Household Debt Overhang and Human Capital Investment

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Abstract

Unlike labor income, human capital is inseparable from individuals and does not accrue to creditors at default. As a consequence, 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 leverage, human capital investment tails off less aggressively as leverage 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 individually identifiable data, we provide empirical support for the model.

Keywords: Household leverage, 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: Because part of labor income accrues to creditors via liability repayment, particularly during default, such wealth transfer discourages households from investing effort in gaining earnings (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 at default (Hart and Moore, 1994) since attained knowledge can not be transferred from individuals to creditors. Therefore, different from labor supply, human capital investment allows households to generate incremental income after default by utilizing their acquired knowledge and skills. This preserved value of human capital investment 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 leverage can feedback into human capital investment decisions.

In this paper, we focus on one type of human capital investment – households' labor skills acquisition after they start their career – to examine how debt affects the incentives in acquiring skills versus labor supply, and how the two actions are interconnected. 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 government policies that can enhance social welfare.

We develop a dynamic model featuring inseparability of human capital at default and an inter-temporal 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 leverage increases, a larger fraction of its income accrues to creditors and the house-

[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.

hold's overall level of consumption declines. In this case, the marginal utility of consumption rises and the benefit of acquiring human capital to raise consumption grows. Under this *decreasing marginal utility* force, effort in skills acquisition is increasing in household leverage.

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 continue to fulfill debt obligations (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 leverage. This second force becomes dominant when household leverage surpasses a threshold and default becomes imminent. The two forces together yield a hump-shaped relation between leverage and skills acquisition.

Labor supply exhibits a similar hump-shape with respect to household leverage – reflecting the interplay of *decreasing 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 much lower level of household leverage, 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 exhibits a greater extent of distortion than skills acquisition, attributed 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 increases households' marginal productivity, this effort is only valuable if households anticipate supplying labor in the future. As such, we find that when labor supply is expected to collapse at high levels of leverage, it brings down 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. Therefore, public policies intended to incentivize the supply of labor through balance sheet interventions (e.g., limiting household debt or making the bankruptcy code more debtor friendly) 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 – much like the case of transitory income from labor supply, the pattern of skills acquisition with household leverage 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 protect themselves from uncertainty, but also increase labor supply accordingly to materialize the premium for skilled labor.

In the next part of our study, we take these theoretical predictions to data. Testing these predictions necessitates information to identify individuals' labor skills acquisition and detailed 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. It provides each household's itemized balance sheets and therefore allows us to construct financial leverage.

Importantly, NLSY79 contains information about individuals' participation in training programs after they start their careers. On-career training creates opportunities for individuals to advance their professional standing, and thus represents well-defined labor skills acquisition (Clifford and Gerken, 2021). By observing whether an individual participates in training and the duration of such participation, we can qualify and quantify skills acquisition.

Several features of the training information are critical to fitting our theoretical framework. First, NLSY79 details the initiation process of training, which allows us to observe whether the training is initiated by an individual or requested by her employer. As such, we can differentiate an individual's voluntary decision – corresponding to the modeled skills acquisition incentive – from obligatory behavior to fulfill employers' training 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, 2020; Lochner and Monge-Naranjo, 2012). In this case, we can isolate how household leverage affects labor skills acquisition by shaping individuals' incentives – the center of our model – instead of their financial limitations. Lastly, the NLSY79 provides each household's week-by-week labor records, which we use 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 baseline hump-shaped relation between household leverage and labor skills acquisition. Specifically, training participation initially increases with leverage; it peaks around 80% of household debt-to-asset ratio before switching to declining with leverage. Labor supply shows a similar hump shape. However, it begins to decrease with household leverage at as early as 70% of debt-to-asset ratio (an earlier manifestation of debt overhang), and the speed of decrease is more rapid than skills acquisition (a sharper manifestation of debt overhang) – both matching the model prediction.

In addition, this hump shape exhibits significant variation in the cross-section as predicted by the comparative statics. Because we observe the starting period of each individual's training program and his/her annual wages surrounding the training, we can proxy for the payoff structure of acquired skills based on whether incremental wages follow a front-loaded (higher depreciation rate) or a more uniform (lower depreciation rate) distribution. 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 leverage, and it drops at a faster rate. This result reinforces the role of human capital's inalienability in driving our results. In a similar vein, we use the volatility of individuals' earnings to proxy for the uncertainty of their income, and observe patterns that closely match the model predictions. Higher volatility of individuals' earnings induces household to increase both skills acquisition and labor supply in order to counter the reduced utility due to greater labor income 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 could explain the relation between household leverage 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 *decreasing* *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, and employer characteristics, among others. 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 leverage and skills acquisition. In addition, for any unobservable confounding factors to explain our results, they must correlate with household leverage in such a way as to differently affect training participation depending on the level of leverage. That is, if certain characteristics encourage households to enroll in training at a lower leverage, then the effect of these characteristics must reverse when leverage becomes higher. To further filter out such possibilities, we follow Bernstein (2021) and perform an instrumental variable analysis 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 leverage 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 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 leverage. 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

[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.

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 leverage 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's balance sheets and skills acquisition.

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.[3] 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 in our context 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 also apply to an extended corporate model, in which the

[3]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).

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 leverage 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 (Di Maggio, Kalda, and Yao, 2019; Ferreira, Gyourko, and Tracy, 2010; Bernstein and Struyven, 2022; Ferreira, Gyourko, and Tracy, 2011; Brown and 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 household 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 leverage) reduces 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 leverage's positive and negative effects co-exist in the context of households' human capital investment. Their presence depends on the regimes of leverage 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 leverage 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:

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

Here 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 his 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. For instance, learning a specific software becomes less useful when the software becomes obsolete over time. Naturally, the depreciation rate varies across different skills, and in later analyses, we study the comparative statics of our model with respect to $\rho > 0$.

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 rate $r > 0$ in order to smooth consumption. Household savings S_t evolve according to:

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

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

$\tau = \inf\{t : S_t \le \underline{s}K_t\}$ denotes the time when households reach their borrowing limit $\underline{s}K_t < 0$, which for tractability reasons is assumed to be proportional to current hourly income. Once the borrowing limit $\underline{s}K_t$ is reached, the household is forced into default. 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 $S_t \ge 0$). This formulation reflects the observation that interest rates for household savings are lower than the those of household debt.

Prior to default, equation (5) states that wages are deposited in the savings account. Savings accrue interest at rate r and are used to pay for household consumption. Upon default, equation (6) states that households discharge all of their debts and are henceforth shun from credit markets, forcing their savings (and debts) to be equal to zero. This equation reflects that (i) a majority of households going through bankruptcy file Chapter 7 – in which case debtors forfeit nonexempt assets in exchange for a discharge of eligible debts, and (ii) default often hurts debtors' credit worthiness, thereby limiting their borrowing capacity (e.g., Dobbie and Song (2015); Dobbie, Goldsmith-Pinkham, Mahoney, and Song (2020); Kleiner, Stoffman, and Yonker (2021)).[4]

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. Different from financial asset returns that accrue to creditors upon default, acquired skills are inseparable from the households at default and preserve their value post default. In the value function, the acquired

[4] 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 exchange of protection of most assets.

labor skills increase hourly wages $K_t \geq 0$ prior to default, and this higher hourly wages carry over to the post-default period, reflecting such inseparability of human capital at default. This feature, as we discuss later, is key for the different relations between household leverage 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 his 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.[5] In Appendix A.3, we 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 (e.g., Bos, Breza, and Liberman, 2018), or because of wage 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 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).

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]

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 become hand-to-mouth, his consumption equals his wages. Effort in acquiring labor skills is inversely proportional

[5]The authors explain that this finding 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).

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

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) is separable from the household at default since it 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:

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

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 GBM dynamics for hourly income, the value function displays homogeneity of degree one. In Appendix A.2, we show that it is possible to numerically characterize the value function and optimal policies as a function of a single state variable L_t, which we interpret as household leverage:

$$L_t = L(S_t, K_t) = \frac{100}{\underline{s}} \frac{S_t}{K_t}. \tag{12}$$

We normalize household leverage to be 100 at default and equal to 0 when the household pays all his debts (i.e., when savings become non-negative). In the next section we explore the empirical implications of our model for the relation between household leverage and skills acquisition. With a slight overload of notation, we denote labor skills acquisition as a function of leverage as $a(L)$ and labor supply as $l(L)$, where

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

2.2 Optimal skills acquisition policy

The solid lines in Figure I illustrate the baseline results of the model. Panel A shows that there is a hump-shaped relation between household leverage and skills acquisition: increasing leverage initially encourages the household to exert higher effort in acquiring labor skills, but discourages it from doing so after leverage 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 leverage 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 in order to raise consumption is large. Under this force, effort in skills acquisition increases with household leverage. When leverage is at a relatively low level, this force, which we refer to as the *decreasing marginal utility*, dominates.

However, when household leverage 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 its effort in acquiring labor skills. Because the household discharges its debts 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 is imminent. This *debt overhang* force makes effort a decreasing function of household leverage, and it is dominant when leverage reaches a high level.[7] The combination of the two forces renders skills acquisition hump-shaped in leverage, as shown in Panel A.

To assess the extent of distortion in households' skills acquisition driven by debt overhang,

[7] 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.

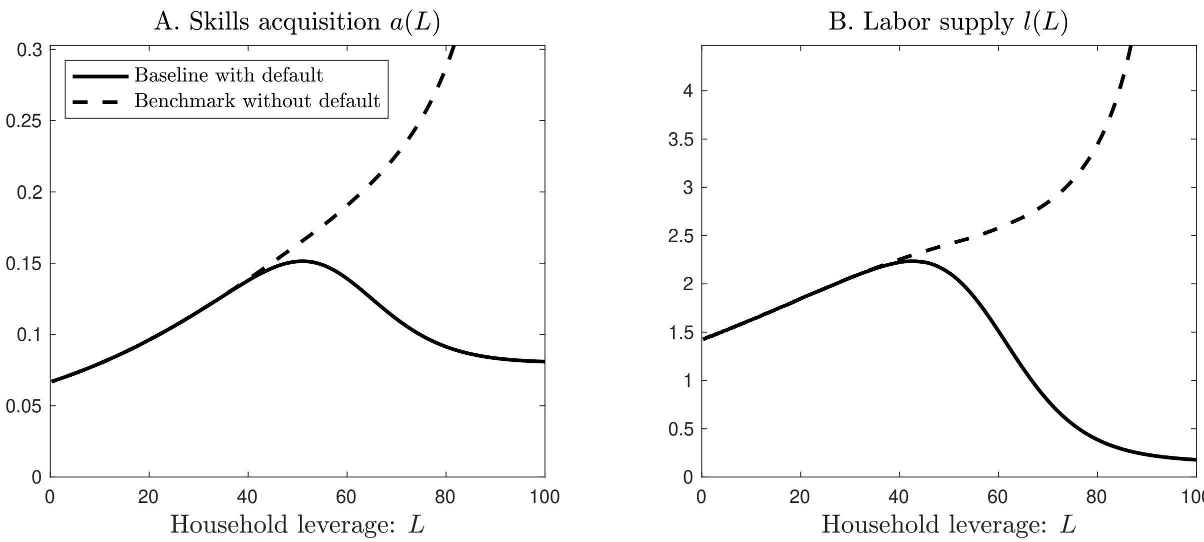

Figure I: **Effort in skill acquisition and household scaled value function.** Parameter values are $\delta = 0.05, r_B = 0.08, r_S = 0.01, \theta_a = 300, \theta_l = 3, \theta_{al} = 0, \rho = 0.15, \sigma = 0.3$.

we include a dashed line in Panel A depicting the benchmark policies in the absence of default.[8] Because the household always repays debt in this case, it becomes the residual 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 leverage is low – when default (and debt overhang) is not an imminent consideration. However, as leverage increases to a higher level, the dashed line does not decline like the solid line does. This is because without debt overhang, only the decreasing marginal utility force is at play, rendering skills acquisition an increasing function of leverage. As such, the wedge between the dashed and solid lines captures the distortionary impact of debt overhang on $a(L)$. As expected, when leverage increases, the debt overhang force becomes increasingly dominant, augmenting the extent of the distortion.

2.3 Contrast between skills acquisition and labor supply

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

First, the peak in labor supply occurs at a lower level of leverage than the peak of skills acquisition – an earlier manifestation of debt overhang. Second, after leverage reaches the threshold,

[8]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.

labor supply decreases at a faster rate than skills acquisition – a sharper manifestation of debt overhang. These dissimilarities are a consequence of the *inseparability* of human capital at default. That is, in the face of default, the household will still reap the benefits of acquired skills and enhanced human capital, as reflected in the higher wages post-default (equation (7)). By contrast, labor supply generates only transitory income, and once it is used to pay creditors, no additional benefits accrue to the household. The more resilience of skills acquisition to debt overhang in turn drives the asymmetric manifestation of debt overhang on skills acquisition versus labor supply. In Section 4.1, we provide empirical evidence that the earlier and sharper manifestation of debt overhang for labor supply is born in the data.

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 leverage) 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.[9]

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 II, we illustrate the role of this dynamic complementarity by changing the degree of substitutability between effort and labor supply. Panels A and B show the optimal policies of the two activities when the costs are independent $\theta_{al} = 0$ (black lines) versus when they are substitutes $\theta_{al} > 0$ (orange lines), respectively.

We start with Panel B. This panel shows that for high leverage (> 40), the supply of labor collapses more quickly for $\theta_{al} > 0$ (the orange line) than for $\theta_{al} = 0$ (the black 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 at bankruptcy 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, we do not see such a fast collapse for skills acquisition during high leverage, as shown in Panel B.

[9] 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", then the thrust of our main findings, i.e., that human capital investment is more resilient to debt overhang than labor supply remains qualitatively robust.

Importantly, this decision on labor supply 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 orange line ($\theta_{al} > 0$) is below the black line ($\theta_{al} = 0$) for all levels of leverage. It suggests that in the case of substitution, the anticipation that the household will not supply much labor in the future discourages it from acquiring human capital ex ante.

This finding implies 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 leverage 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 II suggests 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).

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 result for the case of $\theta_{al} < 0$ as a supplementary analysis to reinforce the intuition we discussed for $\theta_{al} > 0$.

Several differences emerge. Unsurprisingly, Panel D shows that the decline in labor supply for high leverage (> 40) is less prominent under complementarity ($\theta_{al} < 0$) than the black 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, thus encouraging the household to acquire labor skills in the first place – the reverse of the "back-propagation" effect documented for the case

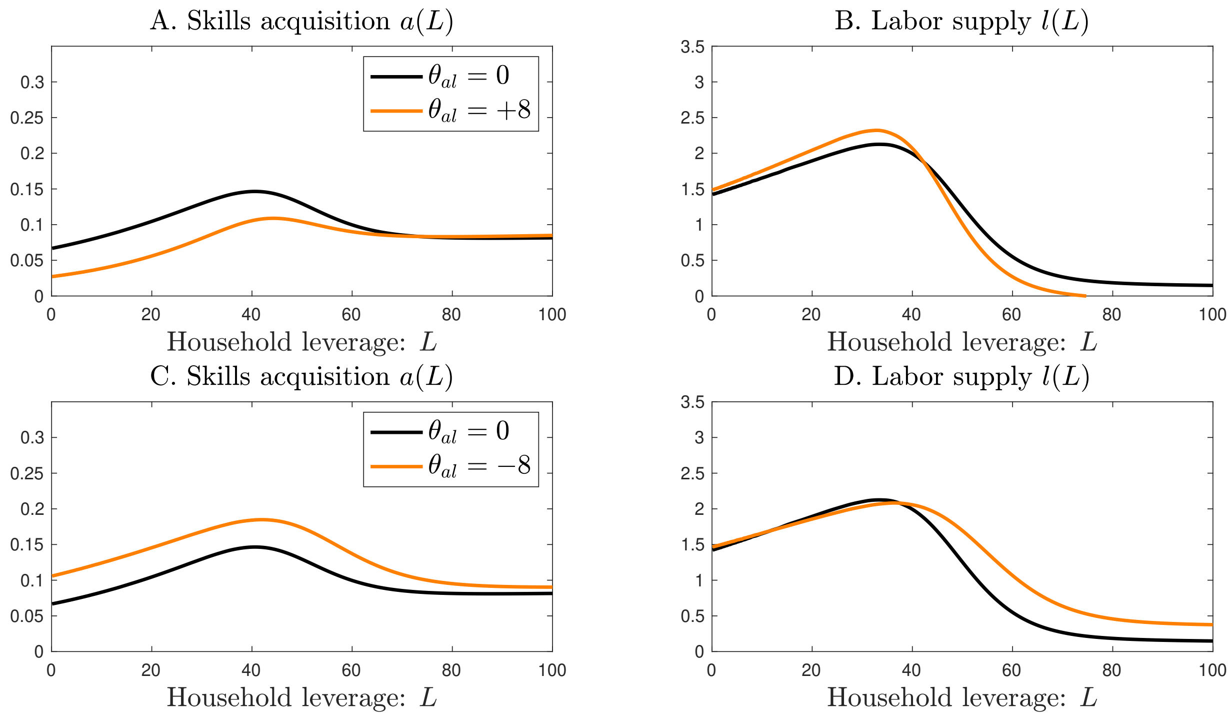

Figure II: **Illustration of dynamic complementarity between human capital and labor supply.** Other parameter values are $\delta = 0.05, r_B = 0.08, r_S = 0.01, \theta_a = 300, \theta_l = 3, \rho = 0.15, \sigma = 0.3$.

of substitution ($\theta_{al} > 0$). Indeed, we see that in Panel C, the orange line lies above the black line, in contrast to Panel A.

2.5 Comparative statics

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

2.5.1 Comparative statics with respect to ρ.

To fix ideas, Panel A of Figure III illustrates the effect of different depreciation rates on 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. When the household is close to default, this larger share will then be allocated to paying back debt, creating a greater transfer of wealth from the household to lenders. In the extreme case when skills depreciate fast enough, all benefit of skills acquisition will be materialized immediately and thus, forfeited to lenders upon default. In this limiting case, skills effectively lose their "inseparability", and becomes the same as labor supply.

Indeed, Panel B shows that for high leverage levels (close to default), skills acquisition declines more sharply when ρ is high (the orange line) than when ρ is low – much like the case of labor supply depicted in Panel B of Figure I. 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), we confirm such a pattern with respect to ρ in the data.

Panel B also shows that faster skills depreciation (i.e., the orange line) 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 the effort of acquiring skills less attractive. On the other hand, faster depreciation decreases household wealth, making the marginal utility of skills acquisition greater. 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 this additional income to optimally smooth its future consumption. Therefore, the incentive to learn 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.

2.5.2 Comparative statics with respect to σ.

Figure IV 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 leverage – 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

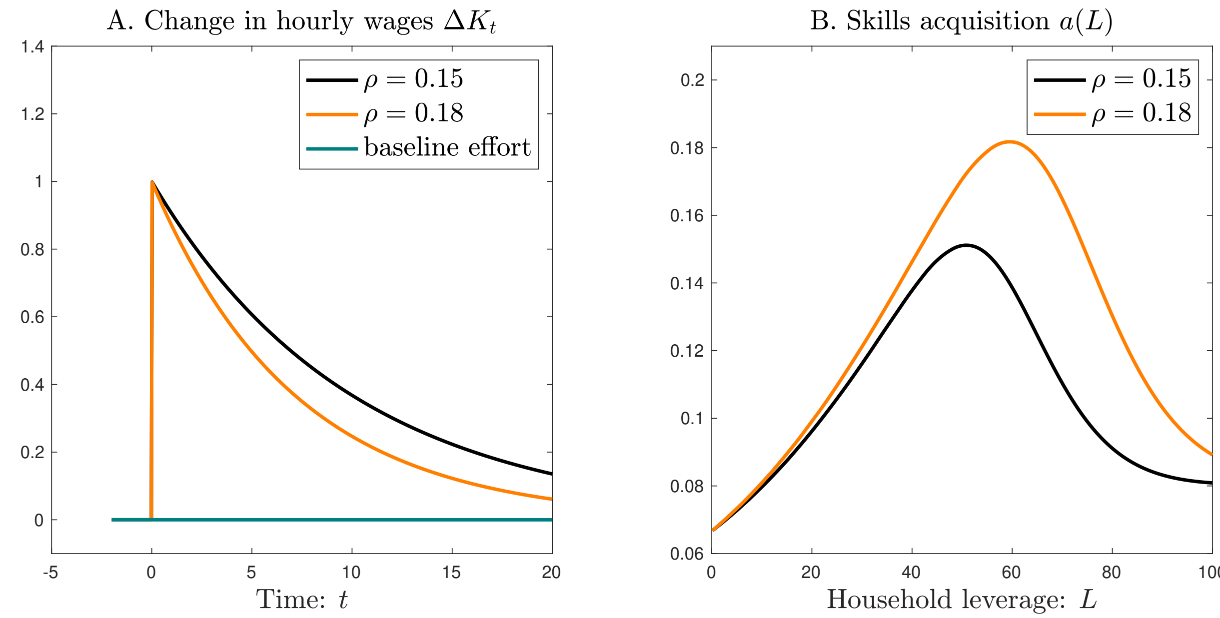

Figure III: **Comparative statics with respect to depreciation rate of labor skills parameter ρ and to hourly wage volatility σ.** Other parameter values are $\delta = 0.05, r_B = 0.08, r_S = 0.01, \theta_a = 300, \theta_l = 3, \theta_{al} = 0, \sigma = 0.3$.

averse household because uncertainty in earnings limits its ability to smooth out consumption. In response, the household needs to 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 Section 2.4. Higher volatility not only encourages skills acquisition out of the precautionary incentives, but also increases households' labor supply for a similar reason, as shown in Figure VI of Appendix A.4. 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

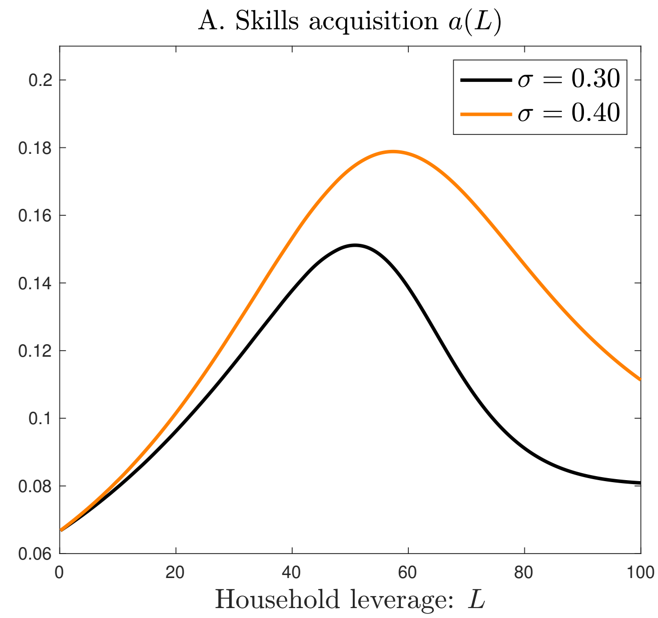

Figure IV: **Comparative statics with respect to hourly wage volatility σ.** Other parameter values are $\delta = 0.05, r_B = 0.08, r_S = 0.01, \theta_a = 300, \theta_l = 3, \theta_{al} = 0, \rho = 0.15$.

was conducted in 1979, when the respondents aged between 14 and 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 consists of 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 and household balance sheets. On-career training creates opportunities for individuals to advance their professional standing, and therefore represents well-defined labor skills acquisition. In each survey, respondents are asked to provide information about the training programs they have taken since the last interview. The information includes whether they have enrolled in any vocational or technical training designed to learn or improve job-related skills;[10] 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);[11] 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 critical to fitting our empirical analyses to the theoretical framework. First, because we observe whether training is initiated by individuals or requested by employers, we can differentiate individuals' incentive in skills acquisition – the focus of our model – from obligatory behavior to fulfil employers' 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 leverage inevitably correlates with financial constraints, that is, households with high (low) leverage are more (less) likely constrained, which can in turn affect their human capital investment decisions (e.g., Chakrabarti, Fos, Liberman, and Yannelis, 2020; Lochner and Monge-Naranjo, 2012). By focusing on self-requested and non-self-paid training participation, our empirical findings speak to how leverage affects skills acquisition through 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 who initiates training) becomes available. We therefore choose the year 1991 as the beginning of sample period.

3.3 Information on household leverage

NLSY79 collects 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

[10] More specifically, NLSY79 classifies individuals' 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.

[11] 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).

loans, and money owed to other individuals or entities. We define household leverage as the amount of total debt divided by the market value of total assets.[12]

Two points about the household balance sheet are worth noting. First, not all items listed above are surveyed in each interview. In Appendix B Table B1 and Table B2, we provide the breakdown of the items surveyed during each round. When calculating household leverage in a year, we use the items surveyed in that 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 balance sheet items consistently surveyed in all interviews (see Table B6 Panel A).

Second, in a few surveys 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 the 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)).[13] 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.

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

[12] By definition, our analyses will generate identical inferences if we alternatively calculate leverage as $\frac{Assets-Ddebt}{Assets}$, where the numerator corresponds to the parameter S in Equation (12). In untabulated results, we further define leverage as $\frac{Assets-Ddebt}{Wage}$, where the denominator is households' hourly wage, corresponding to the parameter K in Equation (12). Our main findings are similar.

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

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 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 worked 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 by a households' total work hours since last survey. This information allows us to contrast the relation between household leverage 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 available. 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), and the ones that are unemployed. This filter ensures that individuals in our sample are in the labor force and the decision of on-career training participation is relevant. We end up with 50,697 respondent-year observations representing 6,729 respondents. This sample constitutes the baseline for our analyses. In Appendix B Figure B1, we report the distribution of race and gender for this sample.

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 individuals' volunteer training decision from employer requirements, but also helps mute the effect of financial constraints (affordability) on the decision. We generate the 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 previous 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 worked since the previous interview. Alternatively, $LaborSupply$ (%) is the total number of hours scaled by available workday hours since the previous interview. These variables are the key dependent variables for our analyses.

The key independent variable is $Leverage$, defined as the ratio of total debt to total asset based on the household balance sheet information. 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), financial assets (such as stocks, bonds, and mutual funds). Table B1 and Table B2 in the Appendix report detailed components of debt and asset, respectively.

We construct a host of control variables. Age, $Male$, and $White$ indicate a respondent's age, gender, and ethnicity. $MaritalStatus$ indicates whether the respondent is married, and $College$ indicates whether the respondent has attended college. For financial status, we use the variable $WageIncome$ to capture a respondent's total wage, and the variable $TotalNetFamilyIncome$ to capture his/her annual net family income. To measure a respondent's family education background, we include $FatherEdu$ ($MotherEdu$), which equals the number of years of schooling a respondent's father (mother) has completed. $EmployerSize$ measures total number of employees of a respondent's current employer. 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, occupations, 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 a survey. We obtain a license to use this information from the Bureau of Labor Statistics.

3.7 Summary statistics

Table 1 Panel A reports the 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 a relatively infrequent activity, in our analyses we use $Training$ as the main variable of interest and confirm our findings using $TrainingTime$ in later robustness tests. *LaborSupply* (in hours) has a mean of 3,530 and a standard deviation of 1,585.[14] The working hours represent, on average, 33% of available hours (based on 24 hours a day and 5 days a week), as shown by *LaborSupply*(%).

The independent variable *Leverage* has a mean of 0.433 and a standard deviation of 0.355. Figure 1 plots patterns of *Leverage*, as well as the mortgage loan-to-value ratio (LTV) – an alternative measure of household leverage, across age cohorts. Household leverage fluctuates modestly around 0.4 and reaches its peak at 0.49 around age 45. LTV peaks at 0.65 around age 28 and declines to 0.41 around age 55. This observation is consistent with Figure B2 of the Appendix B, which plots the histogram of the age of first-time home buyers. It suggests that many homeowners purchase residential properties by the age of 30.

4 Empirical findings

4.1 The baseline hump-shaped relation

Our analyses start with examining whether the relation between household leverage and labor skills acquisition follows a hump-shape, as predicted by the theoretical model. Figure 2 presents a non-parametric graphical analysis. 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 calibration in Panel A of Figure I, skills acquisition exhibits a

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

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

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

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

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 to capture the hump-shaped relation between household 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, annual wage income, annual family net total income, education, marital status, and employer size. Time-invariant characteristics include gender, race, father's education, and mother'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 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, only about 16% of households take training programs more than once. As such, we do not observe sufficient time-series variation in the training participation for a given 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 labor 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 state and 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 greatly 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. 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 when leverage is low, 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. The switching points are about 80%, as reported below the variable coefficients.

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:

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

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 significantly positive β_1 would indicate that a positive relation between household leverage and the likelihood of taking on training when leverage is relatively low (below 80%). A negative β_3 would indicate that such a relation reverses as leverage surpasses the 80% level, and accordingly, $\beta_1 + \beta_3$ would indicate whether the reverse is sufficiently significant such that leverage considerably lowers the training likelihood in the regime of high leverage. Taken together, these observations would indicate a hump-shaped relation between household leverage and training, with approximately 80% of leverage as the switching point.

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), which 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 leverage is associated with 1.1% increase in the likelihood of training participation when household leverage is below 80%; when leverage is above 80%, a one-standard-deviation increase in leverage is associated with 1.0% decrease in the likelihood of training participation. In comparison, the sample average of training participation is 8.8%, as shown in Table 1 Panel A.

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, 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 a sharper manifestation of debt overhang, compared to the case of 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 model support the non-monotonic effect of household leverage on labor skills acquisition, and the contrast between skills acquisition and labor supply due to the inseparability attribute of human capital, as predicted by our model.

4.2 Heterogeneity of baseline hump-shaped relation with respect to ρ

We next examine cross-sectional variations of the baseline hump shape between household leverage and skills acquisition, based on the comparative statics analyses in Section 2.5. We start with ρ – the degree of skills depreciation. We employ two complementary approaches to empirically proxy for skills depreciation, first based on the skills' exposure to technology inspired by recent literature (e.g., Kogan, Papanikolaou, Schmidt, and Seegmiller (2022)), and second based on changes in wage path as modeled in Section 2.5.2.

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 a greater degree of skills depreciation. This channel is particularly germane for our setting because the sample individuals – aged in their twenties during 1980s – underwent the information and communication technology revolution thanks to the fast growing utilization of internet. Therefore, as a first approach, we capture the degree of skills depreciation based on individuals' exposure to the computer and information technology (CIT).

Specifically, for each training program, the NLSY79 specifies type of skills to be acquired. We identify a training program as being exposed to CIT if the acquired skills include "computer skills."[15] We then aggregate such training level exposure to the occupation level by calculating the percentage of CIT-exposed training programs taken by 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 1) it reduces idiosyncratic factors that

[15] Other types of skills include Operate/repair equipment, Read/white/math, Teamwork/problem solve, Management skills, Statistical quality control, New information system, and New product service.

drive individuals' choice of certain training programs and thus their CIT exposure, and 2) we expect that variation in skills acquisition 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 highest CIT exposure and thus a higher 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 regressions models of Table 2 in two sub-samples: for individuals working in occupations with a CIT exposure above the sample 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 black line corresponds to the quadratic specification (column (1) of Table 2), and the dotted orange 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, for high leverage levels, the orange line in Figure 4 declines more sharply than the black line – i.e., sharper manifestation of debt overhang. The switching point in this case also appears at a lower level of leverage – i.e., earlier manifestation of debt overhang. As discussed in Section 2.5.1, 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 for high deprecation stays above the black line across all levels of household leverage, reflecting the stronger incentive to make up for the lower utility due to fast depreciating skills, also consistent with the theoretical predictions in Section 2.5.1.

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 full set of controls as in columns (5) and (10) of Table 2. These additional specifications confirm our interpretation.

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 2.5.2. 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 III. 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 increments following training will 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 a few steps. We start by calculating 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 two ratios capture the wage growth rates following training completion.[16]

Figure B3 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 incremental value of human capital. The growth rate decays over time, suggesting that on average, the value of labor skills depreciates, consistent with the pattern illustrated in Panel A of Figure III.

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 $G_{diffavg}$=$Avg(G_{diff2}, G_{diff3})$.

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

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

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 (i.e., the aggregate level of wage decays post training is above the sample median) versus low depreciation, respectively. The solid black line corresponds to the quadratic specification, and the dotted orange 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 of baseline hump-shaped relation 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 2.5.2 and Figure IV) 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 annual wages in the sample period. As in Section 4.2, we then calculate the occupation level income volatility by taking the average of wage volatility of all individuals working in a given occupation, where occupations are classified based on the BLS. An individual is considered to face higher σ if he/she works in an occupation exhibiting income volatility above the sample median; otherwise, he/she is considered to face lower σ.

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

Figure 4 shows that in the presence of higher income uncertainty, the household exerts higher effort in skills acquisition. This is seen by the higher level of the orange line relative to the black line. These patterns closely match the orange (high σ) and black lines (low σ) in the model calibrations of Figure IV (Section 2.5.2). In Table XXX, we report the results of quadratic regressions with more control variables. Columns (1) to (3) include the case of high uncertainty, and columns (4) to (6) 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 *decreasing 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 to the negative effect of household leverage. As an additional contribution of our study, 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-years where 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 polynomial 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 certain 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 us 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 (individual) 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 households' incentives in skills acquisition. To the extent that individuals degree of connectedness may be correlated with leverage, the "opportunity cap" may confound 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 evolvement of households' mortgage loan-to-value ratios (LTV) – the largest part of households' overall 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 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 here so that it is not likely affected by household-specific factors. $\Delta HPI_{k,c,t}$ is the house price growth rate that varies at county-cohort-time level, calculated using Zillow home value index.[17] $\Delta Synthloan_{c,t}$ 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

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

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 can be 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 polynomial 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 the corresponding polynomial models.

The reduced form IV analyses confirm the hump-shape relation between skills acquisition or labor supply and household leverage. Based on the polynomial 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 at high level of leverage, suggesting the sharper manifestation of debt overhang. This observation is supported by 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 continues to decline considerably as shown in columns (7) and (8). These observations therefore confirm our baseline findings.

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

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

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

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

Both equations (19) and (20) are the first-stage regressions of the two-stage least squares (2SLS) analyses.[18] Equation (21) is the second-stage regression. The piece-wise models are constructed in a similar way.

As in Bernstein (2021), in all estimations, $\eta_{k,t}$ represents county×time fixed effects, and κ_c represents cohort fixed effects. The inclusion of cohort fixed effects ensures that the instrument $SLTV$ does not simply captures an earlier or later home purchasing time – which may directly correlate with an individual's career or life stages and in turn, the training decisions (i.e., a violation of the exclusion criterion). Similarly, region fixed effects ensure that variation of the instrument does not simply stem from different regions, which may vary in the availability of training opportunities, 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 leverage (captured by loan-to-value ratio) 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 polynomial 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.

Note that the coefficients of the instrumented dependent variables are generally larger than those in Table 2.[19] It suggests that certain unobservable factors associated with leverage – e.g., households' (in)ability to discover available training opportunities as previously discussed (despite their motivation 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.

[18] 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.

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

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 polynomial 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 increase 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 of 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.[20] In both panels, we report the polynomial and piece-wise models. Our results are robust.

6 Conclusion

In this paper, we study how household financial leverage affects human capital investment (captured by labor skills acquisition), 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 at default. This attribute

[20]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.

makes skills acquisition more resilient to “debt overhang” as household leverage rises. We show that labor skills acquisition is hump-shaped with respect to the level of household leverage, reflecting the interplay of two forces: *decreasing marginal utility* and *debt overhang*. Although labor supply exhibits a similar hump shape, it tails off more sharply as leverage 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 leverage propagates back in time distorting the skills acquisition decision ex ante.

We test our model using individually identifiable data from the NLSY79 survey. We identify labor skills acquisition based on individuals' voluntary participation in training programs. We calculate household leverage using detailed balance sheet information. We find strong empirical support for the model. When individuals face a relatively low level of leverage, increasing leverage initially encourages them to acquire labor skills, but this relation reverses after leverage reaches a certain level. Labor supply exhibits a similar hump shape but declines more sharply in the face of high leverage. Further, we find that the hump-shaped relation between leverage 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 leverage, 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 government policies, such as household debt forgiveness.

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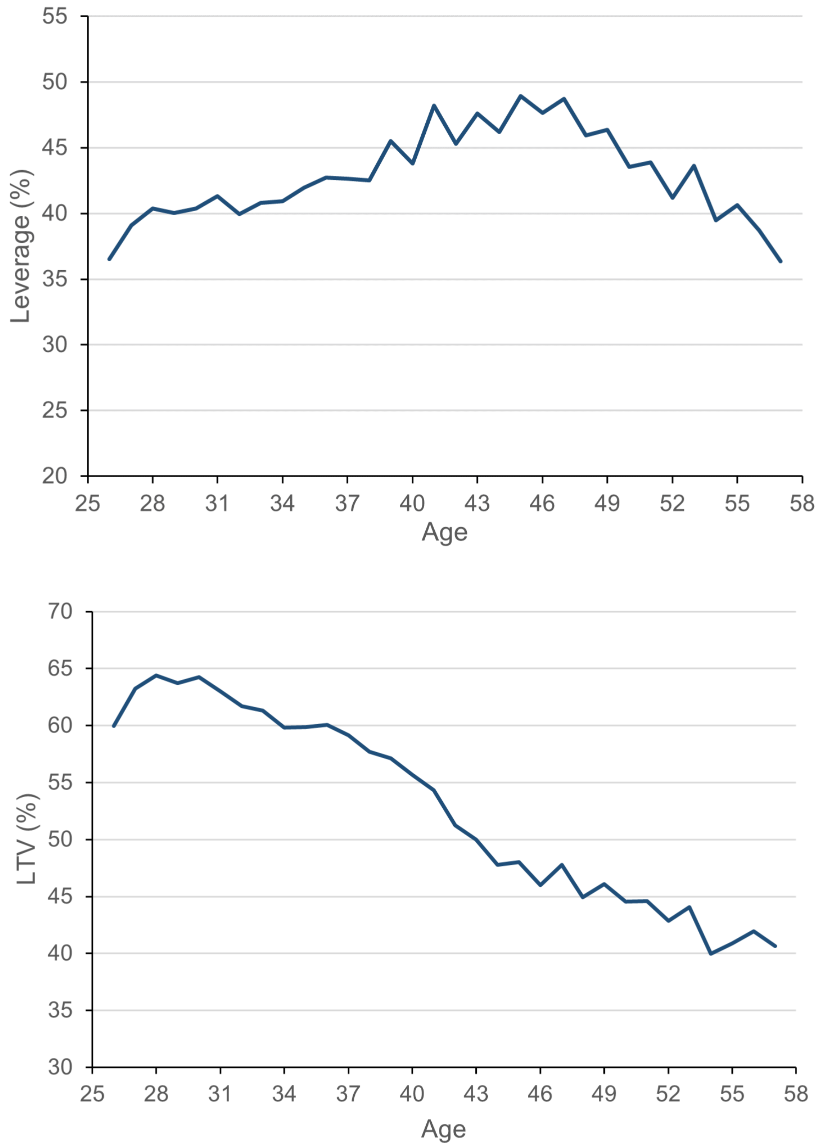
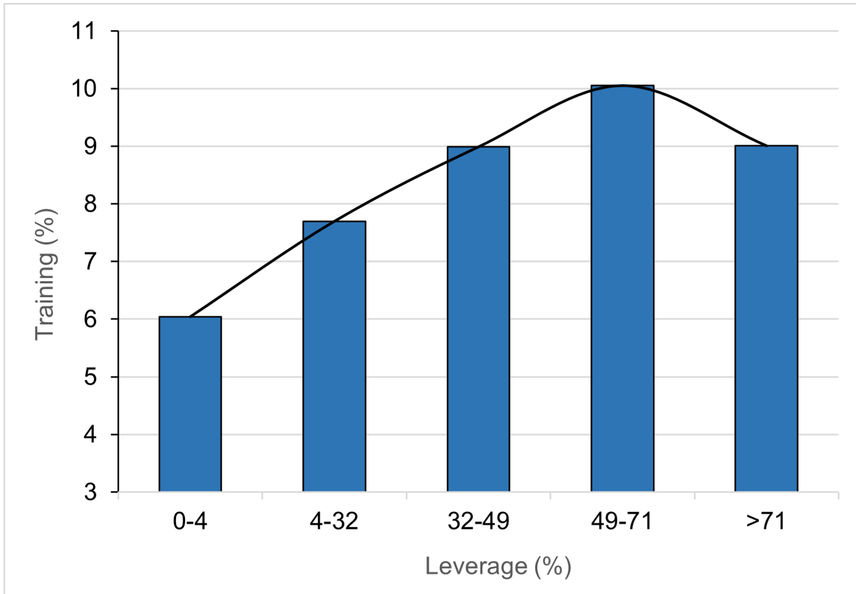


Figure 1: Household leverage over the life cycle

The top panel reports the mean of total leverage across age groups from 25 years old to 57 years old, among respondents in the 1979 National Longitudinal Survey. Total leverage is the ratio of total debt to total asset, defined in Section 3.6. The bottom panel reports the mean of mortgage loan-to-value ratio (LTV) across age groups from 25 years old to 57 years old. Loan-to-value ratio is the ratio of mortgage debt to the market value of the house, defined in Section 3.6.

(A) Skills Acquisition



(B) Labor Supply

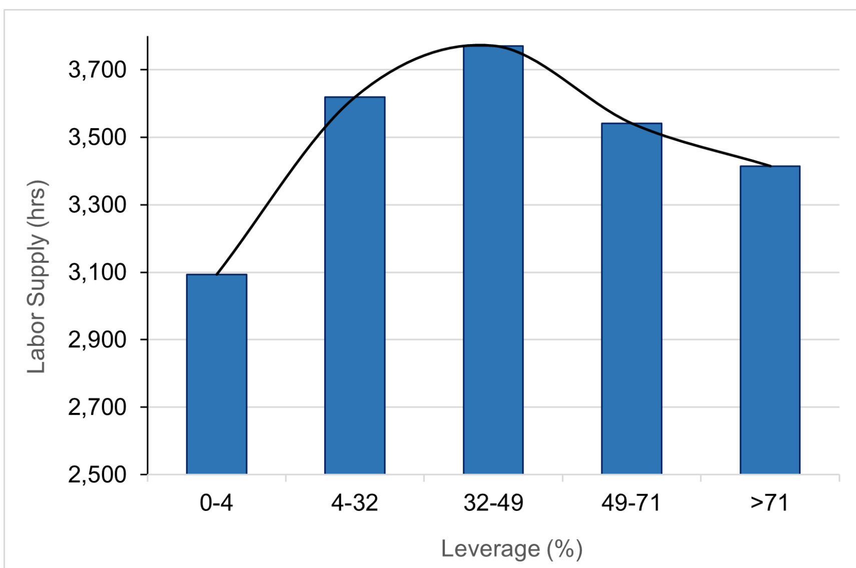


Figure 2: Skills acquisition and labor supply over leverage

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

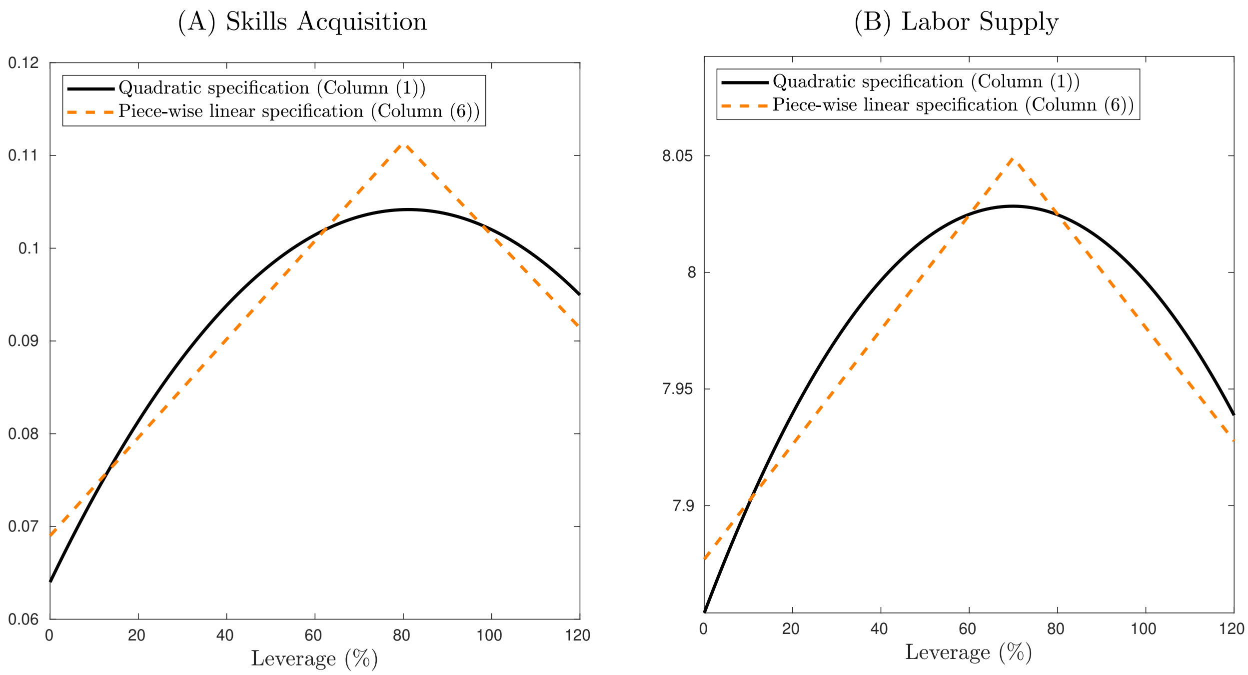


Figure 3: Skills acquisition and labor supply over leverage

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

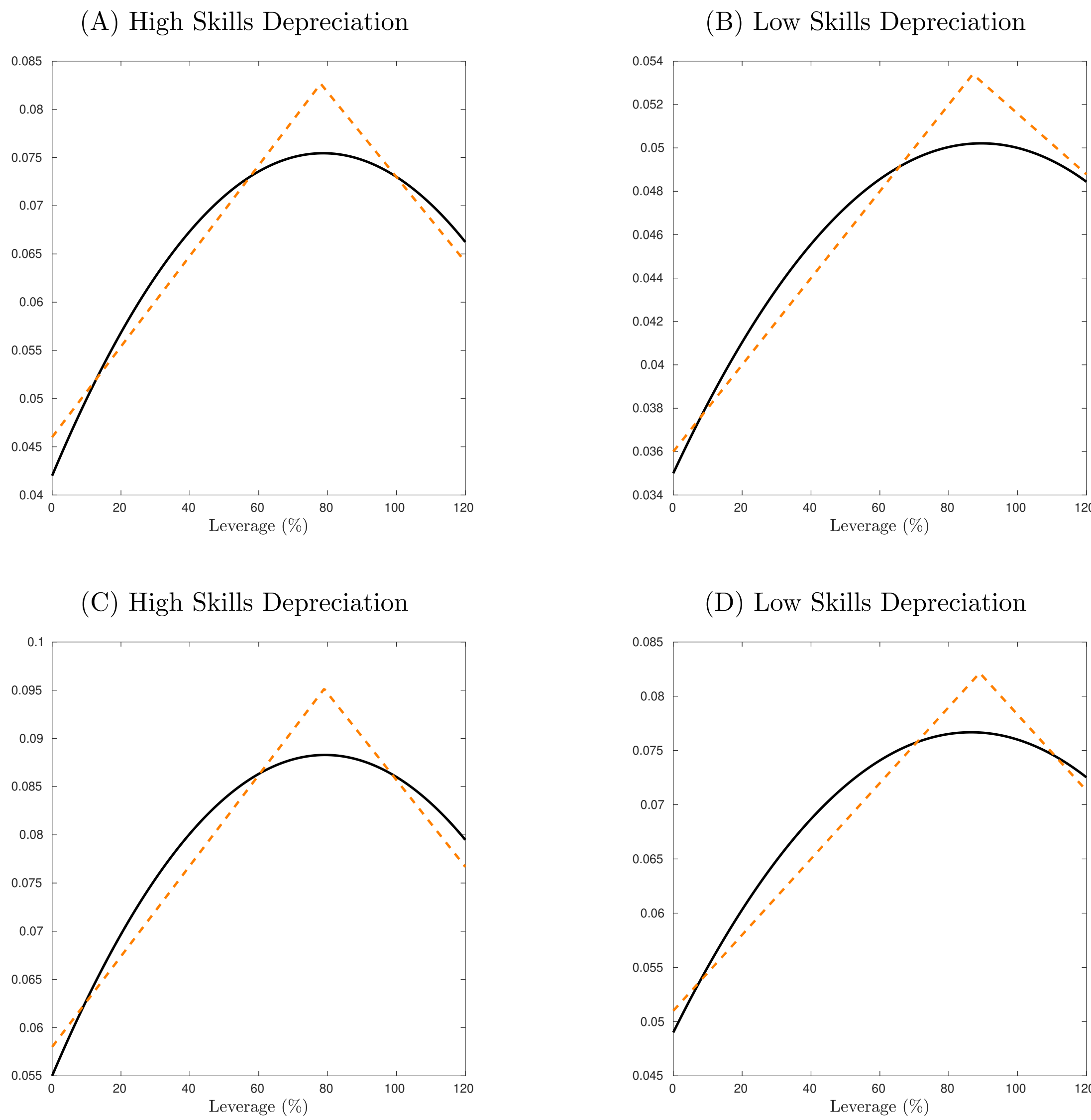


Figure 4: Heterogeneity with respect to the degree of skills depreciation

Panel A and B plot the pattern of skills acquisition with respect to household leverage, separately for individuals facing 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. Panel C and D follow a similar manner as in Panels A and B, but 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 solid black line corresponds to the quadratic specification (as in column (1) of Table 2), and the dotted orange line corresponds to the piece-wise specification (as in column (6) of Table 2)

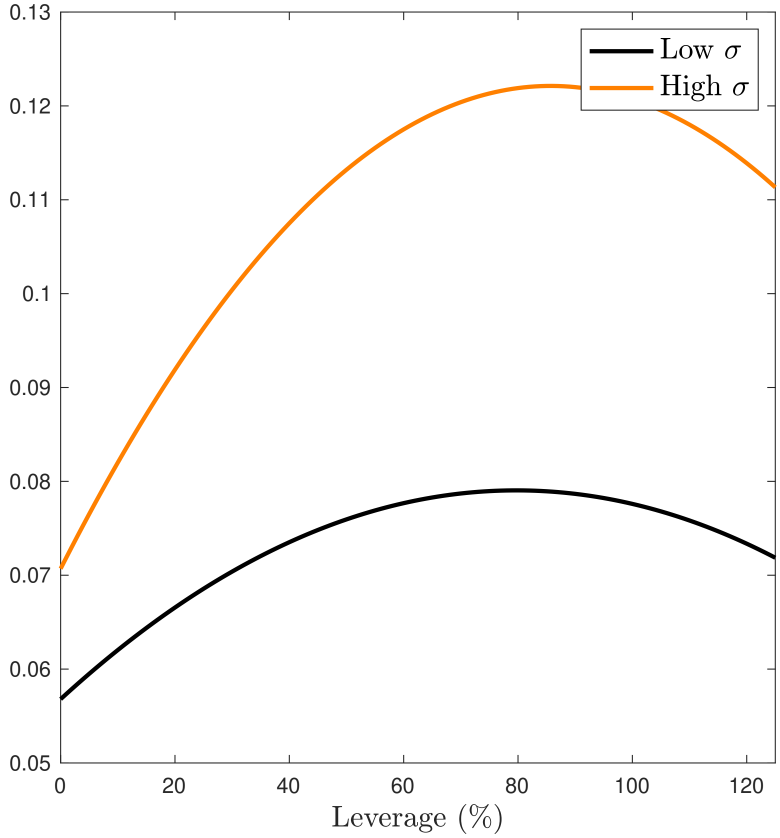


Figure 5: Heterogeneity with respect to labor income uncertainty

This figure plots the relation between household leverage and training participation for individuals with high (the orange line) versus low (the black line) income uncertainty. A household is considered to face high income uncertainty if its wage volatility is above the sample median; otherwise, the household is considered to face low income uncertainty. 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 full 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. *Leverage* is the ratio of total debt to total asset, defined in Section 3.6, measured at the previous interview. *LTV* is the mortgage loan-to-value ratio, 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. *WageIncome* is the respondent's total annual income from wages and salary at the previous interview (in $00,000). *TotalNetFamilyIncome* is the respondent's total annual net family income at the previous interview (in $00,000). *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* (*MotherEdu*) is the number of years of school that a respondent's father (mother) has ever 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, Conditional on training (hrs)	4,695	35.253	36.058	1	20	112
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	0.5	0	1	1
White (d)	50,697	0.647	0.478	0	1	1
WageIncome	50,697	0.33	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
MotherEdu (years)	50,697	11.24	3.088	5	12	16
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 trainings that are not self-paid. Columns (1)-(5) report the polynomial regression model as in equation (1) and Columns (6)-(10) report the piecewise linear regression model as in equation (2). *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 the logarithm of a respondent's age, annual wage income, annual family net total income, employer size, as well as gender, ethnicity, marital status, education, father's education, and mother's education. 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 state-year level and reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var.	*Training*									
	Quadratic Function					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***	0.070***	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***	-0.078***
						(0.012)	(0.012)	(0.012)	(0.012)	(0.013)
ln(Age)		0.017	0.015	0.013	-0.013		0.018	0.016	0.014	-0.012
		(0.019)	(0.019)	(0.019)	(0.022)		(0.019)	(0.019)	(0.019)	(0.022)
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	-0.005		-0.000	0.000	-0.000	-0.005
		(0.003)	(0.003)	(0.003)	(0.004)		(0.003)	(0.003)	(0.003)	(0.004)
WageIncome		0.042***	0.041***	0.040***	0.054***		0.042***	0.042***	0.040***	0.055***
		(0.010)	(0.010)	(0.010)	(0.011)		(0.010)	(0.010)	(0.010)	(0.011)
TotalNetFamilyIncome		-0.019***	-0.018***	-0.019***	-0.025***		-0.018***	-0.017***	-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	0.003
		(0.003)	(0.003)	(0.003)	(0.004)		(0.003)	(0.003)	(0.003)	(0.004)
College		0.019***	0.019***	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***	0.002***		0.001***	0.001***	0.001***	0.002***
		(0.000)	(0.000)	(0.000)	(0.001)		(0.000)	(0.000)	(0.000)	(0.001)
MotherEdu		-0.000	-0.000	-0.000	-0.001		-0.000	-0.000	-0.000	-0.001
		(0.001)	(0.001)	(0.001)	(0.001)		(0.001)	(0.001)	(0.001)	(0.001)
EmployerSize		0.006***	0.007***	0.006***	0.008***		0.006***	0.007***	0.006***	0.008***
		(0.001)	(0.001)	(0.001)	(0.001)		(0.001)	(0.001)	(0.001)	(0.001)
Switching point	**81.148%**	**83.784%**	**82.432%**	**83.333%**	**79.546%**					
F stat of ($\beta_1 + \beta_3 = 0$)						**27.524*** **	**9.049*** **	**8.426*** **	**8.103*** **	**15.818*** **
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 Section 4.2.1. 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 are 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 are those working in occupations with a lower CIT exposure. The detailed classification of CIT exposure are 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 specification as in in column (1) of Table 2), and columns (2) and (4) corresponds to the piece-wise specification as in in column (6) of Table 2). 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 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	**78.410%**		**87.130%**	
F stat of ($\beta_1 + \beta_3 = 0$)		**15.499*** **		**1.153**
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	**78.590%**		**89.080%**	
F stat of ($\beta_1 + \beta_3 = 0$)		**13.975*** **		**6.025*** *
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: Subsample results 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 his/her annual wage volatility is above the sample median; otherwise, the individual is considered to face low income uncertainty. Columns (1)-(3) report the polynomial regression model as in equation (1) and Columns (4)-(6) report the piecewise linear regression model as in equation (2). *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 definitions of the 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 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)	(5)	(6)
Leverage	0.120***	0.082***	0.101***	0.056***	0.033***	0.029**
	(0.011)	(0.012)	(0.015)	(0.011)	(0.012)	(0.014)
$Leverage^2$	-0.070***	-0.049***	-0.064***	-0.035***	-0.019**	-0.017
	(0.009)	(0.010)	(0.012)	(0.008)	(0.009)	(0.010)
Switching point	**85.714%**	**83.673%**	**78.906%**	**80.000%**	**86.842%**	**85.294%**
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	29,207	29,207	29,207	21,490	21,490	21,490
R-squared	0.004	0.053	0.319	0.001	0.055	0.368

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 polynomial regression and piecewise linear regression results, respectively, for the observations where respondents 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 50. Column (5)-(6) present the regression results for the observations where respondents have no 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***	0.036***	0.072***	0.040***
	(0.018)	(0.011)	(0.011)	(0.007)	(0.017)	(0.010)
Leverage^2	-0.057***		-0.039***		-0.050***	
	(0.012)		(0.008)		(0.013)	
$X^{Leverage}$ (β_3)		-0.096***		-0.066***		-0.088***
		(0.023)		(0.014)		(0.023)
Switching point	**76.316%**		**79.487%**		**72.000%**	
F stat of ($\beta_1 + \beta_3 = 0$)		**9.754*** **		**8.171*** **		**8.333*** **
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, where household leverage is instrumented using synthetic loan-to-value ($SLTV$) ratio. The construction of $SLTV$ is discussed in detail in Section 5.2. 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. Panel A reports the reduced form regressions of the instrumental variable analysis. Panel B reports the second stage of the two-stage least squares (2SLS) regressions. 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.

Panel A: Reduced form

Dep. Var.	*Training*				*Labor Supply*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LTV (β_1)	0.134**	0.131**	0.049*	0.050*	0.481***	0.478***	0.254***	0.254***
	(0.056)	(0.056)	(0.029)	(0.029)	(0.180)	(0.174)	(0.091)	(0.087)
LTV^2	-0.141**	-0.137**			-0.509**	-0.510**		
	(0.066)	(0.066)			(0.215)	(0.209)		
X^{LTV} (β_3)			-0.064	-0.064			-0.450***	-0.460***
			(0.053)	(0.054)			(0.167)	(0.163)
Switching point	**47.480%**	**47.820%**			**47.200%**	**46.860%**		
F stat of ($\beta_1 + \beta_3 = 0$)			**0.144**	**0.144**			**2.510**	**2.952***
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

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**	0.947**	0.380*	0.364*	3.575**	3.414**	1.703**	1.620**
	(0.488)	(0.463)	(0.213)	(0.203)	(1.572)	(1.453)	(0.724)	(0.666)
Instrumented LTV^2	-0.795**	-0.767**			-2.853**	-2.792**		
	(0.378)	(0.368)			(1.250)	(1.187)		
Instrumented X^{LTV} (β_3)			-0.623	-0.613			-2.982**	-2.966**
			(0.383)	(0.380)			(1.358)	(1.307)
Switching point	**62.820%**	**61.690%**			**62.670%**	**61.150%**		
F stat of ($\beta_1 + \beta_3 = 0$)			**1.352**	**1.323**			**2.960***	**3.242***
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 previous survey. Columns (1)-(3) report the polynomial regression model and Columns (4)-(6) report the piecewise 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 state-year level and reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var.	*TrainingTime*					
	Quadratic Function			Piecewise Linear Regression		
	(1)	(2)	(3)	(4)	(5)	(6)
Leverage (β_1)	0.285***	0.179***	0.208***	0.156***	0.100***	0.113***
	(0.027)	(0.029)	(0.033)	(0.015)	(0.016)	(0.019)
Leverage^2	-0.179***	-0.107***	-0.130***			
	(0.021)	(0.022)	(0.024)			
$X^{Leverage}$ (β_3)				-0.312***	-0.179***	-0.223***
				(0.041)	(0.041)	(0.046)
Switching point	**79.609%**	**83.645%**	**80.000%**			
F stat of ($\beta_1 + \beta_3 = 0$)				**22.880****	**5.871****	**10.485*****
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 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

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

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:

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

as expected.

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:

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

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,

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

Finally, we numerically solve differential equation (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: $\delta = 0.05, rB = 0.08, rS = 0.01, \theta_a = 300, \theta_l = 3, \theta_{al} = 0, \rho = 0.15, \sigma = 0.3$.

We conclude this Appendix by recalling the change of variables specified in equation (12). This

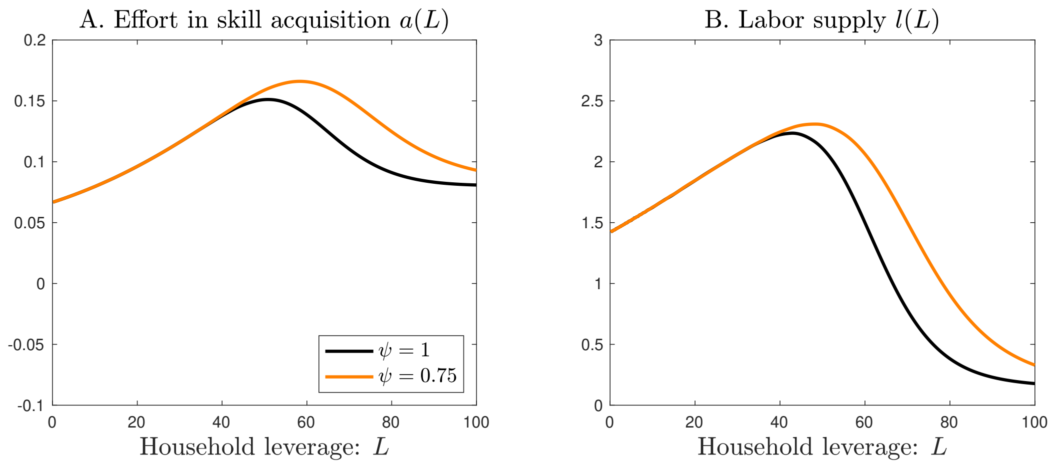


Figure V: **Robustness with respect to ψ.** Other parameter values are $\delta = 0.05, r_B = 0.08, r_S = 0.01, \theta_a = 300, \theta_l = 3, \theta_{al} = 0, \rho = 0.15, \sigma = 0.3$.

change of variables allows us to depict the scaled value function and the optimal controls as a functions of leverage in order to make our theoretical results directly comparable to our empirical findings.

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 that is 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.

In Figure V we depict in black the baseline case, in which human capital remains intact after default ($\psi = 1$), and in orange the case in which there is a 25% human capital decline post default

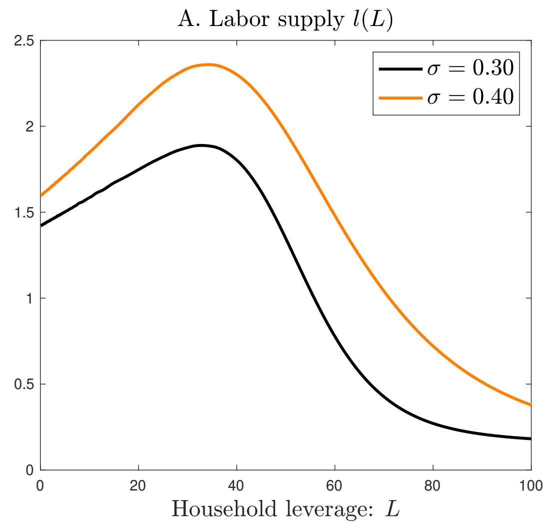


Figure VI: **Comparative statics with respect to hourly wage volatility σ.** Other parameter values are $\delta = 0.05, r_B = 0.08, r_S = 0.01, \theta_a = 300, \theta_l = 3, \theta_{al} = 0, \rho = 0.15$.

($\psi = 0.75$). 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, therefore, 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 Labor supply comparative statics

Figure VI 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.

B Appendix B

Figure B1: Household leverage over the life cycle

This figure plots the frequency by race and gender in each age group as of 1991 among respondents in the 1979 National Longitudinal Survey of Youth. 'WM' stands for white and male. 'WF' stands for white and female. 'NWM' stands for non-white and male. 'NWF' stands for non-white and female. The total number of respondents is 6,661. The frequency is 577 for the age 26 group, 909 for age 27, 919 for age 28, 938 for age 29, 925 for age 30, 796 for age 31, 713 for age 32, 718 for age 33, 166 for age 34.

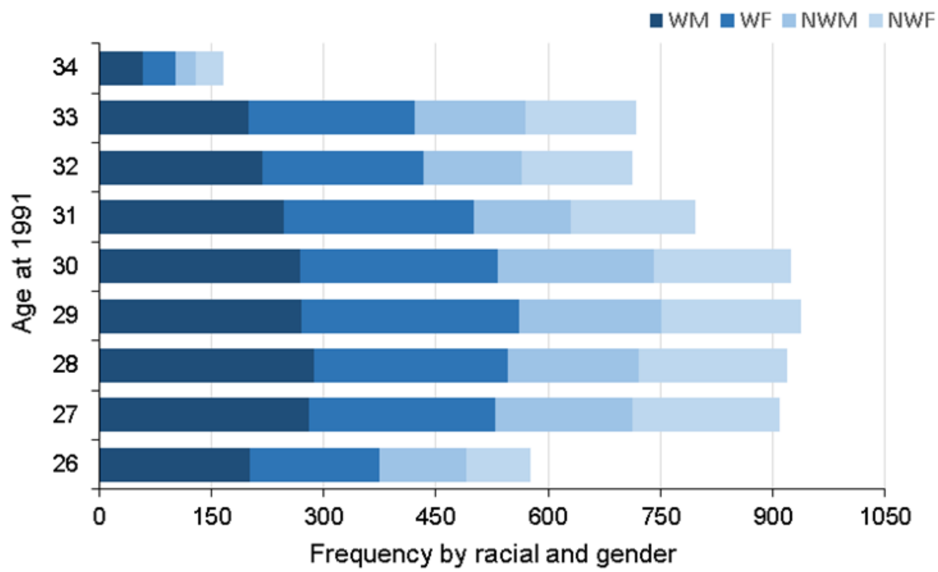


Figure B2: Histogram of the age of first-time house buyers

This figure plots the histogram of the age of first-time house buyers in the 1979 National Longitudinal Survey of Youth.

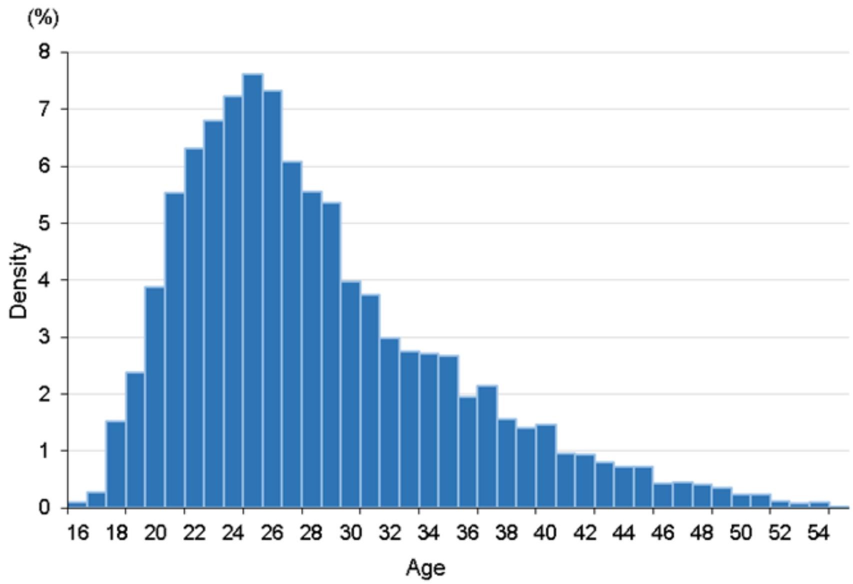


Figure B3: Hourly wage growth rate before and after training

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.

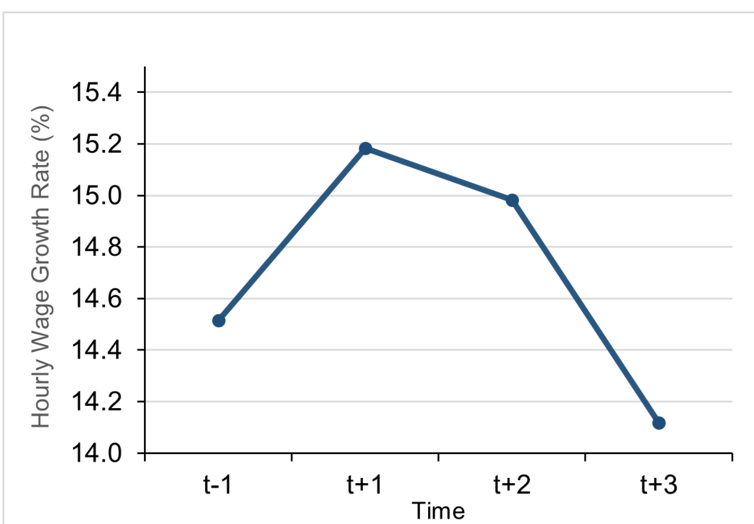


Table B1: Components of total debt

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.

Panel A: Exposure to technology

High Skills Depreciation Occupation	**Job Title Examples**	
Computer and Mathematical	Computer programmer	Statisticians
Architecture and Engineering	Architects	Biomedical engineers
Life, Physical, and Social Services	Economist	Biological scientists
Low Skills Depreciation Occupation		
Healthcare Support	Medical assistants	Nursing aides
Building, Grounds Cleaning and Maintenance	Janitors	Maids
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 breeders	Fisher
Life, Physical, and Social Services	Economist	Biological scientists
Computer and Mathematical	Computer programmer	Statisticians
Low Skills Depreciation Occupation		
Sales and Related	Retail salespersons	Insurance sales agents
Lawyers, Judges and Legal Support Workers	Lawyer	Judge
Healthcare Support	Medical assistant	Nursing aides

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 worked since the previous survey year. Columns (1)-(5) report the polynomial regression model as in equation (1) and Columns (6)-(10) report the piecewise linear regression model as in equation (2). *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 the logarithm of a respondent's age, annual wage income, annual family net total income, employer size, as well as gender, ethnicity, marital status, education, father's education, and mother's education. The definitions of these control variables are in 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 respondentâs industry and occupation, respectively. 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.	Labor Supply									
	Quadratic Function					Piecewise Linear Regression				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Leverage (β_1)	0.499***	0.245***	0.242***	0.238***	0.214***	0.246***	0.126***	0.124***	0.121***	0.110***
	(0.042)	(0.036)	(0.036)	(0.036)	(0.040)	(0.023)	(0.019)	(0.020)	(0.020)	(0.022)
Leverage^2	-0.357***	-0.184***	-0.183***	-0.182***	-0.164***					
	(0.036)	(0.032)	(0.031)	(0.031)	(0.035)					
$X^{Leverage}$ (β_3)						-0.489***	-0.291***	-0.288***	-0.287***	-0.261***
						(0.057)	(0.052)	(0.051)	(0.051)	(0.058)
ln(Age)		-0.192***	-0.191***	-0.194***	-0.170**		-0.190***	-0.189***	-0.193***	-0.169**
		(0.066)	(0.066)	(0.066)	(0.074)		(0.066)	(0.066)	(0.066)	(0.074)
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		-0.009	-0.010	-0.009	-0.016		-0.009	-0.010	-0.009	-0.015
		(0.012)	(0.012)	(0.012)	(0.014)		(0.012)	(0.012)	(0.012)	(0.014)
WageIncome		0.984***	0.981***	0.974***	0.971***		0.986***	0.983***	0.976***	0.973***
		(0.039)	(0.039)	(0.039)	(0.041)		(0.039)	(0.039)	(0.039)	(0.041)
TotalNetFamilyIncome		-0.191***	-0.192***	-0.194***	-0.180***		-0.188***	-0.189***	-0.191***	-0.177***
		(0.023)	(0.024)	(0.024)	(0.025)		(0.023)	(0.024)	(0.024)	(0.025)
MaritalStatus		-0.003	-0.004	-0.004	-0.014		-0.002	-0.002	-0.002	-0.013
		(0.011)	(0.011)	(0.011)	(0.013)		(0.011)	(0.011)	(0.011)	(0.013)
College		0.011	0.012	0.010	0.013		0.011	0.012	0.010	0.013
		(0.010)	(0.010)	(0.010)	(0.011)		(0.010)	(0.010)	(0.010)	(0.011)
FatherEdu		-0.001	-0.001	-0.001	-0.000		-0.001	-0.001	-0.001	-0.000
		(0.002)	(0.002)	(0.002)	(0.002)		(0.002)	(0.002)	(0.002)	(0.002)
MotherEdu		-0.003	-0.003	-0.003	-0.004*		-0.003	-0.003	-0.003	-0.004*
		(0.002)	(0.002)	(0.002)	(0.002)		(0.002)	(0.002)	(0.002)	(0.002)
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)
Switching point	**69.888%**	**66.576%**	**66.120%**	**65.385%**	**65.244%**					
F stat of ($\beta_1 + \beta_3 = 0$)						**29.097*****	**16.183*** **	**16.636*** **	**17.289*** **	**10.939*** **
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 Column (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 Column (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	-0.032	-0.210***	0.221***	0.060***	-0.032	-0.210***	0.220***	0.061***
	(0.057)	(0.071)	(0.023)	(0.012)	(0.057)	(0.071)	(0.023)	(0.012)
$SLTV^2$	0.369***	0.633***			0.369***	0.633***		
	(0.071)	(0.089)			(0.071)	(0.089)		
X^{SLTV}			0.210*	0.359***			0.209**	0.351***
			(0.109)	(0.060)			(0.104)	(0.058)
Cragg-Donald Wald F Stat	20.506		32.969		20.506		33.223	
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, and 2014. Columns (1) and (2) use the polynomial regression model. Columns (3) and (4) use linear piece-wise regression model. All other variables are defined in Table 1. 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

Panel A. Using balance sheet items consistently surveyed

Dep. Var.	*Training*			
	Quadratic Function		Piecewise 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***	-0.047***		
	(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 Function		Piecewise Linear Regression	
	(1)	(2)	(3)	(4)
Leverage (β_1)	0.060***	0.070***	0.034***	0.040***
	(0.010)	(0.011)	(0.005)	(0.006)
Leverage^2	-0.036***	-0.043***		
	(0.008)	(0.008)		
$X^{Leverage}$ (β_3)			-0.063***	-0.079***
			(0.014)	(0.015)
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	43,978	43,978	43,978	43,978
R-squared	0.049	0.264	0.049	0.264