses, we study the comparative statics of our model with respect to ρ.

The total wages W_t are the product of hourly income and the number of working hours:

$$W_t = l_t K_t. \tag{4}$$

Initially, households have complete access to credit markets, and can borrow and save at the risk-free rates in order to smooth consumption. Household savings S_t evolve according to:

$$dS_t = (r(S_t)S_t - C_t + W_t)dt \text{ if } t \leq \tau, \tag{5}$$

$$S_t = 0 \text{ if } t > \tau, \tag{6}$$

where τ denotes the time at which the household's borrowing limit is reached. We model the borrowing limit as a multiple $\underline{s}$ of the household's earnings upon default, and once the borrowing limit is reached, the household is forced into default. This way of modeling reflects an exogenous default formulation akin to that in the dynamic corporate finance literature (e.g., Longstaff and Schwartz, 1995; Bolton, Chen, and Wang, 2011). We set the interest rate $r(S_t) = r_B$ when the household is borrowing (i.e., when $S_t < 0$) and $r(S_t) = r_S < r_B$ when the household is saving (i.e., when $S_t \geq 0$), reflecting the observation that interest rates for household savings are lower than those of household debt.

Prior to default, equation (5) states that wages are deposited in the savings account. Savings accrue interest at rate $r(S_t)$ and are used to pay for household consumption. Upon default, equation (6) states that households discharge all of their debts and are henceforth shunned from credit markets, forcing their savings (and debts) to be equal to zero. This equation reflects that (i) a majority of households that go through bankruptcy file Chapter 7 – in which case debtors discharge eligible debts, and (ii) default often hurts debtors' creditworthiness, thereby limiting their ability to borrow (e.g., Dobbie and Song, 2015; Dobbie, Goldsmith-Pinkham, Mahoney, and Song, 2020; Kleiner, Stoffman, and Yonker, 2021).[5] In

[5] Dobbie and Song (2015) report that almost 80% of debtors in their sample file Chapter 7, and 98.4% of Chapter 7 filings end with a discharge of debt. Under Chapter 7, almost all unsecured debts are eligible for discharge. Alternatively, debtors can file Chapter 13 in which case filers propose repayment plans in

Appendix A.4, we consider the case when default is less punitive (when e.g., the household may partially access the credit market after default). Here due to the lack of credit market access, after default the household will become a hand-to-mouth household, whose consumption equals his total wages (i.e., $C_t = W_t$ for all $t > \tau$).[6]

The household's problem consists of jointly choosing consumption, labor skills acquisition, and labor supply to maximize life-time utility. We denote the household's value function by $F(S, K)$:

$$F(S,K) = \max_{C,a,l} \mathbb{E}\left[\int_0^\tau e^{-\delta t} u(C_t, a_t, l_t)dt + e^{-\delta\tau} H(K_\tau)\right]. \tag{7}$$

The first part of equation (7) pertains to the value prior to default. It is a function of savings, labor skills, and labor supply. The second part of the equation, $H(K)$, is the value post default. This value function integrates an important feature of labor skills acquisition. The acquired labor skills prior to default increase hourly wages $K_t \geq 0$, and the higher hourly wages carry over to the post-default period – reflecting that acquired skills are inseparable from households and thus preserve their value even post default. This feature, as we discuss later, is key for the different relations between household indebtedness and skills acquisition versus labor supply.

In the main model, we assume that after default, the household's human capital remains intact even though it can no longer rely on credit markets to smooth its consumption. This way of modeling is to match empirical findings by Dobbie, Goldsmith-Pinkham, Mahoney, and Song (2020), who show that personal bankruptcy information has an economically trivial impact on future earnings in the U.S. labor market.[7] In Appendix A.3, we consider the possibility that the value of human capital declines moderately after default. This decline may arise because of resistance from employers to the household's unfavorable credit history – resulting in reduced employment (e.g., Bos, Breza, and Liberman, 2018), or because of wage

exchange of protection of most assets.

[6]See Kaplan, Violante, and Weidner (2014) for evidence that a large share of households live hand-to-mouth.

[7]The authors explain that it is likely because bankruptcy contains little incremental value in predicting individuals' future job performance. However, the authors find some modest effects of bankruptcy information on job-finding rates. This latter finding is consistent with Friedberg, Hynes, and Pattison (2022).

garnishment until the household's debts are repaid – which effectively lowers the hourly wage (e.g., Yannelis, 2020; Argyle, Iverson, Nadauld, and Palmer, 2022; DeFusco, Enriquez, and Yellen, 2023). These possibilities would partially undo the value preservation of human capital post default due to its inalienability. We show in Appendix A.3 that our findings are qualitatively unchanged in the context of the empirical measurements in Bos, Breza, and Liberman (2018).

As a baseline analysis, we focus on the case in which the costs of skills acquisition and labor supply are independent from each other (i.e., $\theta_{al} = 0$). Given that $\theta_{al} = 0$, in Appendix A.1 we show that the value function and optimal polices *after* default can be computed in closed-form solution:

$$H(K) = \frac{1}{\delta}\log K - \frac{\delta^2\theta_a \log(\theta_l) + \delta^2\theta_a + \delta\theta_a\left(2\rho + \sigma^2\right) - 1}{2\delta^3\theta_a}, \tag{8}$$

$$C(K) = Kl(K), \qquad a(K) = \frac{1}{\delta\theta_a}, \qquad l(K) = \frac{1}{\sqrt{\theta_l}}. \tag{9}$$

Equation (9) follows a straightforward intuition. Because the household becomes hand-to-mouth, his consumption equals his wages. Effort in acquiring labor skills *after* default is inversely proportional to the cost θ_a and the discount rate δ. Because labor skills increase human capital and have a lasting effect on future wages, patient households will exert more effort in acquiring skills. By contrast, labor supply – whose return (earnings) only impacts current income – depends exclusively on the cost of supplying labor θ_l.

The value function *before* default $F(S, K)$ satisfies the dynamic programming equation:

$$\begin{aligned}\delta F(S,K) = \max_{C,a,l}\Big\{ & \log C - g(a,l) + F_S(S,K)(r(S)S - C + lK) \\ & + F_K(S,K)K(a-\rho) + \frac{1}{2}F_{KK}(S,K)K^2\sigma^2\Big\}.\end{aligned} \tag{10}$$

The first two terms inside the brackets represent the household's instantaneous utility from consumption, skills acquisition and labor supply. The third term captures the change in value for the household from changes in savings. The fourth and fifth terms are the change in value induced by the dynamics of human capital K. The household chooses consumption, skills acquisition, and labor supply in order to maximize the quantity inside the brackets, whose first order conditions are given by:

$$\frac{1}{C(S,K)} = F_S(S,K), \qquad \theta_a a(S,K) = F_K(S,K)K, \qquad \theta_l l(S,K) = F_S(S,K)K. \tag{11}$$

Intuitively, the household chooses consumption in order to equate the marginal benefit of one additional unit of consumption with the marginal cost of reducing savings by one unit. The level of skills acquisition is chosen so that the marginal cost equals the marginal benefit of higher hourly income K. Similarly, labor supply optimally trades off the cost of labor for the benefits of generating higher total income and thereby increasing savings S. Substituting (11) into (7) yields a differential equation for $F(S,W)$, which is solved subject to the boundary condition at default $F(\underline{s}W,W) = H(W)$.

This differential equation cannot be solved analytically. However, due to CRRA preferences and controlled GBM dynamics for hourly income, the value function displays homogeneity of degree one. Hence, in Appendix A.2, we show that the two state variables K and S can be reduced to a single state variable $d_t \in [0,1]$. Importantly, as shown in Figure I, d_t predicts the probability of a household entering default. Therefore, we interpret the state variable d as household indebtedness. More precisely, we define z as the probability that the household eventually files for default given its current level of indebtedness:

$$z(d) = \mathbb{P}(\tau_D < \infty | d_t = d). \tag{12}$$

$z(\cdot)$ is increasing in the level of indebtedness, implying that the household is more likely to default when d is higher. As discussed in Section 3.3, our empirical counterpart for the state variable d will similarly predict household default, resembling the pattern of Figure I.

In the next section we explore the implications of our model for the relation between d (household indebtedness) and skills acquisition versus labor supply. With a slight overload of notation, we denote skills acquisition as a function of indebtedness as $a(d)$ and labor supply

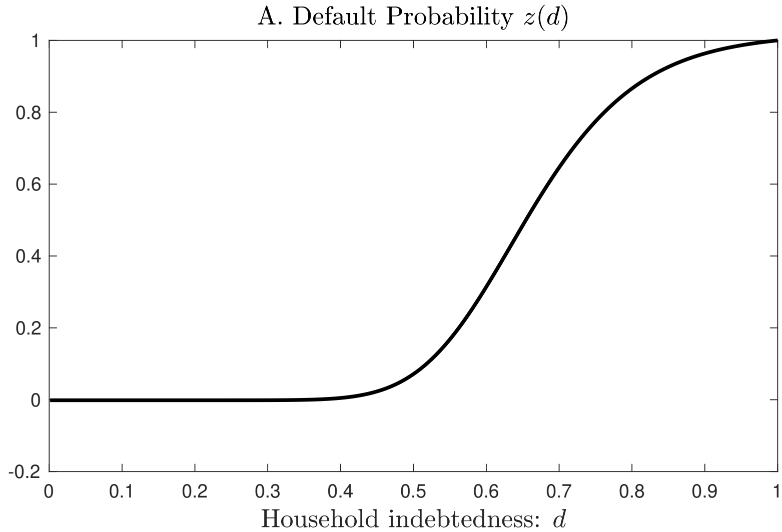

Figure I: **Household default probability as a function of the state variable d.** Parameter values are $\delta = 0.05, r_B = 0.08, r_S = 0.01, \theta_a = 300, \theta_l = 3, \rho = 0.15, \sigma = 0.3$.

as $l(d)$, where

$$a(d_t) = a(d(S_t, K_t)) = a(S_t, K_t), \qquad l(d_t) = l(d(S_t, K_t)) = l(S_t, K_t). \tag{13}$$

2.2 Optimal skills acquisition policy

The solid lines in Figure II illustrate the baseline results of the model. Panel A shows that there is a hump-shaped relation between household indebtedness (normalized between 0 and 1) and skills acquisition: increasing indebtedness initially encourages the household to exert higher effort in acquiring labor skills, but discourages it from doing so after indebtedness reaches a certain threshold.

The optimal choice of skills acquisition depends on the interplay of two forces. The first force arises directly from the conventional diminishing marginal utility of consumption implied by risk-aversion. When a household has high indebtedness and a large fraction of income accruing to creditors, the overall level of consumption is low, pushing up the marginal utility of an additional unit of consumption. As a result, the benefit of increasing human capital to raise consumption is large. Under this force, effort in skills acquisition increases with household indebtedness. When indebtedness is at a relatively low level, this force,

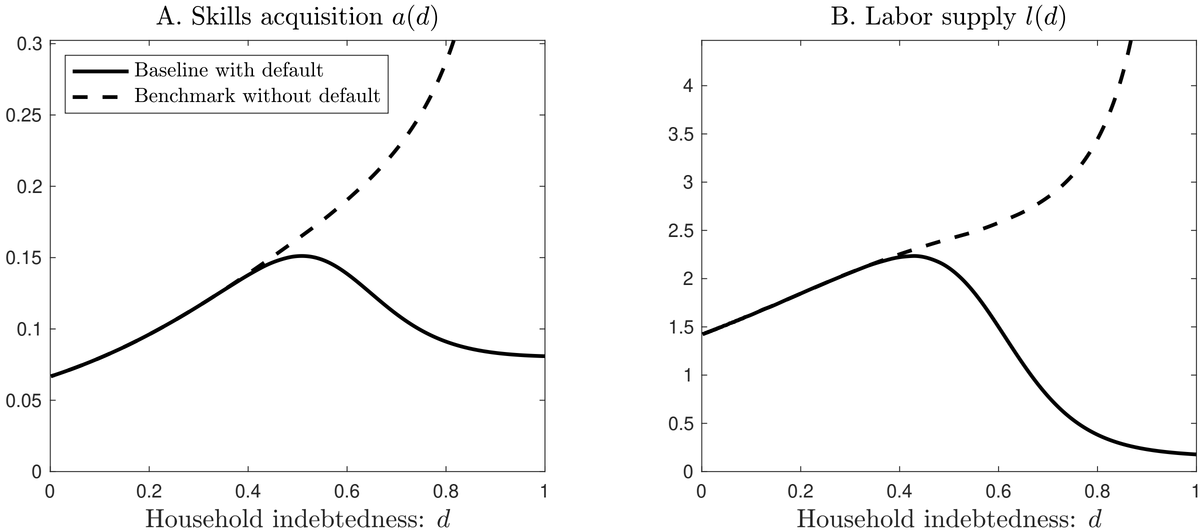

Figure II: **Effort in skills acquisition and household labor supply.** Parameter values are $\delta = 0.05, r_B = 0.08, r_S = 0.01, \theta_a = 300, \theta_l = 3, \theta_{al} = 0, \rho = 0.15, \sigma = 0.3$.

which we refer to as the *diminishing marginal utility* force, dominates.

However, when household indebtedness increases above a threshold, the second force, which we refer to as *debt overhang*, becomes dominant. As the household gets close to bankruptcy, it fails to internalize all the benefits of effort in acquiring labor skills. Because the household discharges its debt in bankruptcy, a fraction of the incremental wages generated by skills acquired *before* default goes to paying debts, constituting a wealth transfer from the household onto lenders. Hence, the household will choose to exert less effort in acquiring skills when bankruptcy becomes more probable. This *debt overhang* force makes effort a decreasing function of household indebtedness. It is dominant when indebtedness reaches a high level and default becomes more probable (Figure I).[8] The combination of the two forces renders skills acquisition hump-shaped in indebtedness, as shown in Panel A.

To assess the extent of distortion in households' skills acquisition driven by debt overhang, we include a dashed line in Panel A depicting the benchmark policies in the absence of default.[9] Because the household always repays debt in this case, it becomes the resid-

[8]Manso (2008) shows that in settings with high investment reversibility, the cost of debt overhang can be arbitrarily small. In our model, however, human capital investment is highly irreversible, making debt overhang economically significant.

[9]We do so by letting $H(K) \to -\infty$ in equation (9). That is, we assume that default is sufficiently punitive such that the household does not find it optimal to default on its debt.

ual claimant of effort and thus, its optimal skills acquisition policy is not distorted by the presence of debt overhang.

Panel A shows that the dashed line overlaps with the solid line when household indebtedness is low – when default (and debt overhang) is not an imminent consideration. As indebtedness increases to a higher level, the dashed line does not decline as the solid line does. This is because without debt overhang, only the diminishing marginal utility force is at play, rendering skills acquisition an increasing function of indebtedness across the entire regime. Accordingly, the wedge between the dashed and solid lines captures the distortionary impact of debt overhang on $a(d)$. As expected, when indebtedness increases, the debt overhang force becomes increasingly dominant, augmenting the extent of distortion.

2.3 Contrast between skills acquisition and labor supply

In Panel B of Figure II, we plot the optimal policy for households' labor supply. There is also a hump-shaped relation between household indebtedness and the supply of labor; this relationship is similarly shaped by the interplay of the two forces as in the case of skills acquisition: *diminishing marginal utility* versus *debt overhang*. However, there are two important differences.

First, the debt overhang for labor supply kicks in at a lower level of household indebtedness than in the case of skills acquisition – an earlier manifestation of debt overhang. Second, after debt overhang kicks in, labor supply decreases at a faster rate than skills acquisition – a sharper manifestation of debt overhang. The intuition of these dissimilarities is as follows. Labor supply generates only transitory income, and once it is used to pay creditors, no additional benefits accrue to the household. As the household is protected by limited liability, it is discouraged from supplying labor because any incremental income will be used to fulfill debt obligations, postponing debt discharge and benefiting the creditors. By contrast, the household will still reap the benefits of acquired skills and enhanced human capital, because human capital is inseparable from the household and preserves its value even after default (as reflected in the higher wages post-default in equation (7)). The higher resilience of skills acquisition to debt overhang in turn drives the asymmetric manifestation of debt overhang on the two activities. In Section 4.1, we provide empirical evidence supporting the earlier and sharper manifestation of debt overhang for labor supply than for skills acquisition.

We similarly plot households' optimal policies in the benchmark case without default (the dashed line in Panel B). As expected, the wedge between the two lines is more prominent (during a high level of indebtedness) than that in Panel A, reflecting a larger extent of distortion in the case of labor supply. This difference is again attributable to the inalienability of household human capital.[10]

2.4 Dynamic complementarity between human capital and labor supply

We next expand the baseline analysis to incorporate the role of dynamic complementarity between skills acquisition and labor supply. In Figure III, we illustrate the role of this dynamic complementarity by changing the degree of substitutability between effort and labor supply, as captured by θ_{al}. Panels A and B show the optimal policies of the two activities when the costs are independent $\theta_{al} = 0$ (black solid lines) versus when they are substitutes $\theta_{al} > 0$ (orange dotted lines), respectively.

We start with Panel B. This panel shows that for high household indebtedness (> 0.4), the supply of labor collapses more quickly for $\theta_{al} > 0$ (the dotted line) than for $\theta_{al} = 0$ (the solid line). Intuitively, when labor supply and skills acquisition are substitutes ($\theta_{al} > 0$), the household must focus on one of the two actions. Because human capital is inseparable and continues to generate value after default, the household chooses skills acquisition over labor supply near bankruptcy. This preference makes labor supply decline even faster – reflecting the aggravated debt overhang – compared to the baseline case ($\theta_{al} = 0$). In contrast, by

[10] In an unreported extension of the model, we consider the possibility of "learning-by-doing", in which individuals can accumulate labor skills at work, and skills acquired this way similarly increase their hourly wages as does a training program. We show that as long as the increment in hourly wages induced by training outpaces that by labor supply – that is, as long as "learning-by-training" remains a more effective way for households to acquire skills than "learning-by-doing", the thrust of our main findings, i.e., human capital investment is more resilient to debt overhang than labor supply, remains qualitatively robust.

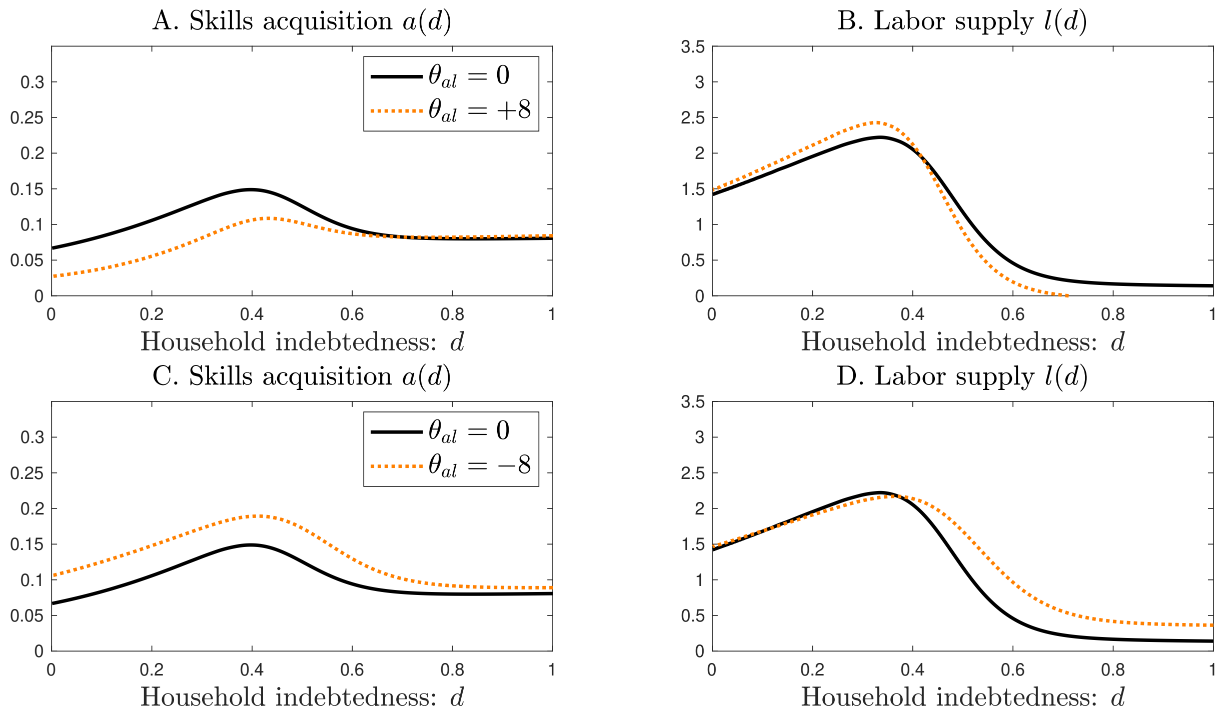

Figure III: **Illustration of dynamic complementarity between human capital and labor supply.** Other parameter values are $\delta = 0.05, r_B = 0.08, r_S = 0.01, \theta_a = 300, \theta_l = 3, \rho = 0.15, \sigma = 0.3$.

comparing the two lines in Panel A, we do not see such a fast collapse in skills acquisition during high indebtedness.

Importantly, this collapse of labor supply (due to aggravated debt overhang) feeds back into the skills acquisition policies. Because effort in skills acquisition increases the household's hourly wage, such effort is only valuable if the household anticipates supplying labor in the future. Put differently, should the household decide to stop working, it would be suboptimal to increase hourly wages (through costly skills acquisition) in the first place. Such a "back-propagation" effect is shown in Panel A. Here we observe that the dotted line ($\theta_{al} > 0$) is below the black line ($\theta_{al} = 0$) during lower levels of household indebtedness. It suggests that in the case of substitution ($\theta_{al} > 0$), the anticipation that the household will quickly cut labor supply in the future discourages it from acquiring human capital ex ante.

In Panels C and D, we perform an analogous exercise for the case of $\theta_{al} < 0$, that is, when the cost of labor supply alleviates the cost of skills acquisition, making them complements.

We note that in practice, the case of $\theta_{al} < 0$ (complementarity) is arguably less common than the case of $\theta_{al} > 0$ (substitution). That is, households are often in need of choosing between skills acquisition and labor supply given their time constraints. Thus, effort in one activity inevitably raises the hurdle for achieving the other. Nevertheless, we present results for the case of $\theta_{al} < 0$ to reinforce the intuition of the back-propagation effect.

Several differences emerge. Unsurprisingly, Panel D shows that the decline in labor supply for high indebtedness (> 0.4) is less prominent under complementarity ($\theta_{al} < 0$) than the solid line ($\theta_{al} = 0$). This pattern reflects that supplying labor now partially offsets the cost of accumulating more valuable human capital, thereby making the household less averse to providing labor than the baseline case (when the two actions are independent). Accordingly, the anticipated ample labor supply makes increasing hourly wages more fruitful, encouraging the household to acquire labor skills in the first place – the reverse of the back-propagation effect. Indeed, we see that in Panel C, the dotted line lies above the solid line, in contrast to Panel A.

2.5 Further illustration of the back-propagation effect and policy implications

Figure IV provides further insights and nuances of the back-propagation effect. In Panel A, the x-axis denotes the extent of labor supply collapse in the regime of high default likelihood, defined as $\max_{[0,1]} l(d) - l(1)$ and obtained for each value of $\theta_{al} \in [-8, 8]$. For instance, the right end of the x-axis, 2.5, corresponds to the case of $\theta_{al} = 8$, in which the household's labor supply collapses – as seen in Panel B of Figure III – from the highest point 2.5 (when the household indebtedness is around 0.4) to the lowest point 0 (when the indebtedness is 1). On the other hand, the left end of the x-axis corresponds to the case of $\theta_{al} = -8$, in which case, labor supply collapses by about 1.7 – as seen in Panel D of Figure III. Intuitively, the higher θ_{al}, the more a household needs to pick one action over the other near default, and thus, the larger the collapse in labor supply.

The y-axis denotes, for each value of θ_{al}, the deviation of optimal skills acquisition from

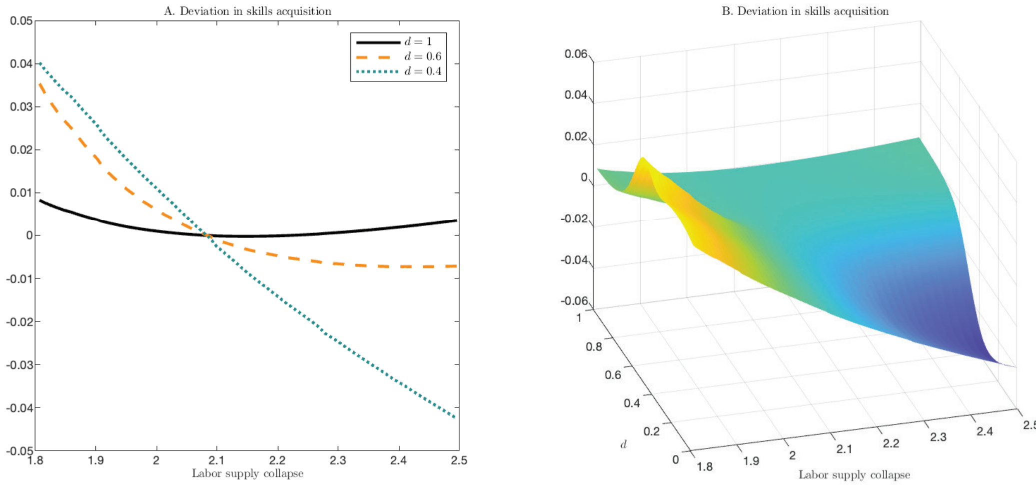

Figure IV: **Back-propagation illustration.** Other parameter values are $\delta = 0.05, r_B = 0.08, r_S = 0.01, \theta_a = 300, \theta_l = 3, \rho = 0.15, \sigma = 0.3$.

the benchmark case when $\theta_{al} = 0$ (i.e., $a(d;\theta_{al}) - a(d;0)$). For example, given $\theta_{al} = 8$ (the right end of the x-axis), this deviation is the distance between the dotted and solid lines in Panel A of Figure III. This distance is calculated at three points of indebtedness: $d = 0.4$ (the green dotted line), $d = 0.6$ (the orange dashed line), and $d = 1$ (the black solid line). From Panel A of Figure III, we previously observe that the skills acquisition given $\theta_{al} = 8$ lies below the benchmark case ($\theta_{al} = 0$) as long as household indebtedness is less than about 0.6. This is why we observe here that the right ends of both dotted ($d = 0.4$) and dashed ($d = 0.6$) lines are negative, whereas the solid line – when ($d = 1$) – is around 0. In contrast, the left ends of all three lines – corresponding to the case when $\theta_{al} = -8$ – are all positive, consistent with the previous observation, in Panel C of Figure III, that skills acquisition with $\theta_{al} = -8$ lies above the benchmark.

Such deviations capture how much skills acquisition is adjusted by the household relative to the benchmark, anticipating the extent of labor supply collapse (the x-axis). Here we observe that the adjustment is more sensitive at at a lower level of household indebtedness (the green dotted line) than a higher level of indebtedness (the black solid line).

Taken together, Figure IV Panel A demonstrates two points. First, skills acquisition suppresses (relative to the benchmark) as the anticipated labor supply collapse becomes aggravated. This is shown by the decreasing pattern of all three lines, and it indicates the presence of the back-propagation effect of labor supply on skills acquisition. Second, the back-propagation effect mostly manifests ex ante – at a lower level of household indebtedness before default probability becomes prominent. This is shown by the greater sensitivity (steeper slope) of the green dotted line than the other two.

Panel B of Figure IV supplements the above analysis by considering a broader spectrum of household indebtedness values (d). It is obtained by stacking the previous three lines ($d = 0.4$, $d = 0.6$, and $d = 1$), along with many others (collectively corresponding to 1,000 values of d), to form a surface. It confirms our findings: the surface slides from the left end of the "labor supply collapse" axis to the right, and the slide becomes more pronounced as the "d" axis approaches from 1 to 0. These observations suggest that the anticipated labor supply reduction discourages the household from acquiring skills – particularly ex ante at a lower level of indebtedness.

Overall, the analyses in Figure IV imply that studying the balance sheet effects on household policies needs to account for the fact that household decisions on skills acquisition and supply labor are intertwined. Public policies intended to incentivize labor supply through balance sheet interventions should account for their impact on skills acquisition due to the dynamic complementarity between the two. This implication complements the study by Donaldson, Piacentino, and Thakor (2018), who show that household indebtedness disincentivizes households to work due to debt overhang, resulting in lower employment in the economy. As such, policies intended to limit household debt can restore labor supply incentives and increase employment (an extensive margin effect). Figure III and Figure IV suggest that the restored labor supply may further increase households' effort in acquiring labor skills ex ante, thereby raising the productivity of employment (the intensive margin effect).

2.6 Comparative statics

In this section, we explore the heterogeneity of the baseline relation between household indebtedness and skills acquisition with respect to the model parameters. As discussed, one unique feature of labor skills acquisition, in contrast to labor supply, is its inseparability. As long as the household can utilize acquired skills, they preserve the value and continue to generate incremental earnings, even after default. We therefore start by considering such preserved value of skills, determined by the degree of skills depreciation ρ.

2.6.1 Comparative statics with respect to ρ.

To fix ideas, Panel A of Figure V illustrates the effect of different depreciation rates on the preserved value of skills. It plots changes in the expected path of hourly wages, denoted ΔK_t, when the household exerts one additional unit of effort at time $t = 0$ (relative to its baseline effort level) for two values of ρ, high versus low. Even though hourly wages in the two cases increase by the same amount in the short term, in the long run, the increments decay more quickly in the case of high depreciation ρ. Therefore, a larger ρ implies that the returns of skills acquisition are more front-loaded in time, that is, a larger proportion of the total benefit from acquiring labor skills is materialized in the shorter term. Therefore, with a higher value of ρ, a larger share of skills' total benefits will be allocated to paying back debt (before default), creating a greater transfer of wealth from the household to lenders. In the extreme case when skills depreciate fast enough, all benefits of skills acquisition will be materialized immediately and thus, accrues to lenders, leaving no further benefit to the households. In this limiting case, skills effectively lose their "inseparability", and become the same as labor supply.

Indeed, Panel B shows that for high indebtedness levels (close to default), skills acquisition declines more sharply when ρ is high (the dotted line) than when ρ is low – much like the case of labor supply depicted in Panel B of Figure II. This sharper decline reflects that skills acquisition under high depreciation is not as resilient to debt overhang any more, due to the loss of its inseparability attribute. In our later empirical analyses (see Section 4.2),

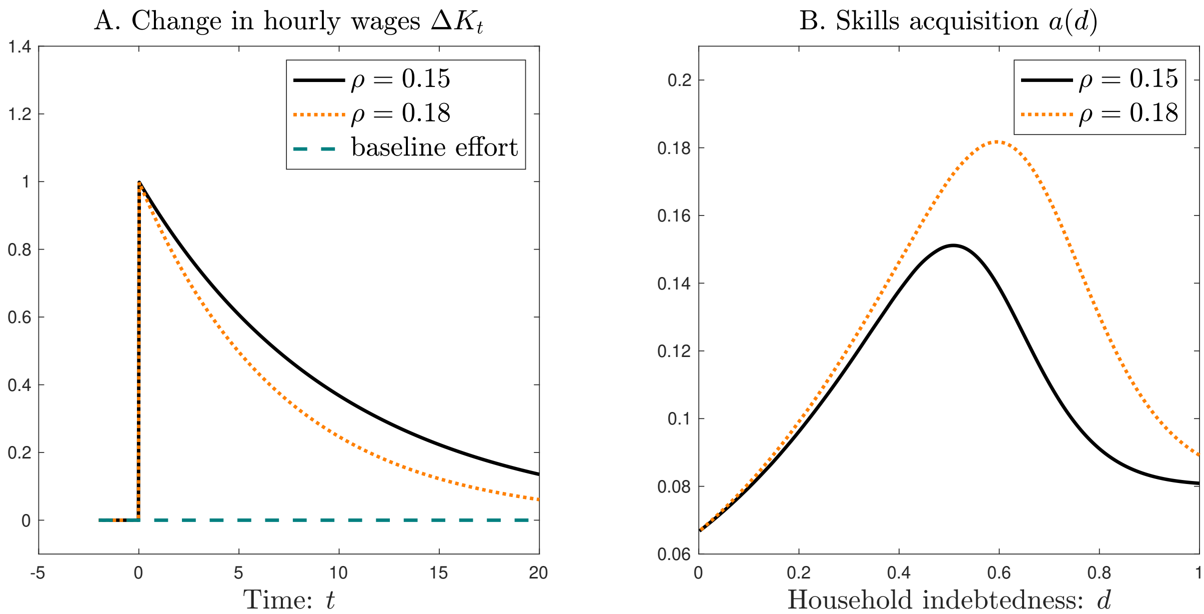

Figure V: **Comparative statics with respect to depreciation rate of labor skills parameter ρ and to hourly wage volatility σ.** Other parameter values are $\delta = 0.05, r_B = 0.08, r_S = 0.01, \theta_a = 300, \theta_l = 3, \theta_{al} = 0, \sigma = 0.3$.

we confirm such a pattern with respect to ρ in the data.

Panel B also shows that faster skills depreciation is associated with a higher level of skills acquisition overall. This result stems from the balance of two opposing effects. On the one hand, faster depreciation lowers the NPV of skills acquisition, making such effort less attractive. On the other hand, faster depreciation decreases household wealth, raising the marginal utility of skills acquisition. In the post-default case without savings, these two opposite effects cancel each other out, rendering skills acquisition independent of the degree of depreciation ρ, as seen in equation (9). By contrast, in the pre-default case, savings amplify the marginal utility of generating income, as the household can preserve the additional income to smooth future consumption. Therefore, the incentive to acquire skills dominates the other force, engendering a higher level of skills acquisition as depicted in Panel B. In our later empirical analyses in Section 4.2, we find a consistent pattern.

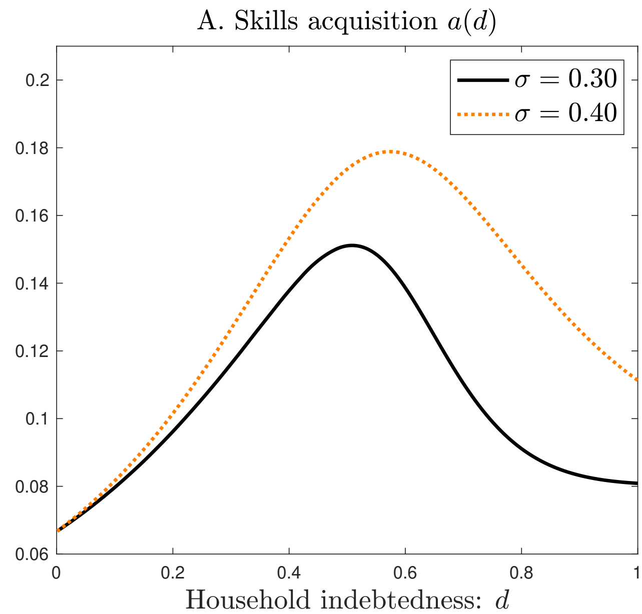

Figure VI: **Comparative statics with respect to hourly wage volatility σ.** Other parameter values are $\delta = 0.05, r_B = 0.08, r_S = 0.01, \theta_a = 300, \theta_l = 3, \theta_{al} = 0, \rho = 0.15$.

2.6.2 Comparative statics with respect to σ.

Figure VI depicts comparative statics with respect to the volatility of hourly wages σ. It shows that households facing higher hourly wage volatility engage in higher skills acquisition uniformly across all levels of household indebtedness – a pattern that we confirm in later empirical analysis (see Section 4.3). This pattern stems from two sources. First, higher volatility is welfare reducing for a risk averse household because uncertainty in earnings limits its ability to smooth out consumption. In response, the household adjust its policies to counter the reduced utility – a "precautionary action" documented in the literature. In our context, the household exerts higher effort in skills acquisition, such that the benefits from increased future wages can partially offset the reduced utility due to wage uncertainty.

The second source relates to the back-propagation effect that we document in Sections 2.4 and 2.5. Higher volatility not only encourages skills acquisition out of precautionary incentives, but also increases households' labor supply for a similar reason, as shown in Figure VII of Appendix A.5. Such increase in labor supply in turn feeds back into to the ex-ante skills acquisition decision, further raising the effort to acquire labor skills.

3 Data, variable construction, and summary statistics

3.1 The 1979 National Longitudinal Survey Youth

Our main data source is the 1979 National Longitudinal Survey Youth (NLSY79), a program run by the U.S. Bureau of Labor Statistics. NLSY79 surveys a sample of Americans born between 1957 and 1964, and follows their lives through multiple rounds of interviews. The first interview was conducted in 1979, when the respondents aged 14 to 22. Follow-up interviews were conducted annually from 1979 to 1994 (round 1 to round 16), and biennially from 1996 to 2016 (round 17 to round 27). As of the 2014 survey – the latest survey included in our analyses, the respondents had turned 49 to 58 years old. Our sample consists of the respondent-interview-year panel (hereafter, respondent-year panel).

The sample of NLSY79 includes 12,686 respondents. Among them, 6,403 are male and 6,283 of them are female, representing 7,510 non-black/non-Hispanic, 3,174 black, and 2,002 Hispanic or Latino. The survey aims to select a sample that represents the nation's population in various dimensions, including demographics, education, economic status, and professional services. Collected information for each respondent includes education background, employment history, household component, income and assets, health status, personal attitudes, and daily activities, among others. The detailed description of the sampling procedure and survey questions are available on the website of the National Longitudinal Surveys (https://www.nlsinfo.org/). Survey data for the entire sample are publicly available.

3.2 Information on labor skills acquisition

Several sets of information from NLSY79 are particularly important for testing our model predictions, including individuals' on-career training participation, labor supply, and household balance sheets. On-career training creates opportunities for individuals to increase their human capital value, and represents well-defined labor skills acquisition (Acemoglu, 1997; Clifford and Gerken, 2021). In each survey, respondents are asked to provide information about the training programs they have taken since the last interview. This information includes whether they have enrolled in any vocational or technical training designed to learn or improve job-related skills;[11] whether the training participation is applied for by the respondents or are required by their employers; the entity that pays for the programs (e.g., employer, self or family, and government);[12] the starting and completion date of each training program, and the average number of hours per week respondents spend on the training program.

This set of information is important for fitting our empirical analyses to the theoretical framework. First, because we observe whether the training is initiated by individuals or requested by employers, we can differentiate individuals' incentives in skills acquisition – the focus of our model – from obligatory behavior to fulfill employer requirements. Second, because we observe which party pays the training cost, we can mute the effect of financial constraints (affordability) in explaining our results by focusing on programs *not* paid by individuals themselves. This is important because household indebtedness correlates with financial constraints, that is, households with high (low) indebtedness are more (less) likely constrained – which may in turn affect their human capital investment decisions (e.g., Chakrabarti, Fos, Liberman, and Yannelis, 2023; Lochner and Monge-Naranjo, 2012).[13] By focusing on self-requested and non-self-paid training participation, our empirical findings speak to how indebtedness affects skills acquisition by shaping individuals' incentives.

The NLSY79 begins to collect basic questions about training participation since the 1979 interview (round 1), and supplements these question over time. Since 1991 (round 13 interview), most information needed for our study (such as which party initiates the training) becomes available. We therefore start our sample from 1991.

[11] More specifically, NLSY79 classifies training purposes into six categories: (1) to maintain and upgrade skills, (2) to learn new methods or processes, (3) to get job promotion or job advancement, (4) to obtain a license or a certificate, (5) to begin a job, and (6) to look for a new job.

[12] Government is a funding source for government sponsored training programs, such as Job training Partnership Act (JTPA), Trade Adjustment Act (TAA), and Work Incentive Program (WIN).

[13] Relatedly, Ji (2021) and Hampole (2023) show that financial frictions related to student debt borrowing may affect individuals' major choice in college and job search trading off initial earnings and lifetime earnings.

3.3 Proxying for the state variable d

NLSY79 collects detailed household balance sheet information. On the asset side, NLSY79 surveys each respondent's estimated market value of residential and non-residential property, market value of vehicles, and the amount of savings and various financial assets (e.g., stocks and bonds). On the debt side, NLSY79 surveys the amount of mortgage loans, auto loans, student loans, credit card loans, and money owed to other individuals or entities.

Our model in Section 2 characterizes the household's optimal policies as a function of the state variable d (indebtedness), which economically captures the probability of a household entering default (Figure I). To find an empirical counterpart of the state variable, we therefore need a measure that analogously captures this default probability. To this end, we use household leverage, defined as the ratio of total debt to total assets. This measure is inspired by Melzer (2017), who documents that the ratio of household mortgage to property value – arguably the largest components of debt and assets among U.S. households – are highly indicative of the default likelihood. In Figure 1, we verify that such an indication continues to hold using the broader measure of total debt to assets ratio.[14]

Specifically, in Figure 1 Panel A, we plot the average household default probability for each 10-point leverage bin from 0% to >140%. Default is identified by whether a household has ever missed any bill payment as of a given year.[15] Overall, default probability increases with leverage: it remains relatively flat when leverage is initially at a lower level, and accelerates once leverage surpasses 50-60% – a pattern largely resembling the relation between the state variable d and default likelihood shown in Figure I of Section 2.1. In Panel B, we alternatively identify default by whether a household has filed for bankruptcy as of a given year. By nature, bankruptcy reflects persistent and extreme financial hardships. The level

[14] An alternative measure to capture household default probability is the debt-to-income ratio, defined as the monthly total debt payment to net income – similar to the interest coverage ratio in corporate finance. This measure, however, is a less suitable proxy for our state variable. The existing literature often uses household income to capture labor supply (e.g., Zator 2020; Bernstein 2021). Therefore, the denominator of the debt-to-income ratio would mechanically embed one of our outcome variables: labor supply.

[15] Missed payments are those at least 60 days past due. The NLSY79 surveys whether an individual has missed payments in the past five years.

of default therefore is lower than that captured by missed payments.[16] Nevertheless, we continue to observe that leverage strongly predicts default, and the increase in the default probability accelerates after leverage reaches a high level (over 90-100%.)

Taken together, Figure 1 verifies that household leverage is a reasonable empirical counterpart of the state variable d in the model. Two points here are worth further noting. First, not all items in a household's balance sheet are surveyed in each interview. In Appendix B Table B1 and Table B2, we provide the breakdown of what items are surveyed in each round. When calculating household leverage, we use items available in a corresponding year. This treatment, however, is unlikely to bias our results because (i) we include survey-year fixed effects in all estimations, and (ii) we check the robustness of our results using reconstructed leverage that only uses items consistently surveyed in all interviews (see Table B6 Panel A).

Second, in the surveys conducted in 1991, 2002, 2006, and 2010, the balance sheet information is completely missing. In this case, we take the average of a respondent's leverage from two adjacent surveys to estimate the leverage of the missing year (e.g., the 2002 leverage is estimated using the average of 2000 and 2004 leverage). Results are qualitatively similar if we exclude observations associated with surveys in 1991, 2002, 2006, and 2010.

3.4 Student loans

Different from other forms of consumer debt (e.g., mortgages and credit cards), student loans in the U.S. are almost completely non-dischargeable in bankruptcy nowadays (Yannelis, 2020).[17] Because delinquent student borrowers are expected to eventually make up missed payments (through, e.g., wage garnishment or loan rehabilitation), non-dischargeability would discourage households from reducing effort in skills acquisition or labor supply, thereby mitigating the debt overhang effect that we study. In a companion paper, Manso, Rivera, Wang, and Xia (2023) formally derive such a "corrective" effect of student loans.

This prediction, however, is unlikely to confound our empirical analyses for two reasons.

[16] In addition, filing for bankruptcy is associated with significant costs – including fees, time, and stigma. See, e.g., Kleiner, Stoffman, and Yonker (2021).

[17] Iuliano (2012) finds that only about 70 borrowers successfully discharged their student loans out of nearly 30 million borrowers in 2007.

First, student loans were made almost non-dischargeable since 1998, when The Higher Education Amendments of 1998 (P.L. 105-244) took effect. Prior to that, borrowers could fully or partially discharge student debt in bankruptcy (Yannelis, 2020). Our sample consists of individuals born between 1957 and 1964, and we track their life activities until 2014. Therefore, for a large proportion of this period, student debt is not different from other consumer debt in terms of dischargeability. Second and importantly, student loans only became a prominent part of household debt over the past two decades. For the generation of our sample individuals (who likely went to college in the early 1980s), merely about 10% of them reported outstanding student loans and the unconditional average student loan amount is about $4,212. This small representation is consistent with Looney and Yannelis (2015) who show that student loan volume in the early 1980s was about one tenth of what it is in recent years. We therefore expect student loans to play a limited role in determining household leverage in our sample.

Indeed, in Appendix B Table B6 Panel B, we re-estimate household leverage by excluding student debt and confirm our main findings.

3.5 Information on labor supply

Lastly, the NLSY79 provides detailed week-by-week records of the respondent's labor force status and associated job(s), if employed, and the total number of hours he/she works each week at any job. This information allows us to identify a respondent's labor force activity, including the working hours, and the periods when he/she is unemployed or out of the labor force. Labor supply during a survey year is measured as a respondent's total working hours since last survey. This information allows us to contrast the relation between household indebtedness and skills acquisition versus labor supply, as predicted in Section 2.3.

3.6 Sample and variable construction

Our sample period is from 1991 to 2014, when information on both training participation and household balance sheet is complete. Among the 12,685 respondents initially surveyed in the 1979 interview (round 1), 9,018 respondents remain in the 1991 survey. For the skills acquisition analysis, we exclude respondent-years when the respondents are younger than 25 or older than 57 (about 10 years before retirement). This filter ensures that individuals in our sample are in the labor force and the decision of on-career training participation is relevant. In addition, we exclude unemployed individuals because by definition, they do not have opportunities to participate in on-career training programs. We end up with 50,697 respondent-year observations representing 6,729 respondents. This sample constitutes the basis for our analyses.

As discussed earlier, we identify labor skills acquisition as an individual's training participation that is requested by the individual and is not self-paid. This identification not only allows us to differentiate individual volunteer training decisions from employer requirements, but also helps mute the confounding effect of financial constraints (affordability) on training decision. We generate an indicator, $Training$, which equals one if the respondent has requested and participated in non-self paid training programs, and zero if the respondent does not take any voluntary training in a given survey year. Alternatively, we generate $TrainingTime$, defined as the total number of hours a respondent spends on voluntary and non-self paid training programs since the last interview. By definition, $TrainingTime$ equals zero if $Training$ is zero. To capture an individual's labor supply, we generate $LaborSupply$ as the total number of hours the individual has worked since the last interview.

The key independent variable is $Leverage$, which corresponds to the modeled household indebtedness and is defined as the ratio of total debt to total asset (see Section 3.3). Total debt is the sum of an individual's total mortgage loans, auto loans, student loans (including the ones taken for the children of an individual), credit card debt, debt on farm/business/other property, and all other debt more than $1000 that is owed to other individuals or entities. Total asset is the sum of an individual's market value of residential property, vehicles, money assets (such as savings accounts, IRA and Keogh accounts), and financial assets (such as stocks and bonds).

We construct a host of control variables. $Male$ and $White$ indicate a respondent's gender and ethnicity. *MaritalStatus* indicates whether the respondent is married, and *College* indicates whether the respondent has attended college as of a survey year. To measure a respondent's family education background, we include *FatherEdu*, which equals the number of years of schooling that a respondent's father has completed. *EmployerSize* measures the number of employees working at a respondent's current employer. To control for factors related to the life cycle of households (and their effect on household decisions), we include the respondent's age and its quadratic form, *Age* and Age^2. We winsorize all continuous variables at the 2.5th and 97.5th percentile to eliminate undue effects of outliers.

In various specifications, we include fixed effects for a respondent's industry, occupation, county×year, and industry×occupation. The geographic location of each respondent is obtained from the restricted-use NLSY79 Geocode files supplementing the main NLSY79 survey. The Geocode files tracks each respondent's residential location in an interview. We obtain a license to use this information from the Bureau of Labor Statistics.

3.7 Summary statistics

Table 1 reports summary statistics of the sample at the respondent-year level. *Training* has a mean of 0.088 and a standard deviation of 0.283. Conditioning on participating in training (i.e., *Training*=1), the variable *TrainingTime* indicates that on average, an individual spends approximately 35 hours on training. This duration is comparable to that of a three-credit hour course at a U.S. university (assuming three hours per week and 12 to 15 weeks per semester). Because training participation is an infrequent activity, we use *Training* as the main variable of interest and confirm our findings using *TrainingTime* in later robustness tests (Table B6). *LaborSupply* (in hours) has a mean of 3,530 and a standard deviation of 1,585.[18] These working hours represent, on average, 33% of available hours (based on 24 hours a day and 5 days a week). The main independent variable *Leverage* has a mean of 0.433 and a standard deviation of 0.355.

[18]Because NLSY79 is conducted biennially since 1996, the total number of working hours since the last survey may reflect two years' workload.

4 Empirical findings

4.1 The baseline hump-shaped relation

Our analyses start with examining whether the relation between household indebtedness and skills acquisition exhibits a hump shape, as predicted by the theoretical model. Figure 2 presents a non-parametric graphical analysis. Household indebtedness is proxied by the leverage ratio, as discussed in Section 3.3. Panel A plots skills acquisition for different leverage groups. The x-axis denotes household leverage by quintile, where the numbers denote the range of household leverage (in percentage) within each quintile. For example, the third quantile consists of households with leverage between 32% and 49%. The y-axis denotes the average percentage of individuals who participate in self-requested and non-self-paid training (i.e., the mean of $Training$).

Consistent with the model prediction in Panel A of Figure II, skills acquisition exhibits a hump shape in household leverage. Individuals are initially more likely to participate in training as leverage rises, but once leverage is above the range of 49-71%, they become less likely to do so.

Panel B plots the relation between labor supply and leverage. The y-axis denotes the average hours of labor supply (i.e., the mean of $LaborSupply$). We observe a similar hump-shaped relation. However, labor supply exhibits an earlier and a sharper manifestation of debt overhang, as predicted by our model. Specifically, the switching point occurs earlier for labor supply, at the leverage level of 32-49% compared to 49-71% for skills acquisition. The decline in labor supply is also steeper: by the highest leverage quintile (>71%), labor supply has decreased by almost half of the previous run-up (from the first three quintiles of leverage), whereas in Panel A, skills acquisition remains at a relatively high level even at the top leverage quintile.

To formalize the graphical evidence, we next estimate two regression models. The first model features a quadratic function and takes the following form:

$$Training_{i,t} = \alpha + \beta_1 Leverage_{i,t-1} + \beta_2 Leverage^2_{i,t-1} + \gamma Z_{i,t-1} + \theta\delta_i + FE + \epsilon_{i,t}. \quad (14)$$

The dependent variable is the indicator $Training$, which takes the value of one if respondent i reports in survey year t that he/she has participated in training programs since the last survey. $Leverage$ is the ratio of total debt to total asset reported by respondent i at the last survey year, $t-1$. The quadratic function is estimated to capture the hump-shaped relation between leverage and training participation, as shown in Figure 2. The vectors Z and δ include time-varying and time-invariant respondent characteristics. Time-varying characteristics include respondent age, college enrollment, marital status, and employer size. Time-invariant characteristics include gender, race, and father's education.

Fixed effects include survey year fixed effects, respondent i's employer industry and occupation or industry×occupation fixed effects, as well as state, state×year or county×year fixed effects. These fixed effects help us control for industry/occupation shocks or county-level economic conditions, which might affect both household leverage and training participation. We do not, however, include household fixed effects in the estimation. This is because by nature, training participation is not a frequently repeated activity for a given household, and in our sample period, about 16% of households take training more than once. Hence we do not observe sufficient time-series variation in the training participation given a household.

Based on Figure 2, we expect β_1 in equation (14) to be positive and β_2 to be negative, indicating a hump-shaped relation between household leverage and skills acquisition. We estimate OLS regressions because they generate more precise estimates of the marginal effects when we include high-dimensional fixed effects (Angrist and Pischke, 2008). Standard errors are clustered at the state-year level.

Table 2 presents the regression results. We start with a parsimonious model in column (1), which only includes $Leverage$ and $Leverage^2$ as the independent variables. The coefficient estimate of $Leverage$ is 0.099 (with a p-value < 0.001), and that of $Leverage^2$ is -0.061 (with a p-value < 0.001). In Panel A of Figure 3, the solid line plots the quadratic functions based on these estimated coefficients, and shows that the shape of training with respect to leverage resembles Figure 2.

In column (2) of Table 2, we include various household characteristics, as well as fixed effects for state, survey year, industry, and occupation, separately.[19] Here we observe that while gender, parental education, and employer size significantly affect training decisions, neither Age or Age^2 is statistically significant. It indicates that factors associated with the life cycle of households – and relatedly, their effect on skills acquisition – is unlikely driving the observe humped-shape relation between training and leverage.[20] This lack of significance is likely because in our sample, the majority (almost 90%) of individuals are between 28 and 50 years old, and are distant from designated retirement. Thus life-cycle considerations are less relevant in our setting.

In column (3), we substitute the state and year fixed effects with state×year fixed effects to absorb common region-by-time variation. In column (4), we substitute the industry and occupation fixed effects with industry×occupation fixed effects to control for variation from occupations within an industry (such as the availability of training for an occupation within an industry). Lastly, in column (5), we include county×year fixed effects which subsume state×year fixed effects. Overall, the results consistently show that households with higher leverage are more likely to participate in training at a lower level of leverage, but this relation reverses once leverage reaches a higher level. Based on the coefficient estimations of β_1 and β_2, we calculate the switching point separating the two regimes (i.e., the peak of the hump shape). The switching points are about 80%, as reported below the variable coefficients.

To formally test the significance of the "switching" presented in the hump shape, we next perform piece-wise linear regressions that take the following form:

$$Training_{i,k,t} = \alpha + \beta_1 Leverage_{i,t-1} + \beta_3 X^{Leverage}_{i,t-1} + \gamma Z_{i,t-1} + \theta \delta_i + FE + \epsilon_{i,k,t}. \tag{15}$$

The variable $X^{Leverage}$ is an interaction term. It is defined as:

[19]We employ 15 industries categorized by NLSY79, and 5 occupation categories including management occupations, skilled labor (such as engineering and legal occupations), craftsmen/foremen/kindred (such as arts and design occupations), office employees (such as sales and administrative support occupations), and labor workers (such as maintenance and construction occupations). We use these broad occupation categories to avoid including numerous indicators in the specifications containing industry×occupation fixed effects.

[20]For instance, one may concern that training participation is more prevalent for mid-aged individuals than either fresh college graduates or soon-to-be retirees – rendering a hump-shaped relation between training and age. Meanwhile, this hump-shaped relation may also apply to household leverage, as people accumulate debt in earlier life, reach the peak in the mid-age, and pay it off in later life. These possibilities thus confound the observed relation between training and leverage.

$$X^{Leverage} = (Leverage - 0.80) \times D^{Leverage}, \tag{16}$$

where $D^{Leverage}$ is an indicator variable that equals one if *Leverage* is larger than 0.80 and zero otherwise. The value of 0.80 is chosen based on the switching points estimated from the quadratic regression model in equation (14); all results are robust to values in the neighborhood of 0.80. In this model, we expect the coefficient β_1 to be positive, the coefficient β_3 to be negative, and the summation of β_1 and β_3 to be significantly negative. A positive β_1 would indicate a positive relation between household leverage and training likelihood when leverage is relatively low (below 80%). A negative β_3 would indicate that such a relation reverses as leverage surpasses the 80% level. Accordingly, a negative and significant $\beta_1 + \beta_3$ would indicate that the reversal is sufficiently sizable such that in aggregate, leverage lowers the training likelihood in this high leverage regime (above 80%).

Columns (6) to (10) of Table 2 display the piece-wise regression estimates. After including various controls, industry×occupation fixed effects, and county×year fixed effects in column (10), the coefficient of *Leverage* (β_1) is 0.040 and the coefficient of $X^{Leverage}(\beta_3)$ is -0.074. Both coefficients are statistically significant at 1% level. The F test also rejects the null hypothesis that $\beta_1 + \beta_3 = 0$ at the 1% significance level. In Panel A of Figure 3, the dashed line plots the piece-wise regression estimates from column (6), and depicts the trends of skills acquisition in a linear manner for the two regimes. These trends closely match those based on the quadratic function estimates (the solid line).

The economic significance of the piece-wise regression estimates is sizable. Based on column (10) of Table 2, a one-standard-deviation increase in household leverage is associated with a 1.4% increase in training likelihood when leverage is below 80%; when leverage is above 80%, a one-standard-deviation increase in leverage is associated with a 1.5% decrease in training likelihood. In comparison, the sample average of training participation is 8.8%, as shown in Table 1.

We repeat the same analyses for labor supply and report the results in Appendix B Table B4. Columns (1) to (5) pertain to the quadratic model. Columns (6) to (10) pertain to the piece-wise regressions. Here we define $X^{Leverage} = (Leverage - 0.70) \times D^{Leverage}$, where the value 0.7 is chosen according to the switching points estimated in columns (1) to (5).

To visualize the regression estimates for labor supply, in Panel B of Figure 3, we plot the estimates of the quadratic model from column (1) – represented by the solid line, and those of the piece-wise regression from column (6) – represented by the dashed line. Comparing Panel B with Panel A, we see that labor supply shows an earlier and sharper manifestation of debt overhang than skills acquisition. The switching point of labor supply is approximately 70%; by the time leverage reaches 120%, labor supply has scaled back by about 50% of its previous run-up. In contrast, in Panel A, the switching point of skills acquisition is around 80% and the magnitude of decline during high leverage is only about 25%.

Overall, both the quadratic model and the piece-wise regression support the non-monotonic effect of household leverage on labor skills acquisition, and the differences between skills acquisition and labor supply due to the inseparability of human capital, as predicted by our model.

4.2 Heterogeneity with respect to ρ

We next examine cross-sectional variations of the baseline hump shape relation between household leverage and skills acquisition, based on the comparative statics analyses in Section 2.6. We start with ρ – the degree of skills depreciation. We employ two complementary approaches to proxy for skills depreciation, first based on the skills' exposure to technology inspired by the literature (e.g., Kogan, Papanikolaou, Schmidt, and Seegmiller, 2022), and second based on changes in wage path as modeled in Section 2.6.2.

4.2.1 Exposure to technology

Recent work by Kogan, Papanikolaou, Schmidt, and Seegmiller (2022) finds that technological advancement displaces labor either through the direct effect of automation (i.e., machine or software performing tasks previously handled by humans), or because it requires new skills that incumbent workers lack. Under the latter channel, workers' existing skills set (and human capital) becomes obsolete as technology evolves into a new vintage, rendering faster skills depreciation. This channel is particularly germane in our setting because the sample individuals – aged in their twenties during 1980s – underwent the information technology revolution thanks to the rapidly growing utilization of internet. Therefore, as a first approach, we capture the degree of skills depreciation based on their exposure to the computer and information technology (CIT).

Specifically, for each training program, the NLSY79 specifies the type of skills acquired. We flag a training program as being exposed to CIT if the acquired skills include "computer skills."[21] We then aggregate the training level CIT exposure to the occupation level by calculating the percentage of CIT-exposed training programs taken by the sample individuals working in a given occupation, where individual occupation is provided by the NLSY79 based on the classifications of the Bureau of Labor Statistics (BLS). We perform this occupation level aggregation because (i) it reduces idiosyncratic factors that drive individuals' choice of training programs and thus their CIT exposure, and (ii) we expect that variation in skills depreciation largely arises across occupations. In Appendix B, Table B3 Panel A, we provide example occupations that have the highest and lowest CIT exposure, along with example job titles of each occupation.

Perhaps unsurprisingly, occupations such as *Healthcare Support* and *Lawyers, Judges and Legal Support Workers* exhibit a low CIT exposure – and thus, are considered to have a relatively low degree of skills depreciation. It is consistent with the finding that occupations associated with interpersonal tasks are typically less subject to disruption from technological innovation (Kogan, Papanikolaou, Schmidt, and Seegmiller, 2022). On the other hand, *Architecture and Engineering* is among occupations with the highest CIT exposure and thus a high degree of skills depreciation, consistent with MacDonald and Weisbach (2004).

In Figure 4 Panels A and B, we plot the pattern of skills acquisition with respect to household leverage, separately for high skills depreciation ρ (Panel A) and low skills depreciation ρ (Panel B). The plot is based on coefficients from regression models of Table 2 in two sub-samples: for individuals working in occupations with a CIT exposure above the sample

[21] Other types of skills include Operate/repair equipment, Read/write/math, Teamwork/problem-solving, Management skills, Statistical quality control, New information system, and New product service.

median (i.e., high skills depreciation), and for those in occupations with a CIT exposure below the sample median (i.e., low skills depreciation). The solid line corresponds to the quadratic model (column (1) of Table 2), and the dashed line corresponds to the piece-wise specification (column (6) of Table 2).

We find empirical patterns consistent with the model predictions regarding both the curvature and levels. First, comparing Panels A and B, we see that when household leverage is high, training participation declines more sharply in Panel A (high ρ) than in Panel B (low ρ) – that is, a sharper manifestation of debt overhang. The switching point in Panel A occurs at a lower level of leverage than Panel B – i.e., an earlier manifestation of debt overhang. As discussed in Section 2.6.1, these patterns reflect the lost inseparability of human capital (and thus the lowered resilience to debt overhang) when skills exhibit a high degree of depreciation. Second, the level of skills acquisition in Panel A is higher than that in Panel B across all levels of household leverage, reflecting the stronger incentive to make up for the utility loss due to fast depreciating skills. This pattern is also consistent with the theoretical predictions in Figure V Panel B.

In Table 3 Panel A, we present regression analyses to formalize these patterns. Columns (1) and (2) examine the case of high skills depreciation, and columns (3) and (4) examine the case of low skills depreciation. Here we include the set of controls as in columns (5) and (10) of Table 2. These additional specifications confirm our interpretation.[22]

4.2.2 Changes in the wage path

Our second approach to proxy for skills depreciation is based on the model intuition outlined in Section 2.6.2. Specifically, we capture changes in the path of each individual's wage after training completion, relative to his/her wage prior to training. The intuition of this approach follows the illustration in Panel A of Figure V. That is, when skills have higher depreciation rates, an individual's wage initially increases after training but the increments decay more quickly in the longer term. In contrast, when skills have lower depreciation rates, the wage

[22] In this analysis, we do not include occupation fixed effects (or their interactions with other fixed effects), because the degree of skills depreciation is identified at the occupation level.

increments following training experience smaller declines.

Based on this intuition, we define the year prior to an individual's training participation as Year -1, and the years following training completion as Year 1 to Year 3. We then classify skills acquired from a training program to have high or low depreciation in the following steps. We first calculate the wage growth rate from Year -1 to Year 1 as: $R_1 = \frac{Wage_{y1} - Wage_{y-1}}{wage_{y-1}}$, where $Wage_{y1}$ and $Wage_{y-1}$ correspond to the individual's wage in Year 1 and Year -1. Similarly, we calculate $R_2 = \frac{Wage_{y2} - Wage_{y1}}{wage_{y1}}$, and $R_3 = \frac{Wage_{y3} - Wage_{y2}}{wage_{y2}}$. These ratios capture the wage growth rates in the second and third year following training completion.[23]

Appendix B Figure B1 plots the path of an average individual's annual wage growth around training completion. The wage growth rate increases significantly following training completion (from Year -1 to Year 1), reflecting the enhanced value of human capital. The growth rate decays over time, suggesting that on average, the value of skills depreciates, consistent with the pattern illustrated in Panel A of Figure V.

Next, we calculate the difference in the wage growth rate between Year 1 and Year 2: $G_{diff2} = R_2 - R_1$. This difference captures how fast wage growth decays from Year 1 to Year 2. The lower its value, the faster the decay. Similarly, we calculate the difference in wage growth rate between Year 2 and Year 3: $G_{diff3} = R_3 - R_2$. The average wage decline after a training program is then denoted as $G_{diffavg}$=$Mean(G_{diff2}, G_{diff3})$.

Lastly, as in Section 4.2.1, we aggregate the training level skills depreciation to occupation level by taking the median of $G_{diffavg}$ associated with all training programs taken by individuals in a given occupation. In Appendix B, Table B3 Panel B, we present example occupations with the highest and lowest skills acquisition under this approach.

In Figure 4 Panels C and D, we plot the pattern of skills acquisition with respect to household leverage for high skills depreciation ρ (Panel C) and low skills depreciation ρ (Panel D). These two panels follow a similar manner as in Panels A and B. They are based on coefficients from regressions including individuals working in occupations with high depreciation (whose aggregate post-training wage decays is above the sample median) versus low

[23]Recall that years here correspond to survey years, which include two calendar years when the survey is conducted biennially since 1996.

depreciation, respectively. The solid line corresponds to the quadratic model, and the dashed line corresponds to the piece-wise specification. We again find empirical patterns consistent with the model predictions regarding both the curvature and levels. Furthermore, in Table 3 Panel B, we present regression analyses with more controls and confirm our interpretation.

4.3 Heterogeneity with respect to σ

Next, we examine variations of the baseline hump shape relation with respect to σ – the degree of labor income uncertainty. Our model (Section 2.6.2 and Figure VI) predicts that households facing higher σ engage in more skills acquisition in order to counter the reduced utility due to greater labor income uncertainty.

To empirically test this pattern, we calculate the volatility of each individual's hourly wages in the sample period (i.e., the volatility of K in equation (3)). As in Section 4.2, we then estimate the occupation level income volatility by taking the average of wage volatility of all individuals working in a given occupation. An individual is considered to face a higher σ if he/she works in an occupation exhibiting income volatility above the sample median; otherwise, he/she is considered to face a lower σ.

We repeat Table 2 regression analyses based on the degree of labor income uncertainty, and plot in Figure 5 the patterns of skills acquisition with respect to household leverage for high (the dashed line) versus low (the solid line) income uncertainty. They are based on regression estimates using specifications in column (1) of Table 2. Because our theoretical prediction regarding σ pertains to the level of skills acquisition, we only plot coefficients from the quadratic model. (The piece-wise regression, on the other hand, mostly concerns the magnitude of switching of the hump-shaped relation.)

Figure 5 shows that in the presence of higher income uncertainty, the household exerts greater effort in skills acquisition. This is seen by the higher level of the dashed line relative to the solid line. These patterns closely match those in Figure VI (Section 2.6.2). In Table 4, we report the results of the quadratic model with more control variables. Columns (1) to (2) include the case of high uncertainty, and columns (3) to (4) include the case of low uncertainty.

5 Alternative theories and additional analyses

5.1 Alternative theories

The hump-shaped relation between household leverage and skills acquisition stems from the interplay of *diminishing marginal utility* and *debt overhang* forces. This non-monotonic relation complements several recent studies that find a negative effect of household leverage on individual decisions, showing that rising debt reduces labor supply or income (Dobbie and Song, 2015; Bernstein, 2021; Di Maggio, Kalda, and Yao, 2019), labor mobility (Ferreira, Gyourko, and Tracy, 2010, 2011; Bernstein and Struyven, 2022; Brown and Matsa, 2020; Di Maggio, Kalda, and Yao, 2019; Gopalan, Hamilton, Kalda, and Sovich, 2021), residential home improvement (Melzer, 2017), and innovation (Bernstein, McQuade, and Townsend, 2021).

Besides debt overhang, these studies discuss a few alternative explanations for the negative effect of household leverage. As an additional contribution, we exploit the rich records provided in NLSY79 to examine these alternative theories in our context.

First, we consider the "housing lock" theory, which posits that heavy leverage, especially an "underwater" mortgage, may "lock in" individuals and refrain them from relocating (Ferreira, Gyourko, and Tracy, 2010, 2011; Bernstein and Struyven, 2022; Brown and Matsa, 2020; Di Maggio, Kalda, and Yao, 2019; Gopalan, Hamilton, Kalda, and Sovich, 2021). If the training programs in our sample require individuals to relocate, then "housing lock" can discourage them from participating, and thus explain the negative effect of leverage on training participation when leverage is high. To examine this possibility, we take advantage of the detailed information on individual home ownership in our data. We exclude all respondent-year observations when respondents report to own a residential property in the prior survey year. We then repeat our analyses among these non-homeowners, which by design are not subject to "housing lock". Table 5 columns (1) and (2) report the results.

Column (1) pertains to the quadratic model and column (2) pertains to the piece-wise model, with the same set of control variables as in Table 2. Similar results to our baseline specification suggest that "housing lock" is unlikely to drive our findings.

Second, we consider the "mental distress" theory, which posits that heavy leverage causes mental disorders and prevents individuals from educational endeavor, likely reversing the initial positive role of leverage in encouraging effort (Deaton, 2012; Currie and Tekin, 2015; Engelberg and Parsons, 2016). To examine this possibility, we obtain each individual's mental health history and identify those that have never been diagnosed with mental issues, such as depression, as of the age of 50. These individuals are therefore less likely to experience intensive mental distress in the face of challenges. We repeat our analyses among this subsample. Table 5 columns (3) and (4) report the results. We again observe a significant hump-shaped relation between household leverage and labor skills acquisition. This observation suggests that "mental distress" is unlikely to drive our findings.

Third, we consider the "inattentiveness" theory, which posits that heavy leverage compels financially burdened individuals to perform routine tasks (such as chores) themselves instead of outsourcing, thereby preventing them from pursuing productive activities like training (Becker, 1965; Baxter and Jermann, 1999; Aguiar, Hurst, and Karabarbounis, 2013). Bernstein, McQuade, and Townsend (2021) suggest that such inattentiveness might explain the negative effect of household leverage on inventors' innovation productivity. To examine this possibility, we utilize information on individuals' family background, and restrict our analyses to those who do not have children. To the extent that individuals without children have fewer daily chores and time constraints, they are less likely to be overwhelmed when challenges arise. We repeat our analyses in this subsample, and again confirm our main findings. Table 5 columns (5) and (6) report the results.

5.2 Instrumental variable analysis

The inclusion of industry×occupation and county×year fixed effects helps control for industry and occupation conditions, and county-level economic conditions that might affect both household leverage and training participation. However, one might still be concerned about confounding factors at the household level. As discussed in the *Introduction*, in order for these factors to explain the documented hump shape, they must correlate with household leverage in such a way that they differently affect training participation depending on the level of leverage. That is, if one argues that households with certain unobservable characteristics are more motivated to enroll in training as leverage initially increases, then one must also argue that the effect of these characteristics reverses when leverage surpasses a certain threshold.

Even though unlikely to drive the formation of the hump shape, such factors may bias the magnitude of this shape. For example, it is possible that individuals who are poorly-connected socially or financially are less able to discover available training opportunities. Such an "opportunity cap" in turn mitigates their intended response to leverage changes, making the estimated hump shape fail to capture the full extent of household incentives in skills acquisition. To the extent that individuals' degree of connectedness may be correlated with household indebtedness, the "opportunity cap" may bias our estimates.

To filter out this potential bias, we perform an instrumental variable analysis based on the interaction of house location and purchase timing. The design of the instrumental variable analysis follows Bernstein (2021). Intuitively, it compares households purchasing properties at a relatively more fortunate time and location – which later experience a greater appreciation in housing prices, with households purchasing properties at relatively less fortunate time and location – which later experience a smaller appreciation. This source of variation predicts different evolutions of households' mortgage loan-to-value ratios (LTV) – the largest part of household leverage (i.e., the inclusion criterion). On the other hand, because this variation comes from households' home purchasing timing and location (instead of simply an earlier or later time overall, or simply different regions), this interaction is plausibly exogenous to local shocks that might be correlated with individual training participation (i.e., the exclusion criterion).

More specifically, the instrument is constructed by estimating a synthetic loan-to-value ratio ($SLTV$) following Bernstein (2021):

$$SLTV_{k,c,t} = LTV_c \times \frac{1 + \Delta Synthloan_{c,t}}{1 + \Delta HPI_{k,c,t}}, \tag{17}$$

where k and t indicate residential county and survey year, respectively; c represents cohort, which is defined as the group of respondents who purchase their residential property during a certain year. LTV_c is the original loan-to-value ratio for each cohort, calculated as the median of the national loan-to-value at the time of home purchasing for this cohort. The national level loan-to-value is used so that it is unlikely affected by household-specific factors. $\Delta HPI_{k,c,t}$ is the house price growth since the time of purchase up to the year t in a county k, calculated using Zillow home value index.[24] $\Delta Synthloan_{c,t}$ is the projected change in mortgage loan balance for each cohort at a given time, which is derived as:

$$\Delta Synthloan_{c,t} = -\frac{(1 + r/12)^{t-c} - 1}{(1 + r/12)^{T} - 1}, \tag{18}$$

where r is median of the national annual mortgage rate (6.2%), based on the historical record of U.S. mortgage rates. T equals 360 months by assuming that the mortgage is a 30-year fixed rate loan. $t - c$ is the number of months passed since loan origination (i.e., home purchasing). As seen in equations (17) and (18), the construction of $SLTV$ captures the housing price variation that stems from the interaction of purchase timing (represented by c) and house location (represented by k).

With the constructed $SLTV$, we follow Bernstein (2021) and start by performing a reduced form instrumental variable (IV) analysis. That is, we directly use $SLTV$ as the independent variables of interest, replacing the previous leverage-related variables. Table 6 Panel A reports the results. Columns (1) to (4) pertain to training participation and columns (5) to (8) pertain to labor supply. Columns (1), (2), (5), and (6) report the quadratic models, and columns (3), (4), (7), and (8) report the piece-wise regressions. The cutoffs in the piece-wise regression (for variable X^{SLTV}) are chosen based on the estimated switching points of

[24]The county-level Zillow home value index is available at https://www.zillow.com/research/data/.

the corresponding quadratic models.

The reduced form IV analyses confirm the hump-shape relation between skills acquisition or labor supply and household leverage. Based on the quadratic models, the switching point for labor supply is at a marginally lower level of leverage than that for skills acquisition (46.86% vs. 47.82%) – consistent with our baseline model. More notably, the decline in labor supply is much sharper than that in skills acquisition once the debt overhang force kicks in, suggesting the sharper manifestation of debt overhang. This observation is supported by the piece-wise regressions, in which the estimated β_3 and $\beta_1 + \beta_3$ are more negative and statistically significant for labor supply (columns (7) and (8)) than those for skills acquisition (columns (3) and (4)). In particular, the economically insignificant β_3 and $\beta_1+\beta_3$ in columns (3) and (4) suggest that in the regime of high leverage, skills acquisition stays relatively flat with respect to household leverage, whereas labor supply declines considerably as indicated by columns (7) and (8). These observations confirm our baseline findings.

Next, we run 2SLS regressions following Bernstein (2021) to perform the IV analysis. For the quadratic models, we estimate:

$$LTV_{i,k,t} = \alpha + \beta_1 SLTV_{k,c,t} + \beta_2 SLTV^2_{k,c,t} + \gamma Z_{i,t-1} + \theta\delta_i + \kappa_c + \eta_{r,t} + OtherFE + \epsilon_{i,k,t}, \quad (19)$$

$$LTV^2_{i,k,t} = \alpha + \beta_1 SLTV_{k,c,t} + \beta_2 SLTV^2_{k,c,t} + \gamma Z_{i,t-1} + \theta\delta_i + \kappa_c + \eta_{r,t} + OtherFE + \epsilon_{i,k,t}, \quad (20)$$

$$Training_{i,k,t} = \alpha + \beta_1 \widehat{LTV_{i,t-1}} + \beta_2 \widehat{LTV^2_{i,t-1}} + \gamma Z_{i,t-1} + \theta\delta_i + \kappa_c + \eta_{r,t} + OtherFE + \epsilon_{i,k,t}. \quad (21)$$

Both equations (19) and (20) are the first-stage regressions of the two-stage least squares (2SLS) analyses.[25] Equation (21) is the second-stage regression. The piece-wise models are constructed in a similar way. Here $\eta_{r,t}$ represents region×time fixed effects, and κ_c represents cohort fixed effects. The inclusion of cohort fixed effects ensures that the $SLTV$ does not simply captures an earlier or later home purchasing time – which may correlate with an individual's career or life stages and in turn, the training decisions (i.e., a violation of

[25]Following Bernstein (2021), here we replace *Leverage* by LTV as our variable of interest based on the assumption that household mortgages constitute a significant proportion of total leverage.

the exclusion criterion). Similarly, region (by time) fixed effects ensure that variation of the instrument does not simply stem from different regions, which may differ in the availability of training opportunities (at a given point in time), affecting individuals' training participation.

The first-stage regressions are presented in Appendix B Table B5, in which we include the corresponding control variables as the second-stage regressions. We see that across all first-stage regressions and for both skills acquisition and labor supply, the instruments significantly predict LTV-related variables (i.e., the endogenous dependent variables of interest). The Cragg-Donald Wald F statistic for the first stages is 20.506 or larger, greater than the 10% critical values.

Table 6 Panel B reports the second-stage regressions, using the instrumented LTV as the variable of interest. The results are presented in a similar way as in Panel A: Columns (1) to (4) pertain to training participation and columns (5) to (8) pertain to labor supply. Columns (1), (2), (5), and (6) report the quadratic models, and columns (3), (4), (7), and (8) report the piece-wise regressions. Overall, these second-stage regressions exhibit similar patterns as in Panel A, providing further support to our baseline findings in Table 2.

The coefficients of the instrumented dependent variables are generally larger than those in Table 2.[26] It suggests that certain unobservable factors associated with leverage – e.g., households' (in)ability to discover available training (or labor supply) opportunities as previously discussed (despite their motives to take on training) – may have flattened out the relation between skills acquisition and leverage. After controlling for these factors using the instrument, we therefore observe a more responsive relation overall.

5.3 An alternative measure of labor skills acquisition

We next repeat our main analyses using an alternative measure of skills acquisition: $TrainingTime$, defined as in Section 3.6. Table 7 reports the results. Columns (1) to (3) report regression results for the quadratic model and columns (4) to (6) report the piece-wise regression model. In a specification without controls or fixed effects (column (4)), a one-standard-deviation in-

[26]The estimated switching points from the quadratic models, however, are approximately 63% and largely in line with that in Table 2.

crease in household leverage raises individuals' training participation by 8.6% of the sample average when household leverage is below 80%. When leverage reaches above 80%, a one-standard-deviation increase in household leverage lowers individuals' training participation by 6.0% of the sample average. Both effects are statistically significant at 1% level. After including household controls, industry×occupation fixed effects, and county×year fixed effects in column (6), we estimate that a one-standard-deviation increase in leverage promotes training by 9.8% of the sample average in the low leverage regime, while it discourages training by 7.9% in the high leverage regime.

5.4 Additional analyses

We provide additional analyses using re-constructed household leverage as the main variable of interest, following discussions in Sections 3.3 and 3.4. In Table B6 Panel A, we construct household leverage using only balance sheet items consistently surveyed in all interviews. In Table B6 Panel B, we exclude student debt from household leverage. Specifically, information about student loans is collected in NLSY79 survey years 2004, 2008, 2010, 2012, and 2014. We exclude households that report outstanding student loans during any of these five years. Estimated leverage from the remaining households is therefore unlikely affected by student debt.[27] In both panels, we report the quadratic and piece-wise models. Our results are robust.

6 Conclusion

In this paper, we study how household indebtedness affects human capital investment, as well as its interaction with labor supply. We develop a dynamic model featuring a risk-averse household investing in acquiring skills – which, different from labor income, is largely inalienable from the household and does not accrue to creditors even at default. This at-

[27] This filter may overlook households that have borrowed student debt and paid it off by 2004. However, as discussed in Section 3.4, student debt was dischargeable in bankruptcy prior to 1998. Therefore, this filter should be, to a large extent, sufficient in identifying households with non-chargeable student debt, which we are most interested in. Among our sample 6,729 household, 866 are excluded in the step.

tribute makes skills acquisition more resilient to debt overhang as household indebtedness rises. We show that skills acquisition is hump-shaped with respect to the level of household indebtedness, reflecting the interplay of two forces: *diminishing marginal utility* and *debt overhang*. Although labor supply exhibits a similar hump shape, it tails off more sharply as indebtedness builds up, reflecting its lower resilience to debt overhang. Moreover, the two actions interact with each other. Because skills acquisition is only valuable when the household expects to supply labor in the future, the response of labor supply to indebtedness propagates back in time distorting the skills acquisition decision ex ante.

We test our model using longitudinal data from the NLSY79 survey. We identify labor skills acquisition based on individuals' voluntary participation in training programs. We capture household indebtedness using detailed balance sheet information. We find strong empirical support for the model. When individuals face a relatively low level of indebtedness, increasing indebtedness initially encourages them to acquire labor skills, but this relation reverses after indebtedness reaches a certain level. Labor supply exhibits a similar hump shape but the debt overhang kicks in early and afterwards, labor supply declines more sharply. Further, we find that the hump-shaped relation between indebtedness and skills acquisition exhibit cross-sectional variation as predicted by the model.

In the wake of the recent skilled labor shortage and historically high level of household indebtedness, our study provides a unified theoretical framework, supplemented by empirical evidence, to study the relation and the interaction among these household decisions. This framework can be useful for counterfactual analysis and the design of public policies, such as household debt forgiveness.

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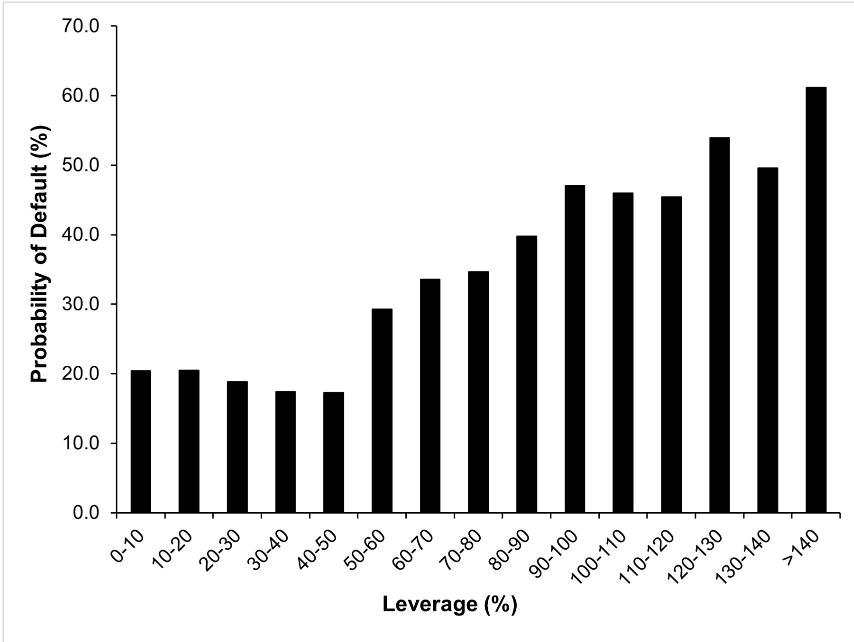
(A) Late Payments



(B) Bankruptcy

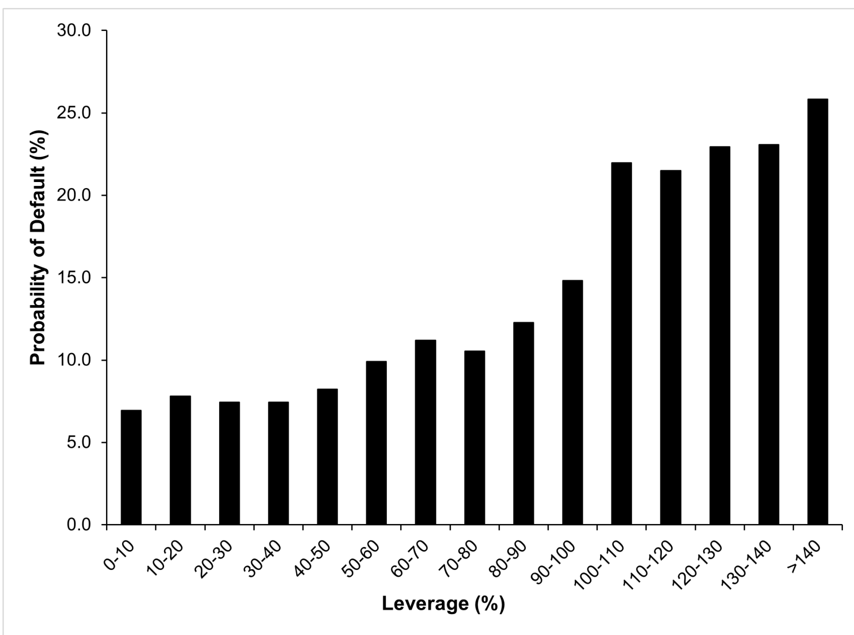
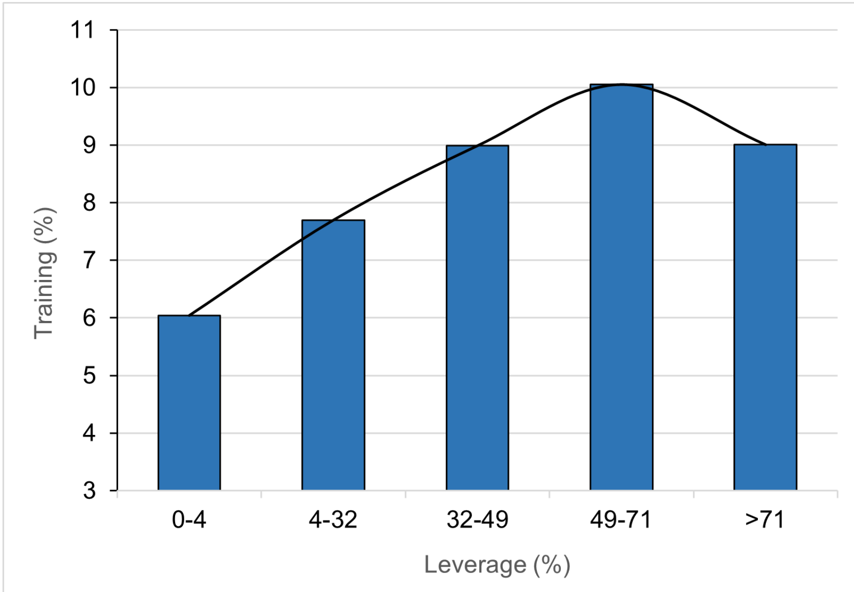


Figure 1: Default probability and household leverage

This figure uses survey data from the NLSY79 to plot the default probability for each 10-point household leverage bin. In Panel A, default is identified by whether a household has missed mortgage or rent payment as of a given year. Missed payments are those at least 60 days past due. The NLSY79 surveys whether an individual has missed payments in the past five years. In Panel B, default is identified by whether a household has filed for bankruptcy as of a given year. Household leverage (in percentage) is the ratio of total debt to total asset, as defined in Section 3.6.

(A) Skills Acquisition



(B) Labor Supply

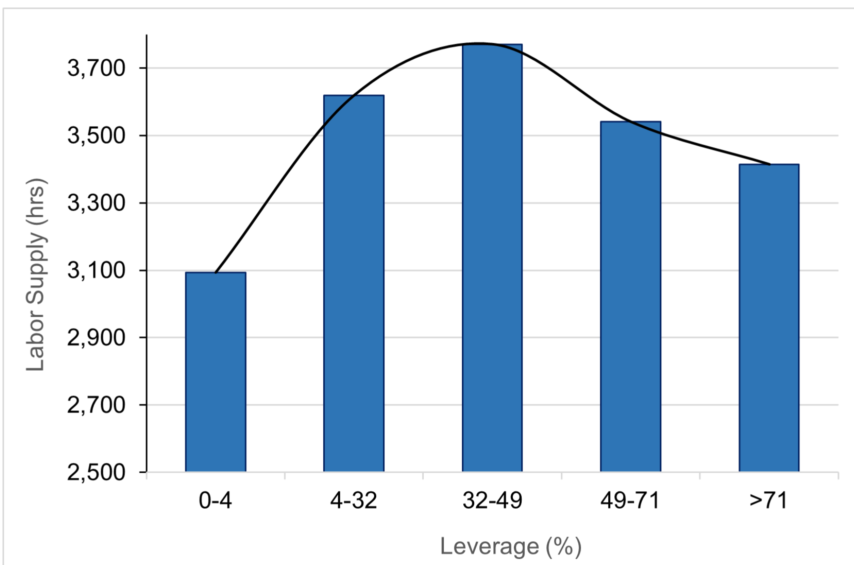


Figure 2: Skills acquisition and labor supply over leverage

Panel A reports average percentage of individuals who have participated in self-requested training programs that are not self-paid since the previous interview among respondents from the 1979 National Longitudinal Survey. The bin of 0-4 consists of respondents whose household leverage is in the lowest quintile of the sample distribution of household leverage (between 0-4%). The bin of 4-32 consists of respondents whose leverage is in the second quintile (between 4-32%), and so forth. Household leverage (in percentage) is the ratio of total debt to total asset, as defined in Section 3.6. Panel B reports the average number of hours that individuals have worked since the previous interview, across leverage bins.

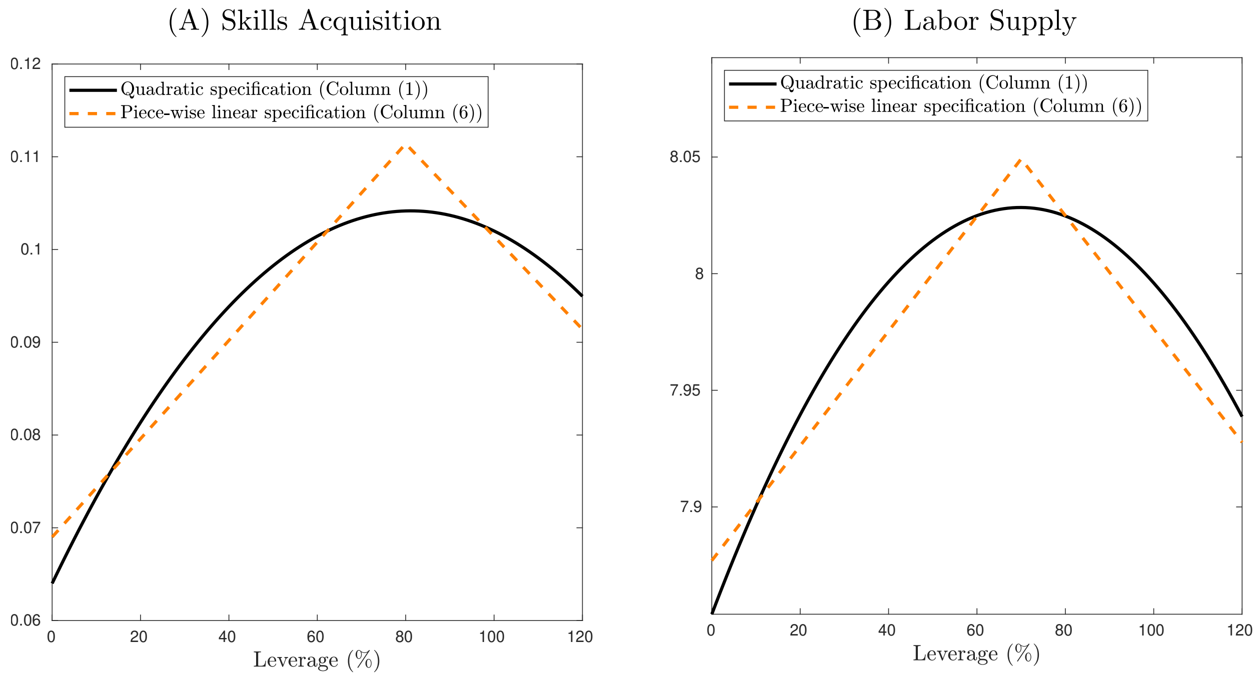


Figure 3: Skills acquisition and labor supply over leverage based on regression estimates

Panel A plots the relation between household leverage and labor skills acquisition based on the regression coefficients estimated in the quadratic model (the black solid line) and the piece-wise specification (the orange dashed line). The quadratic specification corresponds to column (1) of Table 2 and the piece-wise specification corresponds to column (6) of Table 2. Panel B plots the relation between household leverage and labor supply in a similar manner, based on the coefficients of the quadratic model and piece-wise specification as in column (1) and column (6) of Appendix B Table B4. Household leverage (in percentage) is the ratio of total debt to total asset, as defined in Section 3.6.

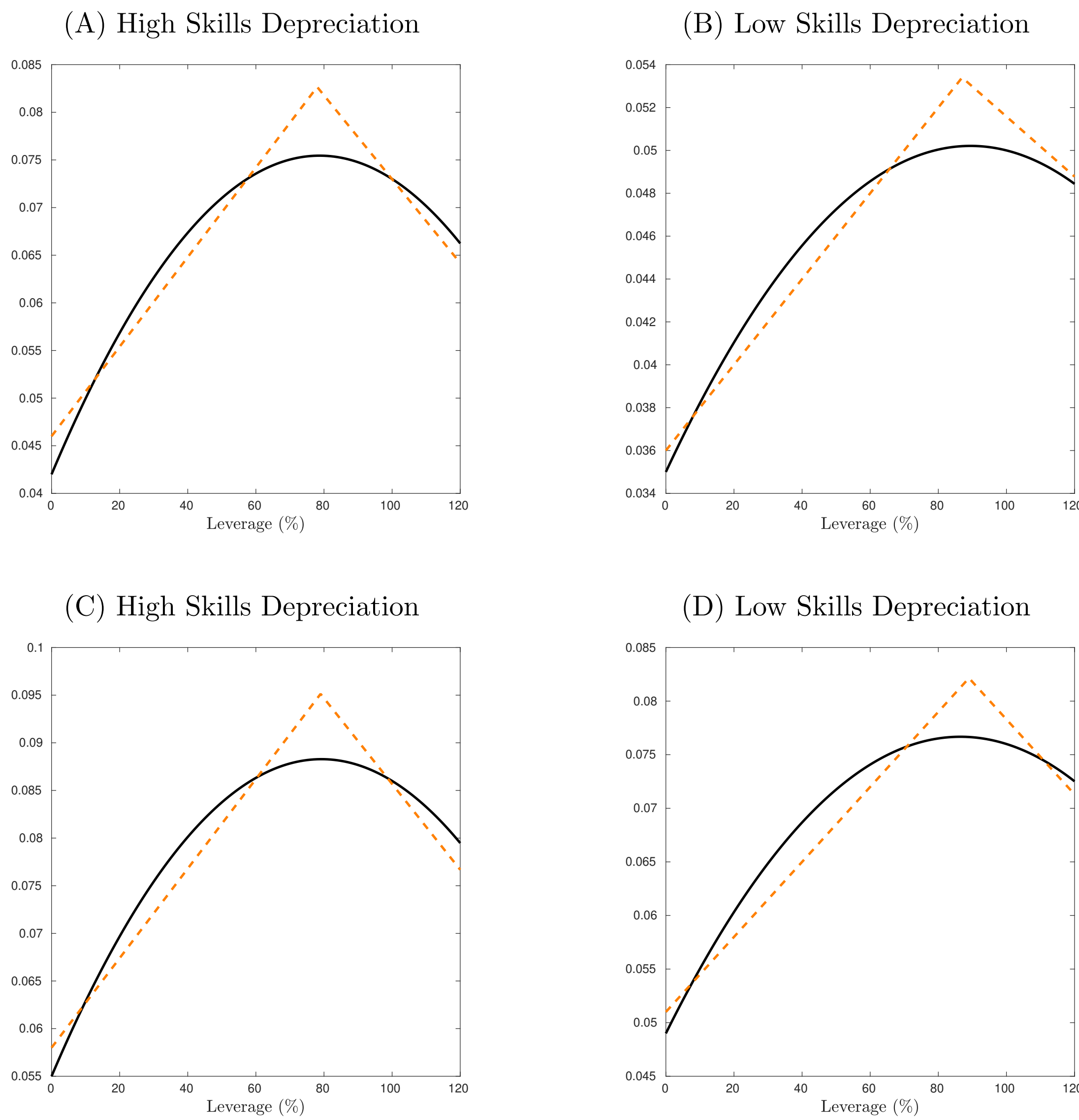


Figure 4: Heterogeneity with respect to the degree of skills depreciation

Panels A and B plot the pattern of skills acquisition with respect to household leverage, separately for individuals facing a high and low degree of skills depreciation. Individuals facing high skills depreciation are those working in occupations with a greater exposure to computer and information technology (CIT), and those facing low skills depreciation are the ones working in occupations with a lower CIT exposure. The identification and classification of CIT exposure are described in Section 4.2.1. Panels C and D follow a similar manner as in Panels A and B, and identifies the degree of skills deprecation based on individuals' changes in the wage path after training completion. The detailed approach is described in Section 4.2.2. In each panel, the black solid line corresponds to the quadratic model (as in column (1) of Table 2), and the orange dashed line corresponds to the piece-wise specification (as in column (6) of Table 2). Household leverage (in percentage) is the ratio of total debt to total asset, as defined in Section 3.6.

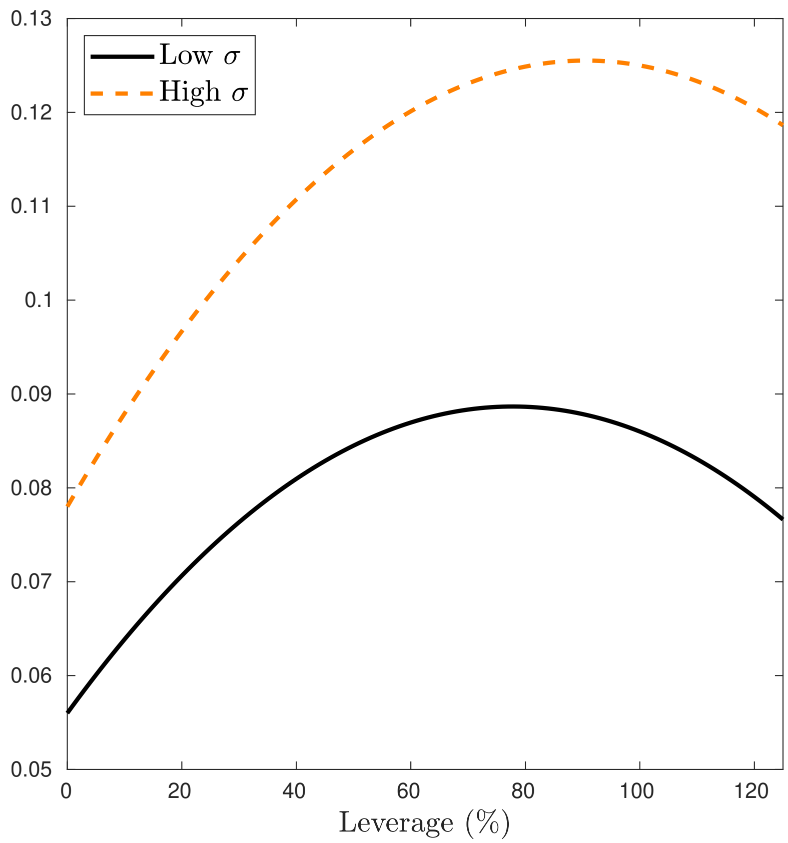


Figure 5: Heterogeneity with respect to labor income uncertainty

This figure plots the relation between household leverage and training participation for individuals with high (the orange dashed line) versus low (the black solid line) income uncertainty. Households are considered to face high income uncertainty if they work in occupations exhibiting wage volatility above the sample median; otherwise, households are considered to face low income uncertainty. The detailed approach is described in Section 4.3. Household leverage (in percentage) is the ratio of total debt to total asset, as defined in Section 3.6.

Table 1: Summary Statistics

This table reports summary statistics of the sample. *Training* is an indicator variable that equals one if a respondent has participated in self-requested training programs that are not self-paid since the previous interview, and zero otherwise. *TrainingTime* is the number of hours a respondent spends on self-requested and non-self-paid training programs since the previous interview. *Labor Supply* is the total number of hours the individual has worked since the previous interview. *Leverage* is the ratio of total debt to total asset, defined in Section 3.6, measured at the previous interview. *Age* is a respondent's age at the current interview. *Male* and *White* are indicators of a respondent's gender and ethnicity. *MaritalStatus* is an indicator for whether a respondent is married, measured at the previous interview. *College* is an indicator for whether a respondent has attended college as of the previous interview. *FatherEdu* is the number of years of school that a respondent's father has completed. *EmployerSize* (in thousands) is the total number of employees of a respondent's current employer. Dummy variables are denoted by (d).

Variable	N	Mean	S.D.	p5	p50	p95
Training (d)	50,697	0.088	0.283	0	0	1
TrainingTime (hrs)	50,697	3.116	14.665	0	0	16
TrainingTime (hrs), Conditional on training	4,695	35.253	36.058	1	20	112
Labor Supply (hrs)	50,697	3,530.32	1,584.94	1,020	3,885	6,151
Leverage	50,697	0.433	0.355	0	0.415	1.042
Age	50,697	38.975	7.643	28	38	52
Male (d)	50,697	0.521	0.500	0	1	1
White (d)	50,697	0.647	0.478	0	1	1
WageIncome	50,697	0.330	0.224	0.030	0.280	0.850
TotalNetFamilyIncome	50,697	0.563	0.381	0.120	0.467	1.550
MaritalStatus(d)	50,697	0.631	0.483	0	1	1
College (d)	50,697	0.556	0.497	0	1	1
FatherEdu (years)	50,697	11.258	3.858	4	12	17
EmployerSize	50,697	0.498	1.209	0.002	0.055	3

Table 2: Baseline regressions of household leverage and labor skills acquisition

This table presents regression analyses of the effect of household leverage on *Training*, an indicator of whether the respondent has requested and participated in training that are not self-paid. Columns (1)-(5) report the quadratic regression model as in equation (14) and columns (6)-(10) report the piece-wise linear regression model as in equation (15). *Leverage* is the ratio of total debt to total asset. $Leverage^2$ is the square of *Leverage*. $X^{Leverage}$ is an interaction term, defined as $(Leverage - 0.8) \times D^{Leverage}$, where $D^{Leverage}$ is an indicator of whether the respondent has a *Leverage* that is larger than 0.8. The control variables include a respondent's age, gender, ethnicity, marital status, college enrollment, father's education, and employer size. The definitions of these control variables are in Table 1. State FE are indicators of the respondent's residential state. County FE are indicators of the respondent's residential county. Year FE are indicators of survey year. Industry FE and Occupation FE are indicators of the respondent's industry and occupation, respectively. Each regression includes a separate intercept. Standard errors are clustered at the state-year level and reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var.	*Training*									
	Quadratic Model					Piece-wise Linear Regression				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Leverage (β_1)	0.099***	0.062***	0.061***	0.060***	0.069***	0.053***	0.034***	0.034***	0.034***	0.038***
	(0.008)	(0.009)	(0.009)	(0.009)	(0.010)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
Leverage^2	-0.061***	-0.037***	-0.037***	-0.036***	-0.044***					
	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)					
$X^{Leverage}$ (β_3)						-0.103***	-0.063***	-0.062***	-0.061***	-0.077***
						(0.012)	(0.012)	(0.012)	(0.012)	(0.013)
Male		-0.010***	-0.009***	-0.010***	-0.011***		-0.010***	-0.009***	-0.010***	-0.011***
		(0.003)	(0.003)	(0.003)	(0.003)		(0.003)	(0.003)	(0.003)	(0.003)
White		-0.001	-0.000	-0.001	-0.006		-0.001	-0.000	-0.001	-0.006
		(0.003)	(0.003)	(0.003)	(0.004)		(0.003)	(0.003)	(0.003)	(0.004)
WageIncome		0.042***	0.041***	0.039***	0.054***		0.042***	0.041***	0.040***	0.055***
		(0.010)	(0.010)	(0.010)	(0.011)		(0.010)	(0.010)	(0.010)	(0.011)
TotalNetFamilyIncome		-0.019***	-0.019***	-0.019***	-0.025***		-0.018***	-0.018***	-0.018***	-0.024***
		(0.006)	(0.006)	(0.006)	(0.007)		(0.006)	(0.006)	(0.006)	(0.007)
MaritalStatus		0.002	0.002	0.002	0.003		0.003	0.003	0.003	0.004
		(0.003)	(0.003)	(0.003)	(0.004)		(0.003)	(0.003)	(0.003)	(0.004)
College		0.019***	0.018***	0.018***	0.019***		0.019***	0.019***	0.018***	0.019***
		(0.003)	(0.003)	(0.003)	(0.003)		(0.003)	(0.003)	(0.003)	(0.003)
FatherEdu		0.001***	0.001***	0.001***	0.001**		0.001***	0.001***	0.001***	0.001**
		(0.000)	(0.000)	(0.000)	(0.001)		(0.000)	(0.000)	(0.000)	(0.001)
EmployerSize		0.006***	0.007***	0.006***	0.007***		0.006***	0.007***	0.006***	0.007***
		(0.001)	(0.001)	(0.001)	(0.001)		(0.001)	(0.001)	(0.001)	(0.001)
Age		0.002	0.002	0.002	-0.000		0.003	0.002	0.003	-0.000
		(0.003)	(0.003)	(0.003)	(0.003)		(0.003)	(0.003)	(0.003)	(0.003)
Age^2		-0.000	-0.000	-0.000	0.000		-0.000	-0.000	-0.000	-0.000
		(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)
Switching point	**81.148%**	**83.784%**	**82.432%**	**83.333%**	**78.409%**					
F stat of ($\beta_1 + \beta_3 = 0$)						**27.524*****	**9.008*****	**8.377*****	**8.050*****	**15.598*****
State FE	NO	YES	NO	NO	NO	NO	YES	NO	NO	NO
Year FE	NO	YES	NO	NO	NO	NO	YES	NO	NO	NO
Industry FE	NO	YES	YES	NO	NO	NO	YES	YES	NO	NO
Occupation FE	NO	YES	YES	NO	NO	NO	YES	YES	NO	NO
State × Year FE	NO	NO	YES	YES	NO	NO	NO	YES	YES	NO
Industry× Occupation FE	NO	NO	NO	YES	YES	NO	NO	NO	YES	YES
County × Year FE	NO	NO	NO	NO	YES	NO	NO	NO	NO	YES
Observations	50,697	50,697	50,697	50,697	50,697	50,697	50,697	50,697	50,697	50,697
R-squared	0.003	0.028	0.043	0.045	0.247	0.002	0.028	0.043	0.045	0.247

Table 3: Cross-sectional variation based on the degree of skills depreciation

This table presents sub-sample analyses based on the degree of skills depreciation. The degree of skills deprecation is proxied using two complementary approaches described in Sections 4.2.1 and 4.2.2. Panel A is based on exposure to technology advancement, and Panel B is based on changes in individual wage path after training. In Panel A, columns (1) and (2) consist of individuals facing high skills depreciation, identified as those working in occupations with a greater exposure to computer and information technology (CIT). Columns (3) and (4) consist of individuals facing low skills depreciation, identified as those working in occupations with a lower CIT exposure. The detailed classification of CIT exposure is described in Section 4.2.1. Panel B identifies the degree of skills deprecation based on individuals' changes in the wage path after training completion, and this approach is described in Section 4.2.2. In each panel, columns (1) and (3) corresponds to the quadratic model as in column (1) of Table 2, and columns (2) and (4) corresponds to the piece-wise specification as in column (6) of Table 2. County FE are indicators of the respondent's residential county. Year FE are indicators of survey year. Industry FE are indicators of the respondent's industry. We do not include occupation FE because the degree of skills depreciation is identified at the occupation level. Each regression includes a separate intercept. Standard errors are clustered at the state-year level and reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Exposure to technology

Dep. Var.	*Training*			
	High Skills Depreciation		Low Skills Depreciation	
	(1)	(2)	(3)	(4)
Leverage (β_1)	0.058***	0.033***	0.025***	0.013***
	(0.008)	(0.005)	(0.008)	(0.004)
Leverage^2	-0.037***		-0.014**	
	(0.006)		(0.006)	
$X^{Leverage}$ (β_3)		-0.066***		-0.023**
		(0.011)		(0.012)
Switching point	**78.330%**		**87.240%**	
F stat of ($\beta_1 + \beta_3 = 0$)		**15.504*** **		**1.146**
Controls	YES	YES	YES	YES
State FE	NO	NO	NO	NO
Year FE	NO	NO	NO	NO
Industry FE	NO	NO	NO	NO
Occupation FE	NO	NO	NO	NO
State×Year FE	NO	NO	NO	NO
Industry×Occupation FE	YES	YES	YES	YES
County×Year FE	YES	YES	YES	YES
Observations	49,766	49,766	48,797	48,797
R-squared	0.259	0.259	0.247	0.247

Panel B: Changes in the wage path

Dep. Var.	*Training*			
	High Skills Depreciation		Low Skills Depreciation	
	(1)	(2)	(3)	(4)
Leverage (β_1)	0.060***	0.033***	0.046***	0.027***
	(0.009)	(0.005)	(0.009)	(0.005)
Leverage^2	-0.038***		-0.026**	
	(0.007)		(0.006)	
$X^{Leverage}$ (β_3)		-0.066***		-0.050**
		(0.012)		(0.013)
Switching point	**78.600%**		**89.140%**	
F stat of ($\beta_1 + \beta_3 = 0$)		**13.965*** **		**6.014**
Controls	YES	YES	YES	YES
State FE	NO	NO	NO	NO
Year FE	NO	NO	NO	NO
Industry FE	NO	NO	NO	NO
Occupation FE	NO	NO	NO	NO
State×Year FE	NO	NO	NO	NO
Industry×Occupation FE	YES	YES	YES	YES
County×Year FE	YES	YES	YES	YES
Observations	50,423	50,423	49,900	49,900
R-squared	0.246	0.246	0.241	0.241

Table 4: Cross-sectional variation based on the degree of labor income uncertainty

This table presents subsample results based on the degree of individual's labor income uncertainty. An individual is considered to face high income uncertainty if he/she works in an occupation exhibiting average hourly wage volatility above the sample median; otherwise, the individual is considered to face low income uncertainty. The detailed classification is described in Section 4.3. Columns (1)-(2) consist of individuals facing high income volatility and columns (3)-(4) consist of individuals facing low income volatility. *Leverage* is the ratio of total debt to total asset. *Leverage*^{2} is the square of *Leverage*. The definitions of the control variables are in Table 1. County FE are indicators of the respondent's residential county. Year FE are indicators of survey year. Industry FE are indicators of the respondent's industry. We do not include occupation FE because the degree of income uncertainty is identified at the occupation level. Each regression includes a separate intercept. Standard errors are clustered at the state-year level and reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var.	*Training*			
	High Wage Volatility		Low Wage Volatility	
	(1)	(2)	(3)	(4)
Leverage	0.110***	0.124***	0.075***	0.057***
	(0.016)	(0.022)	(0.010)	(0.013)
Leverage^2	-0.058***	-0.089***	-0.048***	-0.036***
	(0.013)	(0.017)	(0.008)	(0.009)
Controls	NO	YES	NO	YES
State FE	NO	NO	NO	NO
Year FE	NO	NO	NO	NO
Industry FE	NO	NO	NO	NO
Occupation FE	NO	NO	NO	NO
State×Year FE	NO	NO	NO	NO
Industry×Occupation FE	NO	YES	NO	YES
County×Year FE	NO	YES	NO	YES
Observations	19,630	19,630	28,983	28,983
R-squared	0.003	0.392	0.002	0.305

Table 5: Alternative theories

This table reports the OLS regression results to examine alternative theories to explain our findings. Column (1) and (2) report the quadratic model and piece-wise linear regression results, respectively, among respondents who do not own a residential property. Column (3)-(4) show the regression results for the subsample of respondents that have never been diagnosed as suffering from depression as of age 50. Column (5)-(6) present the regression results among respondents who do not have children. Definitions of all variables are in Table 1 and Table 2. Each regression includes a separate intercept. Standard errors are clustered at state-year level and reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var.	*Training*					
	Non-homeowner		No mental stress history		No kids	
	(1)	(2)	(3)	(4)	(5)	(6)
Leverage (β_1)	0.087***	0.051***	0.062***	0.035***	0.072***	0.040***
	(0.018)	(0.011)	(0.011)	(0.007)	(0.017)	(0.010)
Leverage^2	-0.056***		-0.039***		-0.050***	
	(0.012)		(0.008)		(0.013)	
$X^{Leverage}$ (β_3)		-0.095***		-0.065***		-0.088***
		(0.023)		(0.014)		(0.023)
Switching point	**76.679%**		**79.487%**		**72.000%**	
F stat of ($\beta_1 + \beta_3 = 0$)		**9.458*** **		**7.899*** **		**8.430*** **
Controls	YES	YES	YES	YES	YES	YES
State FE	NO	NO	NO	NO	NO	NO
Year FE	NO	NO	NO	NO	NO	NO
Industry FE	NO	NO	NO	NO	NO	NO
Occupation FE	NO	NO	NO	NO	NO	NO
State×Year FE	NO	NO	NO	NO	NO	NO
Industry×Occupation FE	YES	YES	YES	YES	YES	YES
County×Year FE	YES	YES	YES	YES	YES	YES
Observations	16,796	16,796	40,034	40,034	18,896	18,896
R-squared	0.376	0.376	0.27	0.27	0.385	0.385

Table 6: Instrumental variable analyses

This table reports the instrumental variable analysis for the effect of household financial leverage on labor skills acquisition and labor supply, in whic household leverage is instrumented using synthetic loan-to-value ($SLTV$) ratio. The construction of $SLTV$ is discussed in detail in Section 5.2. Panel A reports the reduced form regressions of the instrumental variable analysis. $SLTV^2$ is the square of $SLTV$. X^{SLTV} in columns (3) and (4) is an interaction term, defined as $(SLTV - 0.48) \times D^{SLTV}$, where D^{SLTV} is an indicator of whether the respondent has a $SLTV$ ratio that is larger than 0.48. X^{SLTV} in columns (7) and (8) is an interaction term, defined as $(SLTV - 0.47) \times D^{SLTV}$, where D^{SLTV} is an indicator of whether the respondent has a $SLTV$ ratio that is larger than 0.47. Panel B reports the second stage of the two-stage least squares (2SLS) regressions. X^{LTV} in columns (3) and (4) is an interaction term, defined as $(LTV - 0.62) \times D^{LTV}$, where D^{LTV} is an indicator of whether the respondent has a LTV ratio that is larger than 0.62. X^{LTV} in columns (7) and (8) is an interaction term, defined as $(LTV - 0.61) \times D^{LTV}$, where D^{LTV} is an indicator of whether the respondent has a LTV ratio that is larger than 0.61. Cohort FE are indicators of the survey year when the respondent becomes the owner of the house. Definitions of other variables are in Table 1 and Table 2. Standard errors are clustered at the state-year level and reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Reduced form

Dep. Var.	*Training*				*Labor Supply*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SLTV (β_1)	0.134**	0.128**	0.049*	0.049*	0.481***	0.469***	0.253***	0.252***
	(0.056)	(0.056)	(0.029)	(0.029)	(0.181)	(0.174)	(0.091)	(0.087)
$SLTV^2$	-0.141**	-0.132**			-0.509**	-0.496**		
	(0.066)	(0.067)			(0.216)	(0.210)		
X^{SLTV} (β_3)			-0.064	-0.061			-0.450***	-0.453***
			(0.054)	(0.054)			(0.168)	(0.164)
Switching point	**47.518%**	**48.485%**			**47.250%**	**47.278%**		
F stat of ($\beta_1 + \beta_3 = 0$)			**0.143**	**0.096**			**2.489**	**2.771***
Controls	NO	YES	NO	YES	NO	YES	NO	YES
Cohort FE	YES	YES	YES	YES	YES	YES	YES	YES
State×Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry×Occupation FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	16,355	16,355	16,355	16,355	16,355	16,355	16,355	16,355

Panel B: Second stage of 2SLS

Dep. Var.	*Training*				*Labor Supply*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Instrumented LTV (β_1)	0.999**	0.950**	0.381*	0.365*	3.575**	3.446**	1.713**	1.634**
	(0.488)	(0.478)	(0.212)	(0.204)	(1.572)	(1.488)	(0.726)	(0.673)
Instrumented LTV^2	-0.795**	-0.770**			-2.853**	-2.824**		
	(0.378)	(0.382)			(1.250)	(1.220)		
Instrumented X^{LTV} (β_3)			-0.631	-0.620			-2.988**	-2.990**
			(0.385)	(0.389)			(1.356)	(1.319)
Switching point	**62.830%**	**61.688%**			**62.653%**	**61.150%**		
Chi-squared stat of ($\beta_1 + \beta_3 = 0$)			**1.398**	**1.315**			**2.975***	**3.256***
Controls	NO	YES	NO	YES	NO	YES	NO	YES
Cohort FE	YES	YES	YES	YES	YES	YES	YES	YES
State×Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry×Occupation FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	16,356	16,356	16,356	16,356	16,356	16,356	16,356	16,356

Table 7: An alternative measure of human capital investment: Duration of training

This table presents regression analyses using an alternative measure of human capital investment, *TrainingTime*, defined as the number of hours the respondent has spent on training programs that are self-requested and are not self-paid since the last interview. Columns (1)-(3) report the quadratic regression model and columns (4)-(6) report the piece-wise linear regression model. All other variables and fixed effects are defined in Table 1 and Table 2. Each regression includes a separate intercept. Standard errors are clustered at the state-year level and reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var.	*TrainingTime*					
	Quadratic Model			Piece-wise Linear Regression		
	(1)	(2)	(3)	(4)	(5)	(6)
Leverage (β_1)	0.285***	0.178***	0.207***	0.156***	0.099***	0.112***
	(0.027)	(0.029)	(0.033)	(0.015)	(0.016)	(0.019)
Leverage^2	-0.179***	-0.106***	-0.129***			
	(0.021)	(0.022)	(0.024)			
$X^{Leverage}$ (β_3)				-0.312***	-0.178***	-0.221***
				(0.041)	(0.041)	(0.046)
Switching point	**79.609%**	**83.962%**	**80.233%**			
F stat of ($\beta_1 + \beta_3 = 0$)				**22.880*****	**5.761****	**10.258*****
Controls	NO	YES	YES	NO	YES	YES
State FE	NO	NO	NO	NO	NO	NO
Year FE	NO	NO	NO	NO	NO	NO
Industry FE	NO	YES	NO	NO	YES	NO
Occupation FE	NO	YES	NO	NO	YES	NO
State×Year FE	NO	YES	NO	NO	YES	NO
Industry×Occupation FE	NO	NO	YES	NO	NO	YES
County×Year FE	NO	NO	YES	NO	NO	YES
Observations	50,697	50,697	50,697	50,697	50,697	50,697
R-squared	0.002	0.040	0.246	0.002	0.040	0.246

A Internet Appendix A

A.1 Households' value function post default

In this Appendix we compute the household's value function post default for the baseline case in which the household is entirely excluded from credit markets (i.e., when the household is not allowed to save or borrow, thus living hand-to-mouth). In order to ease notation we assume without loss of generality that $\theta_{al} = 0$.

Household value $H(W)$ in this case depends entirely on his current hourly wages K_t. The Hamilton-Jacobi-Bellman (HJB) equation is given by

$$\delta H(K) = \max_{a,l} \left\{ \log lK + \theta_a \frac{a^2}{2} + \theta_l \frac{l^2}{2} + H'(K)K(a-\rho) + \frac{1}{2}H''(K)K^2\sigma^2 \right\}. \tag{22}$$

We conjecture that the value function takes the form:

$$H_1 + \frac{1}{\delta}\log K, \tag{23}$$

where H_1 is a constant to be determined. Substituting (23) into (22) and collecting terms yields that:

$$H_1 = -\frac{\delta^2\theta_a \log\theta_l + \delta^2\theta_a + \delta\theta_a\left(2\rho+\sigma^2\right) - 1}{2\delta^3\theta_a}, \qquad a(K) = \frac{1}{\delta\theta_a}, \qquad l(K) = \frac{1}{\sqrt{\theta_l}}. \tag{24}$$

A.2 Households' value function before default

In this Appendix we compute the household value function before default denoted $F(S,K)$. We recall the HJB satisfied by this value function:

$$\begin{aligned}\delta F(S,K) = \max_{C,a,l} \Bigg\{ & \log C - g(a,l) + F_S(S,K)(r(S)S - C + lK) \\ & + F_K(S,K)K(a-\rho) + \frac{1}{2}F_{KK}(S,K)K^2\sigma^2 \Bigg\}\end{aligned} \tag{25}$$

where the first order conditions (FOCs) for the optimal controls are given by:

$$\frac{1}{C(S,K)} = F_S(S,K), \qquad \theta_a a(S,K) = F_K(S,K)K, \qquad \theta_l l(S,K) = F_S(S,K)K. \tag{26}$$

Because the household has logarithmic preferences for consumption, separable cost of effort, and hourly wages following a controlled GBM process, we conjecture and verify that the value function is homogeneous of degree one and takes the form:

$$f(s) + \frac{1}{\delta}\log K, \tag{27}$$

where $f(s)$ is a function to be determined that only depends on scaled savings $s = S/K$. Substituting (27) into (26), we obtain the optimal controls as functions of $f(s)$:

$$C(S,K) = \frac{K}{f'(s)}, \qquad a(S,K) = \frac{1 - s\delta f'(s)}{\delta\theta_a}, \qquad l(S,K) = \frac{f'(s)}{\theta_l}. \tag{28}$$

Next, we substitute (27) and (28) into the HJB (25) to obtain an ordinary differential equation (ODE) for $f(s)$:

$$\begin{aligned} 0 =& 2\delta s f'(s)\left(\delta\theta_a\left(\rho+\sigma^2\right) + \delta\theta_a r(s) - 1\right) + \frac{\delta^2 f'(s)^2\left(\theta_a + \theta_l s^2\right)}{\theta_l} + \delta^2\theta_a s^2\sigma^2 f''(s) + 1 \\ & - \delta\theta_a\left(2\delta + 2\delta\log\left(f'(s)\right) + 2\delta^2 f(s) + 2\rho + \sigma^2\right). \end{aligned} \tag{29}$$

Because equation (29) is a second order ODE, we need two boundary conditions. The first boundary condition is obtained by matching the payoff to the household at the default boundary $\underline{s}$ with the post-default value function computed in Appendix A.1. That is,

$$f(\underline{s}) = -\frac{\delta^2\theta_a\log\theta_l + \delta^2\theta_a + \delta\theta_a\left(2\rho+\sigma^2\right) - 1}{2\delta^3\theta_a} = H_1. \tag{30}$$

The second boundary condition is obtained by noting that the limiting case – when the household has no labor income (i.e., when wages are zero) – implies that the household consumes fraction δ of his savings due to logarithmic preferences. That is,

$$\lim_{K\to 0} C(S,K) = \delta S \iff \lim_{s\to\infty} sf'(s) = \frac{1}{\delta}. \tag{31}$$

Finally, we numerically solve ODE (29) subject to boundary conditions (30) and (31) using a standard ODE solver. The baseline calibration for our numerical exercises is based on the parametric specification: $\delta = 0.05, r_B = 0.08, r_S = 0.01, \theta_a = 300, \theta_l = 3, \theta_{al} = 0, \rho = 0.15, \sigma = 0.3$.

We conclude this Appendix by noting that indebtedness (d) can alternatively be used as the single state variable in our model, where d is defined as:

$$d_t = \frac{S_t}{l_{\tau_D}\underline{s}K_t} = \frac{S_t\sqrt{\theta}}{\underline{s}K_t}. \tag{32}$$

The equality follows from substituting the labor supply at default from Equation (9). Therefore, $|\underline{s}|$ represents the highest earnings multiple the household is allowed to borrow, since $d_t \leq 1$ implies that $S_t \leq \underline{s}l_{\tau_D}K_t$, for all t. Finally, since $s = S/K$ and d are linearly related, it is straightforward to go from the scaled savings s to the state variable of interest – indebtedness d – for all of the model's variables.

A.3 Wage reduction and garnishment post default

In our baseline model, we assume that a household's human capital remains intact after default, in the spirit of Dobbie, Goldsmith-Pinkham, Mahoney, and Song (2020). We now consider the possibility that the value of human capital declines moderately after default. Such decline may arise because of resistance from employers to the household's unfavorable credit history – resulting in reduced employment, or because of wage garnishment until the household's debts are repaid – which effectively lowers the hourly wage. These possibilities can in turn partially undo the value preservation of human capital due to its inalienability.

In this Appendix, we relax our baseline assumption and show that the hump-shape relation between skills acquisition and leverage (resp. labor supply and leverage) is robust to a post-default decline in human capital. To this end, we extend the model to incorporate a parameter $\psi > 0$ that captures the fraction of human capital retained by the household upon default. That is, the value function post default for the household now becomes $H(\psi K)$. $1 - \psi > 0$ thus captures the magnitude of human capital decline after default.

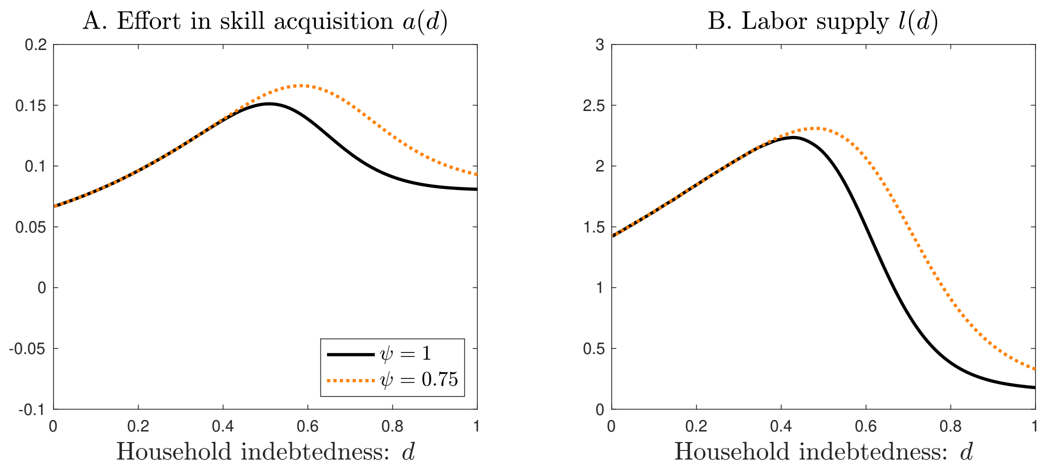


Figure V: **Robustness with respect to ψ.** Other parameter values are $\delta = 0.05, r_B = 0.08, r_S = 0.01, \theta_a = 300, \theta_l = 3, \theta_{al} = 0, \rho = 0.15, \sigma = 0.3$.

In Figure V we depict the baseline case (black solid line), in which human capital remains intact after default ($\psi = 1$), and the case in which there is a 25% human capital decline post default ($\psi = 0.75$). Bos, Breza, and Liberman (2018) estimate that bankruptcy is associated with 3% loss in subsequent employment and a wage earning reduction of \$1,000. In addition, the U.S. federal laws allow wage garnishment to amount to up to 25% of household disposable earnings (Title III of Consumer Credit Protection Act). We therefore re-calibrate our model using the more conservative parameter, 25%, as the loss of human capital value. This parameter encompasses the magnitude of both wage reduction and garnishment after household default in practice. Even so, we show that our patterns remain robust – that is, both activities exhibit a hump-shaped relation with household leverage, and importantly, labor supply exhibits an earlier and sharper manifestation of debt overhang than skills acquisition.

A.4 Default with less punitive outcomes

In our baseline model, we assume that households can not borrow or save after default. We now consider the case in which default is less punitive and show that the hump-shape relation between skills acquisition and leverage – and the greater resilience of skills acquisition to debt overhang – is robust to this alternative. To this end, we extend the model to incorporate a parameter $\kappa > 0$ that captures, in reduced-form, a higher payoff upon default relative to the baseline case (when households are entirely shun from credit markets). This higher payoff can result from, e.g., the household continuing to have partial access to credit markets after default, thereby allowing it to smooth consumption and increase utility. As such, the value function post default for the household becomes $H(K) + \kappa$, reflecting a less punitive formulation upon default.

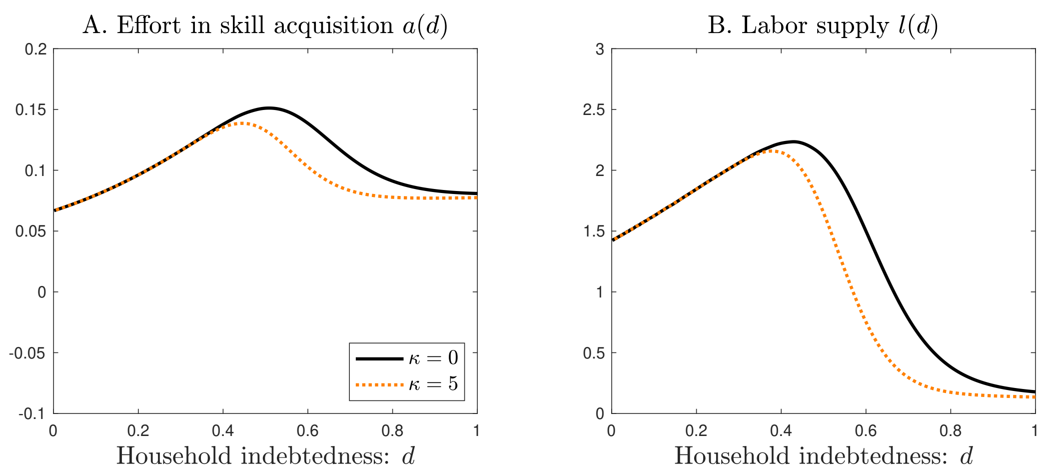


Figure VI: **Robustness with respect to κ.** Other parameter values are $\delta = 0.05, r_B = 0.08, r_S = 0.01, \theta_a = 300, \theta_l = 3, \theta_{al} = 0, \rho = 0.15, \sigma = 0.3$.

In Figure VI we depict the baseline case (solid black line corresponding to $\kappa = 0$), and the case when default is less punitive (dotted orange line corresponding to $\kappa = 5$). Adding $\kappa = 5$ to the household's utility upon default reduces the punishment of default by the same extent as a 28.4% increase of the household's hourly wages would in our baseline calibration. With less punitive default, we continue to observe that our main prediction is robust, in that skills acquisition is more resilient to debt overhang relative to labor supply.

A.5 Labor supply comparative statics

Figure VII depicts comparative statics of labor supply with respect to the volatility of hourly wages σ. As discussed in the body of the paper, the precautionary effect makes labor supply increasing in σ.

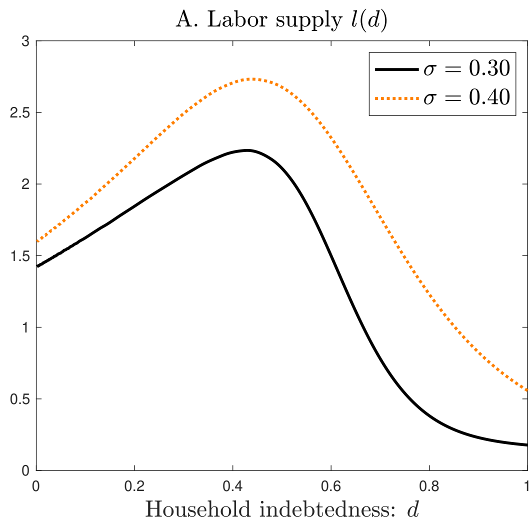


Figure VII: **Comparative statics with respect to hourly wage volatility σ.** Other parameter values are $\delta = 0.05, r_B = 0.08, r_S = 0.01, \theta_a = 300, \theta_l = 3, \theta_{al} = 0, \rho = 0.15$.

B Internet Appendix B

Figure B1: Hourly wage growth rate before and after training

This figure plots the growth rate of individual hourly wages before and after the training completion. Year -1 denotes the survey year prior to an individual's training participation; Year 1 denotes the survey year following training completion; Year 2 and Year 3 denote the second and third survey years following training completion.

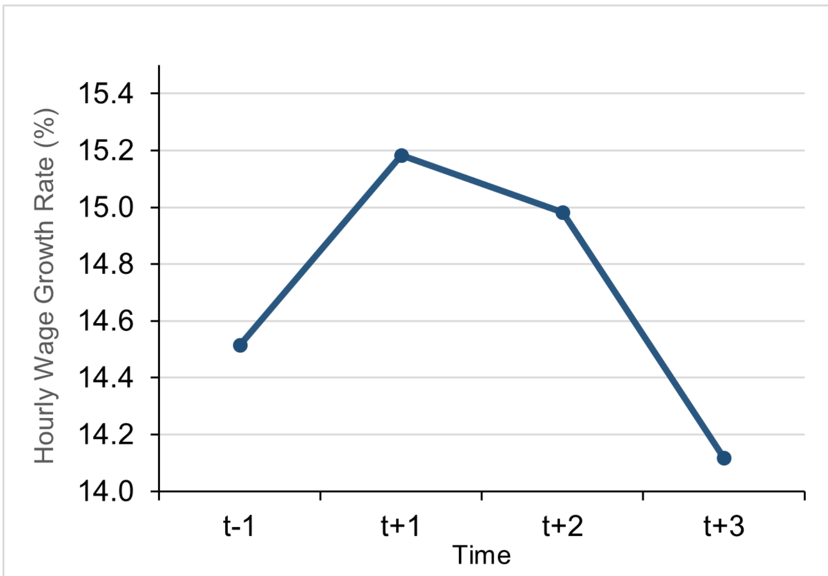


Table B1: Components of total debt

Components of total debt	**Survey question**	**Survey year**
Mortgage debt on residential property	AMOUNT OF MORTGAGES & BACK TAXES R/SPOUSE OWE ON RESIDENTIAL PROPERTY	1985, 1986, 1987, 1988, 1989, 1990,1992, 1993, 1994, 1996, 1998, 2000, 2004, 2008, 2012
Auto debt	TOTAL AMOUNT OF MONEY R/SPOUSE OWE ON VEHICLES INCLUDING AUTOMOBILES	1985, 1986, 1987, 1988, 1989, 1990, 1992, 1993, 1994, 1996, 1998, 2000, 2004, 2008, 2012
Money owed to other business	TOTAL AMOUNT R-SPOUSE OWES TO OTHER BUSINESSES AFTER MOST RECENT PAYMENT	2004, 2008, 2010, 2012, 2014
Credit card debt	TOTAL BALANCE OWED ON ALL CREDIT CARD ACCOUNTS TOGETHER	2004, 2008, 2010, 2012, 2014
Debts on farm/business/ other property	TOTAL AMOUNT OF DEBTS ON FARM/BUSINESS/OTHER PROPERTY R/SPOUSE OWE	1985, 1986, 1987, 1988, 1989, 1990, 1992, 1993, 1994, 1996, 1998, 2000, 2004, 2008, 2012
Student loan	TOTAL AMOUNT R-SPOUSE OWES ON STUDENT LOANS	2004, 2008, 2010, 2012, 2014
Money owed to other person, institution or companies that is more than $1000	TOTAL AMOUNT OF DEBT OWED TO OTHER PERSONS, INSTITUTIONS, OR COMPANIES	2004, 2008, 2010, 2012, 2014
Student loan for children	TOTAL AMOUNT OWED ON STUDENT LOANS FOR CHILDREN	2004, 2008, 2010, 2012, 2014

Table B2: Components of total asset

Components of total asset	Survey question	Survey year
Market value of residential property	MARKET VALUE OF RESIDENTIAL PROPERTY R/SPOUSE OWN	1985, 1986, 1987, 1988, 1989, 1990,1992, 1993, 1994, 1996, 1998, 2000, 2004, 2008, 2012
Market value of all vehicles	TOTAL MARKET VALUE OF ALL VEHICLES INCLUDING AUTOMOBILES R/SPOUSE OWN	1985, 1986, 1987, 1988, 1989, 1990,1992, 1993, 1994, 1996, 1998, 2000, 2004, 2008, 2012
Amount of money asset such as savings account	TOTAL AMOUNT OF MONEY ASSETS LIKE SAVINGS ACCOUNTS OF R/SPOUSE	1985,1986, 1987, 1988, 1989, 1990,1992, 1993, 1994, 1996, 1998, 2000, 2004, 2008,2012
Market value of farm, business, or other property	TOTAL MARKET VALUE OF FARM/BUSINESS/OTHER PROPERTY R/SPOUSE OWN	1985, 1986, 1987, 1988, 1989, 1990,1992, 1993, 1994, 1996, 1998, 2000, 2004, 2008, 2012
Amount of money asset such as IRAs or Keough	TOTAL AMOUNT OF MONEY ASSETS LIKE IRAS OR KEOUGH OF R/SPOUSE	1994, 1996, 1998, 2000, 2004, 2008, 2012
Market value of stocks, bonds, or mutual funds	TOTAL MARKET VALUE OF STOCKS/BONDS/MUTUAL FUNDS	1988, 1989, 1990,1992, 1993, 1994, 1996, 1998, 2000, 2004, 2008, 2012

Table B3: List of Occupations

This table provides example occupations with high and low degrees of skills depreciation, along with example job titles in each occupation. The degree of skills deprecation is proxied using two complementary approaches. Panel A is based on exposure to technology advancement, and Panel B is based on changes in individual wage path after training. The details description of these approaches are described in Section 4.2.1 and Section 4.2.2.

Panel A: Exposure to technology

High Skills Depreciation Occupation	**Job Title Examples**	
Computer and Mathematical	Computer programmer	Statistician
Architecture and Engineering	Architect	Biomedical engineer
Life, Physical, and Social Services	Economist	Biological scientist
Low Skills Depreciation Occupation	**Job Title Examples**	
Healthcare Support	Medical assistant	Nursing aide
Building, Grounds Cleaning and Maintenance	Janitor	Maid
Lawyers, Judges and Legal Support Workers	Lawyer	Judge

Panel B: Changes in the wage path

High Skills Depreciation Occupation	**Job Title Examples**	
Farming, Forestry, and Fishing	Animal breeder	Fisher
Life, Physical, and Social Services	Economist	Biological scientist
Computer and Mathematical	Computer programmer	Statistician
Low Skills Depreciation Occupation	**Job Title Examples**	
Sales and Related	Retail salesperson	Insurance sales agent
Lawyers, Judges and Legal Support Workers	Lawyer	Judge
Healthcare Support	Medical assistant	Nursing aide

Table B4: Baseline regressions of household leverage and labor supply

This table presents regression analyses of the effect of household leverage on *Labor Supply*, the logarithm of one plus the number of hours a respondent has worked since the previous survey year. Columns (1)-(5) report the quadratic model and columns (6)-(10) report the piece-wise linear regression model. *Leverage* is the ratio of total debt to total asset. $Leverage^2$ is the square of *Leverage*. $X^{Leverage}$ is an interaction term, defined as $(Leverage - 0.7) \times D^{Leverage}$, where $D^{Leverage}$ is an indicator of whether the respondent has a *Leverage* that is larger than 0.7. The control variables include a respondent's age, gender, ethnicity, marital status, college enrollment, father's education, and employer size. The definitions of these control variables are in Table 1. State FE are indicators of the respondent's residential state. County FE are indicators of the respondent's residential county. Year FE are indicators of survey year. Industry FE and Occupation FE are indicators of the respondent's industry and occupation, respectively. Each regression includes a separate intercept. Standard errors are clustered at the state-year level and reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var.	*Labor Supply*									
	Quadratic Model					Piece-wise Linear Regression				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Leverage (β_1)	0.499***	0.243***	0.240***	0.236***	0.213***	0.246***	0.125***	0.123***	0.120***	0.110***
	(0.042)	(0.036)	(0.036)	(0.036)	(0.040)	(0.023)	(0.020)	(0.020)	(0.020)	(0.022)
Leverage^2	-0.357***	-0.184***	-0.182***	-0.181***	-0.163***					
	(0.036)	(0.032)	(0.031)	(0.031)	(0.035)					
$X^{Leverage}$ (β_3)						-0.489***	-0.289***	-0.286***	-0.285***	-0.259***
						(0.057)	(0.052)	(0.051)	(0.051)	(0.058)
Male		0.181***	0.179***	0.177***	0.174***		0.180***	0.178***	0.177***	0.174***
		(0.011)	(0.011)	(0.011)	(0.013)		(0.011)	(0.011)	(0.011)	(0.013)
White		-0.012	-0.012	-0.011	-0.019		-0.011	-0.012	-0.011	-0.018
		(0.011)	(0.011)	(0.011)	(0.013)		(0.011)	(0.011)	(0.011)	(0.013)
WageIncome		0.983***	0.981***	0.974***	0.971***		0.986***	0.983***	0.976***	0.972***
		(0.039)	(0.039)	(0.039)	(0.041)		(0.039)	(0.039)	(0.039)	(0.041)
TotalNetFamilyIncome		-0.193***	-0.194***	-0.196***	-0.182***		-0.189***	-0.191***	-0.192***	-0.179***
		(0.024)	(0.024)	(0.024)	(0.025)		(0.024)	(0.024)	(0.024)	(0.025)
MaritalStatus		-0.003	-0.003	-0.003	-0.013		-0.001	-0.001	-0.002	-0.011
		(0.011)	(0.011)	(0.011)	(0.013)		(0.011)	(0.011)	(0.011)	(0.013)
College		0.009	0.010	0.008	0.010		0.010	0.010	0.008	0.011
		(0.010)	(0.010)	(0.010)	(0.011)		(0.010)	(0.010)	(0.010)	(0.011)
FatherEdu		-0.003**	-0.003**	-0.003**	-0.002*		-0.003**	-0.003**	-0.003**	-0.002*
		(0.001)	(0.001)	(0.001)	(0.001)		(0.001)	(0.001)	(0.001)	(0.001)
EmployerSize		-0.004	-0.004	-0.004	-0.005		-0.004	-0.004	-0.004	-0.005
		(0.003)	(0.003)	(0.003)	(0.004)		(0.003)	(0.003)	(0.003)	(0.004)
Age		-0.002	-0.001	-0.001	-0.007		-0.002	-0.001	-0.001	-0.007
		(0.010)	(0.010)	(0.010)	(0.011)		(0.010)	(0.010)	(0.010)	(0.011)
Age^2		-0.000	-0.000	-0.000	0.000		-0.000	-0.000	-0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)
Switching point	**69.888%**	**66.033%**	**65.934%**	**65.193%**	**65.337%**					
F stat of ($\beta_1 + \beta_3 = 0$)						**29.097*** **	**16.062*** **	**16.497*** **	**17.147*** **	**10.758*** **
State FE	NO	YES	NO	NO	NO	NO	YES	NO	NO	NO
Year FE	NO	YES	NO	NO	NO	NO	YES	NO	NO	NO
Industry FE	NO	YES	YES	NO	NO	NO	YES	YES	NO	NO
Occupation FE	NO	YES	YES	NO	NO	NO	YES	YES	NO	NO
State×Year FE	NO	NO	YES	YES	NO	NO	NO	YES	YES	NO
Industry×Occupation FE	NO	NO	NO	YES	YES	NO	NO	NO	YES	YES
County×Year FE	NO	NO	NO	NO	YES	NO	NO	NO	NO	YES
Observations	51,127	51,127	51,127	51,127	51,127	51,127	51,127	51,127	51,127	51,127
R-squared	0.005	0.164	0.175	0.178	0.359	0.003	0.164	0.175	0.178	0.359

Table B5: First stage of 2SLS

This table reports the the first stage of the two-stage least squares (2SLS) regressions. LTV^2 is the square of LTV. X^{LTV} in columns (3) and (4) is an interaction term, defined as $(LTV - 0.48) \times D^{LTV}$, where D^{LTV} is an indicator of whether the respondent has a LTV that is larger than 0.48. X^{LTV} in columns (7) and (8) is an interaction term, defined as $(LTV - 0.47) \times D^{LTV}$, where D^{LTV} is an indicator of whether the respondent has a LTV that is larger than 0.47. Cohort FE are indicators of the survey year when the respondent becomes the owner of the house. Control variables corresponding to column (5) of Table 2 are included. Standard errors are clustered at the state-year level and reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var.	*Training*				*Labor Supply*			
	LTV	LTV^2	LTV	X^{LTV}	LTV	LTV^2	LTV	X^{LTV}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SLTV	-0.041	-0.217***	0.222***	0.059***	-0.041	-0.217***	0.220***	0.061***
	(0.057)	(0.071)	(0.023)	(0.012)	(0.057)	(0.071)	(0.024)	(0.012)
$SLTV^2$	0.383***	0.643***			0.383***	0.643***		
	(0.071)	(0.090)			(0.071)	(0.090)		
X^{SLTV}			0.220*	0.363***			0.216**	0.348***
			(0.112)	(0.061)			(0.103)	(0.057)
Cragg-Donald Wald F Stat	19.455		32.179		19.455		32.670	
Controls	NO	YES	NO	YES	NO	YES	NO	YES
Cohort FE	YES	YES	YES	YES	YES	YES	YES	YES
State×Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry×Occupation FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	16,356	16,356	16,356	16,356	16,356	16,356	16,356	16,356

Table B6: Additional robustness tests

Panel A reports estimates of baseline regressions based on reconstructed total debt and total assets using balance sheet items that are surveyed in all interviews. Total debt now includes mortgage debt on residential property, auto debt, and debts on farm/business/other property. Total assets now include the market value of residential property, vehicles, farm/business/other property, stock/bonds/mutual funds, and amount of savings account. Panel B reports baseline regressions after dropping households that have outstanding student loans during survey years 2004, 2008, 2010, 2012, or 2014. Columns (1) and (2) report the quadratic model. Columns (3) and (4) report the linear piece-wise regression model. All other variables are defined in Table 1 and Table 2. Each regression includes a separate intercept. Standard errors are clustered at the state-year level and reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively

Panel A. Using balance sheet items consistently surveyed

Dep. Var.	*Training*			
	Quadratic Model		Piece-wise Linear Regression	
	(1)	(2)	(3)	(4)
Leverage (β_1)	0.062***	0.068***	0.035***	0.038***
	(0.011)	(0.012)	(0.005)	(0.006)
Leverage^2	-0.041***	-0.046***		
	(0.011)	(0.012)		
$X^{Leverage}$ (β_3)			-0.067***	-0.084***
			(0.020)	(0.021)
Controls	YES	YES	YES	YES
State FE	NO	NO	NO	NO
Year FE	NO	NO	NO	NO
Industry FE	NO	NO	NO	NO
Occupation FE	NO	NO	NO	NO
State×Year FE	YES	NO	YES	NO
Industry×Occupation FE	YES	YES	YES	YES
County×Year FE	NO	YES	NO	YES
Observations	50,648	50,648	50,648	50,648
R-squared	0.045	0.247	0.045	0.247

Panel B. Excluding households with student loans

Dep. Var.	*Training*			
	Quadratic Model		Piece-wise Linear Regression	
	(1)	(2)	(3)	(4)
Leverage (β_1)	0.063***	0.075***	0.035***	0.042***
	(0.010)	(0.011)	(0.005)	(0.006)
Leverage^2	-0.037***	-0.046***		
	(0.007)	(0.008)		
$X^{Leverage}$ (β_3)			-0.067***	-0.085***
			(0.014)	(0.016)
Controls	YES	YES	YES	YES
State×Year FE	YES	NO	YES	NO
Industry×Occupation FE	YES	YES	YES	YES
County×Year FE	NO	YES	NO	YES
Observations	43,978	43,978	43,978	43,978
R-squared	0.049	0.263	0.049	0.263