Household Debt Overhang and Human Capital Investment

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Abstract

Unlike labor income, human capital is inseparable from individuals and does not completely accrue to creditors. Therefore, human capital investment is more resilient to "debt overhang" than labor supply. We develop a dynamic model displaying this difference. We find that while both labor supply and human capital investment are hump-shaped in household indebtedness, human capital investment declines less aggressively as indebtedness builds up. Importantly, because human capital is only valuable when households expect to supply labor, the greater reduction in labor supply due to debt overhang back-propagates into ex-ante human capital investment. We provide empirical support for the model.

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

JEL: G28, G50, G51, J20, J24.

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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 sheets.[1] Recent studies find that household leverage induces a "debt overhang" effect on individuals' labor supply, particularly when default is expected. Households in the U.S. are often protected by limited liability. Therefore, any incremental income earned from labor supply is partially used to fulfill debt obligations (via liability repayment), postponing the discharge of debt through bankruptcy. In this case, households bear the full cost of supplying labor while part of the benefits accrue to creditors. Such wealth transfer discourages households from exerting effort ex ante (e.g., Donaldson, Piacentino, and Thakor, 2019; Bernstein, 2021). Less well understood, however, is an equally important aspect of household decisions – human capital investment.

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

In this paper, we examine how household debt differentially affects the incentives for human capital investment versus labor supply, and how the two actions are interconnected. We focus on one type of human capital investment – households' labor skills acquisition after they start their career – because an important part of human capital accumulation takes place within firms (Acemoglu, 1997), and because this is the type for which we have

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

compelling empirical identification. Given the indisputable role of human capital in delivering sustained economic growth and the importance of mitigating human capital depreciation (e.g., Goldin and Katz, 2010; Dinerstein, Megalokonomou, and Yannelis, 2022), this study provides relevant implications for public policies regarding household wealth and social welfare.

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

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

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

Importantly, the sharp decay of labor supply feeds back into households' skills acquisition decisions ex ante. Because skills acquisition effort increases households' marginal productivity, this effort is only valuable if households anticipate supplying labor in the future. As such, we find that when labor supply is expected to collapse due to debt overhang, it suppresses households' incentives 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 this case, households optimally choose skills acquisition over labor supply near bankruptcy (because of human capital's preserved value), and the 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.

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

In the next part of our study, we take the theoretical predictions to data. Our empirical analyses employ the 1979 National Longitudinal Surveys (hereafter, NLSY79). 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 throughout their lives. The survey provides itemized balance sheet information, which allows us to measure household indebtedness.

Importantly, NLSY79 contains information about individuals' participation in training programs after the start of their careers – which we employ to capture labor skills acquisition and thereby, human capital investment. This measurement is inspired by Acemoglu (1997), who posits that "*in modern economics, a large portion of human capital investments takes place within firms in the form of training.*"[2] By observing whether an individual participates in training and the duration of the participation, we can study how skills acquisition varies with debt overhang arising from household indebtedness. In contrast, college education – another type of human capital investment – is mostly funded by federal student debt. Because this type of debt is non-dischargeable in bankruptcy, it largely mutes the debt overhang force that we aim to study.[3]

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

We construct a sample of 6,867 individuals surveyed by NLSY79. We find that our theoretical predictions are born in the data. We first document a hump-shaped relation between household indebtedness and skills acquisition. Training participation initially increases with indebtedness, and it peaks around 59% of household leverage.[4] After that point, further

[2]Relatedly, Clifford and Gerken (2021) find that in the financial service industry, financial advisors advance their human capital through the attainment of professional licenses after starting their careers.

[3]Section 3.4 provides more detailed discussions of this point. See also Yannelis (2020) and Manso, Rivera, Wang, and Xia (2024) for related analyses.

[4]We discuss the measurement of household leverage in Section 3.3.

increase in indebtedness switches to discouraging training take-up. Labor supply shows a similar hump shape. However, it begins to decline at a significantly lower level of household indebtedness (around 33%), indicating the earlier manifestation of debt overhang predicted by the model.[5]

In addition, this hump shape exhibits variation with respect to skills' depreciation rates and income uncertainty, in line with the model's comparative statics. We capture skills depreciation based on their exposure to technology in the spirit of Kogan, Papanikolaou, Schmidt, and Seegmiller (2024), as well as changes in an individual's wage path around the completion of skills acquisition. We find that 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 lower level of household indebtedness, giving rise to the earlier manifestation of debt overhang. This result reinforces the role of human capital's inalienability in driving our results. We also find similar patterns regarding income uncertainty as per the model's prediction.

Our empirical results are obtained after we include a host of control variables including individuals' gender, ethnicity, education level, marital status, employment status, life-cycle related factors, as well as multiple layers of fixed effects. In addition, for any unobservable confounding factors to explain our results, they must correlate with household indebtedness in such a way as to differentially affect training participation (or labor supply) depending on the level of indebtedness. For instance, if certain characteristics encourage households to enroll in training at a lower household indebtedness, then the effect of these characteristics must reverse when indebtedness becomes higher. Nevertheless, to further filter out such possibilities, we perform an instrumental variable analysis, in the spirit of Bernstein (2021) and Gopalan, Hamilton, Kalda, and Sovich (2021), based on plausibly exogenous variation in individuals' mortgage-loan-to-value ratio due to the dynamics of housing market conditions. We confirm our main findings.

The effect of household debt on individual decisions has received growing attention in recent literature. Using a labor-search model, Donaldson, Piacentino, and Thakor (2019) study labor supply decisions of indebted households protected by limited liability. They

[5]In supplementary analyses, we also find that the decline in labor supply is sharper than that in skills acquisition. See Online Appendix B.2.

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. Donaldson, Piacentino, and Thakor (2019) posit that policies intended to reduce household debt can mitigate debt overhang, restore labor supply incentives, and increase employment.

We perform a simulation analysis to derive implications regarding debt forgiveness, complementing those from Donaldson, Piacentino, and Thakor (2019). We focus on the two extensions of our model relative to theirs: (i) household risk aversion and (ii) skills acquisition. We show that debt forgiveness programs may initially promote households' skills acquisition and labor supply – due to the mitigation of debt overhang; however, excessive debt forgiveness undermines any benefits of moderate indebtedness – due to the diminishing marginal utility force implied by risk aversion. Hence, an optimal level of debt forgiveness obtains for both actions. Furthermore, because the effect of household indebtedness switches (from encouraging to discouraging efforts) at different indebtedness levels for skills acquisition and labor supply, the optimal debt forgiveness varies accordingly across the two actions. There exists a region in which mitigating an additional dollar of debt promotes labor supply while impeding skills acquisition. To the extent that skills acquisition entails a longer-term impact on household income than labor supply, such a trade-off should be considered by policymakers regarding short-term and longer-term income generation. In Section 5, we discuss practical scenarios in which this trade-off can be relevant for policymakers.

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

More broadly, our paper is related to the theoretical literature studying household work incentives. Lazear (2000) provides a framework to study on-the-job incentives. Lazear, Shaw, and Stanton (2016) rationalize the finding that worker productivity increases during recessions thereby "making do with less." Their key mechanism hinges upon the greater incentives to exert effort in workplaces since unemployment goes up in recessions, increasing the opportunity cost of shirking. Chetty and Szeidl (2007) explain high short-term elasticity of labor supply as a result of high risk-aversion induced by consumption commitment with respect to small and short-lived shocks. Our paper abstracts from the impact of macroeconomic conditions and consumption commitments on household work incentives, and instead focuses on the relationship between household balance sheets and skills acquisition.[6]

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.[7] 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), among others. Our paper contributes to this literature by developing the first dynamic household finance model examining debt overhang on human capital investment. Unlike canonical models of corporate finance – in which the firm "ceases to exist" or is transferred to creditors after bankruptcy, households carry on with their lives post bankruptcy, offering them opportunities to materialize the continuation value of acquired human capital.[8]

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

[7]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).

[8]To this end, our implications can apply to an extended corporate model, in which the existing intangible

On the empirical side, existing literature finds both a negative and positive effect of household indebtedness on individual decisions. Regarding negative effects, the growing literature finds that rising household debt reduces labor income and mobility.[9] Household debt may also reduce residential home improvement (Melzer, 2017) and inventors' productivity (Bernstein, McQuade, and Townsend, 2021). Regarding positive effects, Zator (2025) shows that higher mortgage interest rates encourage households to work and earn more to cover increased mortgage payments.[10] Our main contribution to this literature is to document, in a unified theoretical framework, that household indebtedness's positive and negative effects co-exist and their presence depends on the regimes of indebtedness. As such, our work depicts a fuller picture of the relationship between household indebtedness and decisions.

2 Model

2.1 Model setup

An infinitely lived household derives utility from consumption C_t, and dis-utility from exerting effort in acquiring labor skills a_t. Labor skills increase the household's productivity and hourly wage. The household is free to choose how many hours to work – i.e., its labor supply (l_t) – at a given hourly wage. Similar to skills acquisition, labor supply is costly and generates dis-utility for the household.

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

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

assets (e.g., supplier or bank relationships) can be redeployed after bankruptcy, by the same set of prior shareholders for a new venture.

[9] See Ferreira, Gyourko, and Tracy (2010, 2011); Dobbie and Song (2015); Brown and Matsa (2020); Bernstein and Struyven (2022); Gopalan, Hamilton, Kalda, and Sovich (2021); Di Maggio, Kalda, and Yao (2024).

[10] Studying lottery settings, Imbens, Rubin, and Sacerdote (2001) and Cesarini, Lindqvist, Notowidigdo, and Östling (2017) find that increases in household wealth (ceteris paribus a reduction in household indebtedness) reduce labor supply. On the other hand, Rizzo and Zeckhauser (2003) find that wealth shortfalls from a reference point incentivize households to boost earnings.

θ_a and θ_l denote the marginal cost of skills acquisition and labor supply, respectively. θ_{al} captures the relative complementarity between exerting effort in skills acquisition and supplying labor. A negative θ_{al} indicates that the cost of skills acquisition partially offsets the cost of labor supply (or vice versa), yielding a high level of complementarity. Conversely, a positive θ_{al} indicates a low level of complementarity (or a high level of substitution). In the baseline model, we focus on the case in which skills acquisition and labor supply costs are independent of each other (i.e., $\theta_{al} = 0$). We then explore the rich nuances of the model when θ_{al} varies. Importantly, to match our empirical focus on training programs not paid by individuals themselves (see Section 3), skills acquisition does not command a monetary cost in our model.

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

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

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

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

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

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

Total wages $W_t = l_t K_t$ are the product of hourly income and the number of working hours (labor supply). Initially, households have complete access to credit markets, and can borrow and save at the risk-free rates in order to smooth consumption. Household savings

S_t evolve according to:

$$dS_t = (r(S_t)S_t - C_t + W_t)dt \text{ if } t \leq \tau_D, \tag{4}$$

$$S_t = 0 \text{ if } t > \tau_D, \tag{5}$$

where τ_D denotes the time at which the household chooses to default. Households face a maximum borrowing limit, which we model as a multiple $|\underline{s}|$ of the household's earnings upon default. At the time when the borrowing limit is reached, denoted by τ, the household defaults, implying that $\tau_D \leq \tau$. This modeling choice reflects an exogenous borrowing limit akin to that in the dynamic corporate finance literature. See, e.g., Longstaff and Schwartz (1995) and *Section V* in Bolton, Chen, and Wang (2011). We set the interest rate $r(S_t) = r_B$ when the household is borrowing (i.e., when $S_t < 0$) and $r(S_t) = r_S < r_B$ when the household is saving (i.e., when $S_t \geq 0$), reflecting the observation that interest rates for household savings are lower than those of household debt.

Prior to default, equation (4) states that wages are deposited in the savings account. Savings accrue interest at rate $r(S_t)$ and are used to pay for household consumption. Upon default, equation (5) states that households discharge all of their debts and are henceforth shunned from credit markets, forcing their savings (and debts) to be zero. This equation reflects that (i) a majority of households that go through bankruptcy file Chapter 7 – in which case debtors discharge eligible debts, and (ii) default often hurts debtors' creditworthiness, thereby limiting their ability to borrow (e.g., Dobbie and Song, 2015; Dobbie, Goldsmith-Pinkham, Mahoney, and Song, 2020; Kleiner, Stoffman, and Yonker, 2021).[11] In Online Appendix A.6, we consider the case when default is less punitive (when e.g., the household may partially access credit markets and saving technologies after default). Here due to the lack of credit market access, after default the household will become a hand-to-mouth household, whose consumption equals his total wages (i.e., $C_t = W_t$ for all $t > \tau_D$).[12]

The household's problem consists of jointly choosing consumption, labor skills acquisi-

[11] 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.

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

tion, labor supply, and a default policy to maximize lifetime utility. We denote the household's value function by $F(S, K)$:

$$F(S,K) = \max_{C,a,l,\tau_D \leq \tau} \mathbb{E}\left[\int_0^{\tau_D} e^{-\delta t} u(C_t, a_t, l_t)dt + e^{-\delta \tau_D} H(K_{\tau_D})\right]. \tag{6}$$

The first part of equation (6) pertains to the value prior to default. It is a function of savings, labor skills, labor supply, and the default decision. The second part of the equation, $H(K)$, is the value post default. This value function integrates an important feature of labor skills acquisition. Labor skills prior to default increase hourly wages $K_t \geq 0$, and the higher hourly wages carry over to the post-default period – reflecting that acquired skills are inseparable from households and thus preserve their value even post default. This feature, as we discuss later, is key for the different relations between household indebtedness and skills acquisition versus labor supply.

In the main model, we assume that after default, the household's human capital remains intact even though it can no longer rely on credit markets to smooth its consumption. This way of modeling is to match empirical findings by Dobbie, Goldsmith-Pinkham, Mahoney, and Song (2020), who show that personal bankruptcy information has an economically trivial impact on future earnings in the U.S. labor market.[13] In Online Appendix A.5, we consider the possibility that the value of human capital declines moderately after default. This decline may arise because of resistance from employers to the household's unfavorable credit history – resulting in reduced employment (e.g., Bos, Breza, and Liberman, 2018), or because of wage garnishment until the household's debts are repaid – effectively lowering the hourly wage (e.g., Yannelis, 2020; Argyle, Iverson, Nadauld, and Palmer, 2022; DeFusco, Enriquez, and Yellen, 2024). These possibilities would partially undo the value preservation of human capital post default due to its inalienability. We show in Online Appendix A.5 that our findings are qualitatively unchanged in the context of the empirical measurements in Bos, Breza, and Liberman (2018).

As a baseline analysis, we focus on the case in which the costs of skills acquisition and labor supply are independent from each other (i.e., $\theta_{al} = 0$). In Online Appendix A.1 we show

[13] The authors explain that it is likely because bankruptcy contains little incremental value in predicting individuals' future job performance. However, the authors find some modest effects of bankruptcy information on job-finding rates. This latter finding is consistent with Friedberg, Hynes, and Pattison (2021).

that the value function and optimal policies *after* default can be computed in closed-form:

$$H(K) = \frac{1}{\delta}\log K - \frac{\delta^2\theta_a \log(\theta_l) + \delta^2\theta_a + \delta\theta_a\left(2\rho + \sigma^2\right) - 1}{2\delta^3\theta_a}, \tag{7}$$

$$C(K) = Kl(K), \qquad a(K) = \frac{1}{\delta\theta_a}, \qquad l(K) = \frac{1}{\sqrt{\theta_l}}. \tag{8}$$

Equation (8) follows a straightforward intuition. Because the household becomes hand-to-mouth, its consumption equals total wages. Effort in acquiring labor skills is inversely proportional to the cost θ_a and the discount rate δ. Because labor skills increase human capital and have a lasting effect on future wages, patient households will exert more effort in acquiring skills. By contrast, labor supply – whose return only impacts current income – depends exclusively on the cost of supplying labor θ_l.

To solve the household optimization problem (6), we first uncover, in the following lemma, an important simplification that characterizes the optimal endogenous default policy.

Lemma 1. *The household's optimal default policy sets* $\tau_D = \tau$.

The proof is in Online Appendix A.2. Intuitively, because debt is dischargeable upon default, a household has nothing to gain from defaulting prior to exhausting its debt limit, and therefore setting $\tau_D < \tau$ is never optimal.

Next, we proceed to compute the value function *before* default $F(S, K)$, which satisfies the dynamic programming equation:

$$\begin{aligned}\delta F(S,K) = \max_{C,a,l} \Big\{ & \log C - g(a,l) + F_S(S,K)(r(S)S - C + lK) \\ & + F_K(S,K)K(a-\rho) + \frac{1}{2}F_{KK}(S,K)K^2\sigma^2 \Big\}.\end{aligned} \tag{9}$$

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:

$$\frac{1}{C(S,K)} = F_S(S,K), \qquad \theta_a a(S,K) = F_K(S,K)K, \qquad \theta_l l(S,K) = F_S(S,K)K. \tag{10}$$

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 (10) into (6) yields a differential equation for $F(S,W)$, which is solved subject to the boundary condition at default $F(\underline{s}W,K) = H(K)$.

This differential equation cannot be solved analytically. However, due to CRRA preferences and controlled GBM dynamics for hourly income, the value function displays homogeneity of degree one. Hence, in Online Appendix A.3, we show that the two state variables K and S can be reduced to a single state variable d_t, defined as:

$$d_t = \frac{S_t}{\underline{s} l_{\tau_D} K_t}. \tag{11}$$

As implied by equation (5) and Lemma 1, the household defaults (at time τ_D) when reaching the maximum borrowing limit, and this limit is denoted as a multiple $|\underline{s}|$ of the household's earnings upon default – i.e., the denominator of d_t. Therefore, d_t captures the household's savings ($S_t > 0$) or borrowing ($S_t < 0$) relative to this borrowing limit. Its upper bound $d = 1$ corresponds to the instance when the household has reached the borrowing limit and defaults (note that $\underline{s} < 0$). The region of $d_t < 1$ implies that $S_t > \underline{s} l_{\tau_D} K_t$ (for all t) and accordingly, the instance when the household is away from default. Theoretically, $d_t \in (-\infty, 1]$, with the negative region indicating that household savings become arbitrarily large. In the following, we choose for cosmetic purposes to focus on values of $d \geq 0$ in such a way that the lower bound $d = 0$ represents a debt free household.[14]

[14]The model is solved in the entire state space of $d \leq 1$. In Online Appendix A.8, we present figures expanding d_t to the negative region. This expansion does not alter the main takeaway. Visually, however, the hump shape appears more clustered due to the long left tail – corresponding to the region of substantial household savings and where the optimal skills acquisition and labor supply policies are not influenced by debt overhang. For the ease of exposition, the figures hereafter are confined to $d \in [0, 1]$.

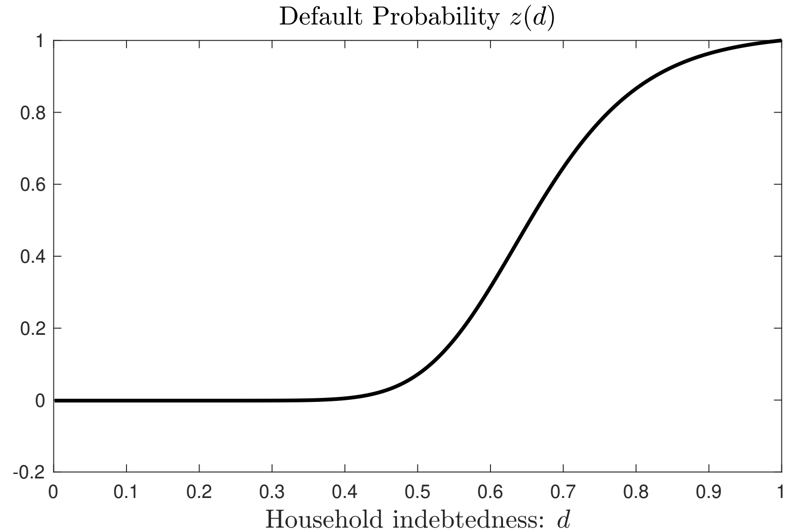

Figure I: **Household default probability as a function of the state variable d.** Parameter values are $\delta = 0.05, r_B = 0.08, r_S = 0.01, \theta_l = 3, \theta_a = 300, \rho = 0.15, \sigma = 0.3, \underline{s} = -4.5$. The discount rate δ is taken from the estimates in Laibson, Repetto, and Tobacman (2007). Savings interest rate (r_S) is based on the FDIC non-jumbo deposits interest rate, and the borrowing rate (r_B) is chosen between the average bank prime (mortgage) lending rate and credit card rate within our sample period (Section 3). The cost of supplying labor (θ_l) is set such that the annual labor supply is around 2,000 hours. The cost of skills acquisition (θ_a) is set such that the growth rate in hourly wages is comparable to the skills' depreciation rate (ρ). Wage volatility (σ) is based on the recent literature examining household earnings volatility (e.g., Shin and Solon 2011). We set the limit for borrowing (i.e., the negative of saving) $\underline{s}$ to match approximately the 85th percentile of our sample distribution of the debt-to-income ratio when individuals file for bankruptcy.

Importantly, as shown in Figure I, d_t predicts the probability of a household entering default. More precisely, we define z as the probability that the household eventually defaults given its current level of indebtedness:

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

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

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

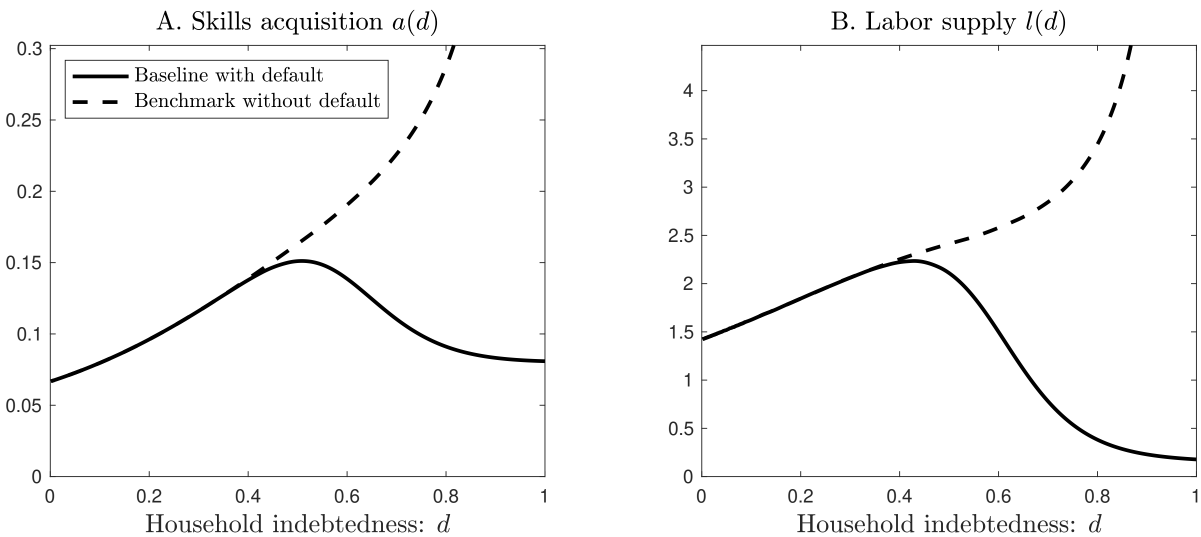

Figure II: **Effort in skills acquisition and household labor supply.** Parameter values follow those of Figure I.

notation, we denote skills acquisition as a function of indebtedness as $a(d)$ and labor supply as $l(d)$, where

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

The parameters used in the following numerical solutions are described in the caption of Figure I. We verify that the main mechanisms of our baseline findings are robust to variations of these parameter values.

2.2 Optimal skills acquisition policy

The solid lines in Figure II illustrate the baseline results of the model. Panel A shows that there is a hump-shaped relation between household indebtedness (confined between 0 and 1 as discussed in equation (11)) and skills acquisition: increasing indebtedness initially encourages the household to exert higher effort in acquiring labor skills, but discourages it from doing so after indebtedness reaches a certain threshold.

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

However, when household indebtedness increases above a threshold, the second force, *debt overhang*, becomes dominant. As the household gets close to bankruptcy, it fails to internalize all the benefits of effort in acquiring labor skills. Because the household discharges its debt in bankruptcy, a fraction of the incremental wages generated by skills acquired *before* default goes to paying debts, constituting a wealth transfer from the household onto lenders. Hence, the household will choose to exert less effort in acquiring skills when it is near bankruptcy. This *debt overhang* force makes effort a decreasing function of household indebtedness. It is dominant when indebtedness reaches a high level and default becomes more probable (Figure I).[15] The combination of the two forces renders skills acquisition hump shaped with respect to indebtedness, as shown in Panel A.

To assess the extent of distortion in households' skills acquisition driven by debt overhang, we include a dashed line in Panel A depicting the benchmark policies in the absence of default.[16] 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 indebtedness is low – i.e., when default (and debt overhang) is not an imminent consideration. As indebtedness increases to a higher level, the dashed line does not decline as the solid line does. This is because without debt overhang, only the diminishing marginal utility force is at play, rendering skills acquisition an increasing function of indebtedness across the entire regime. Accordingly, the wedge between the dashed and solid lines captures the distortionary impact of debt overhang on $a(d)$. As expected, when indebtedness increases, the debt overhang force becomes increasingly dominant, augmenting the extent of distortion.

[15] 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.

[16] We do so by letting $H(K) \to -\infty$ in equation (8). That is, we assume that default is sufficiently punitive such that the household does not find it optimal to default on its debt.

2.3 Contrast between skills acquisition and labor supply

In Panel B of Figure II, we plot the optimal policy for households' labor supply. There is also a hump-shaped relation between household indebtedness and the supply of labor. This relationship is similarly shaped by the interplay of the two forces: *diminishing marginal utility* versus *debt overhang*. However, an important difference emerges.

Relatively to the case of skills acquisition, the debt overhang for labor supply emerges at a lower level of household indebtedness – an earlier manifestation of debt overhang. The intuition of this dissimilarity is as follows. Labor supply generates only transitory income, and once it is used to pay creditors, no additional benefits accrue to the household. Given that the household is protected by limited liability, it is discouraged from supplying labor because any incremental income will be used to fulfill debt obligations, postponing debt discharge and benefiting the creditors. By contrast, the household will still reap the benefits of enhanced human capital, which is inseparable from the household and preserves its value even after default (as reflected in equation (6)). Such different resilience to debt overhang in turn drives the asymmetric manifestation of debt overhang – that is, the "switching point" of the hump shape for labor supply occurs at an earlier stage (a lower level of indebtedness) than that for skills acquisition. In Section 4.1, we provide empirical evidence supporting this asymmetric pattern.[17]

Incorporating skills acquisition extends the findings on labor supply in Donaldson, Piacentino, and Thakor (2019). In Section 5, we build on this extension, along with household risk aversion introduced in our model, to derive policy implications for debt forgiveness policies.

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 (at the high level of indebtedness) than that in Panel A, reflecting a larger extent of distortion in the case of labor supply. This difference is again attributable to the inalienability of household human capital.[18]

[17] In addition, we also observe that after debt overhang kicks in, labor supply decreases more substantially than skills acquisition – a sharper manifestation of debt overhang. This observation likewise follows the intuition that skills acquisition is more resilient to debt overhang.

[18] In an unreported extension of the model, we consider the possibility of "learning-by-doing" (Arrow, 1962), in which individuals can accumulate labor skills at work, and skills acquired this way similarly increase their hourly wages as does training. We show that as long as the increment in hourly wages induced by training

2.4 Dynamic complementarity between human capital and labor supply

We next expand the baseline analysis to incorporate the role of dynamic complementarity between skills acquisition and labor supply. In Figure III, we illustrate the role of this dynamic complementarity by changing the degree of substitutability between effort and labor supply, as captured by θ_{al}. Panels A and B show the optimal policies of the two actions when the costs are independent $\theta_{al} = 0$ (solid lines) versus when they are substitutes $\theta_{al} > 0$ (dotted lines), respectively. In reality, households are often in need of choosing between skills acquisition and labor supply due to, e.g., time constraints. Thus, effort in one action inevitably raises the cost of performing the other, making them substitutes.

We start with Panel B. This panel shows that for high household indebtedness (> 0.4), the supply of labor collapses more quickly for $\theta_{al} > 0$ (the dotted line) than for $\theta_{al} = 0$ (the solid line). Intuitively, when labor supply and skills acquisition are substitutes, the household must focus on one of the two actions. Because human capital is inseparable and continues to generate value after default, the household chooses skills acquisition over labor supply near bankruptcy. This preference makes labor supply decline even faster – reflecting the aggravated debt overhang – compared to the baseline case ($\theta_{al} = 0$). In contrast, by comparing the two lines in Panel A, we do not see such a fast collapse in skills acquisition during high indebtedness.

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

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outpaces that by labor supply – that is, as long as "learning-by-training" remains a more effective way to acquire skills than "learning-by-doing", the thrust of our main findings, i.e., human capital investment is more resilient to debt overhang than labor supply, remains qualitatively robust.

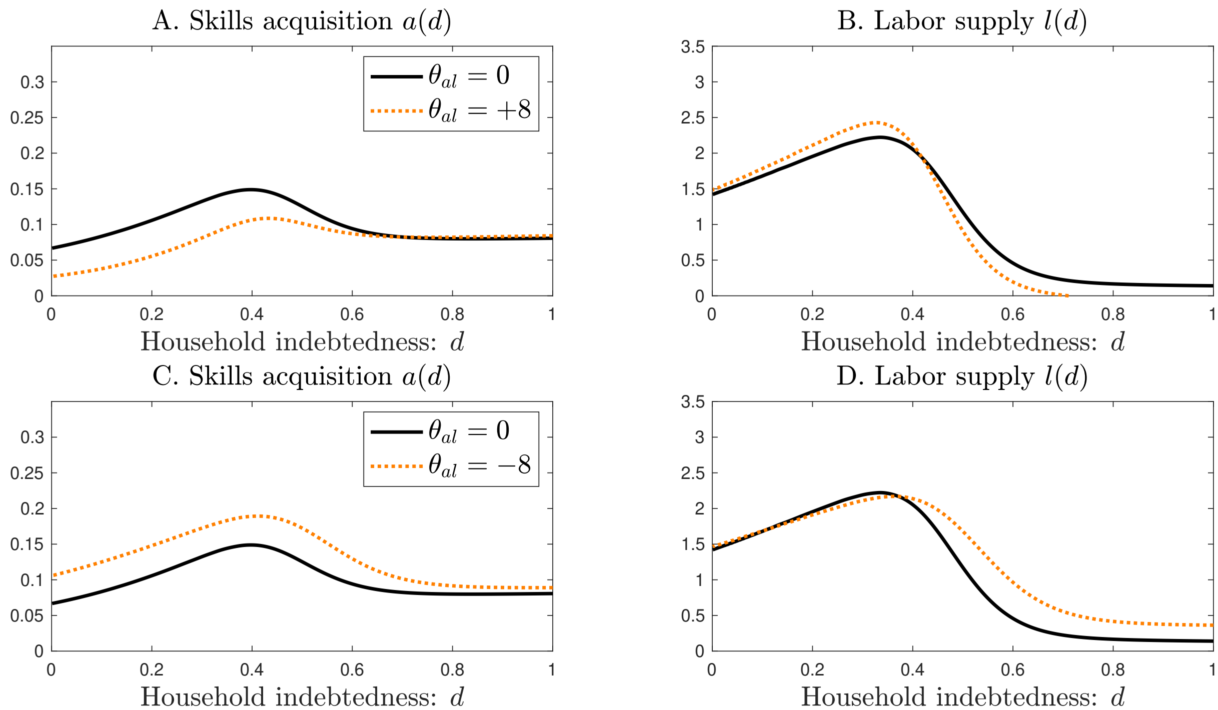

Figure III: **Illustration of dynamic complementarity between human capital and labor supply.** Other parameter values follow those of Figure I.

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. In practice, the case of complementarity is arguably less common than the case of substitution. Nevertheless, complementarity may happen when, e.g., the intellectual improvement from training programs enhances an individual's competence at work, thus lowering the psychological burden and the utility cost of labor supply.

Several differences emerge in the case of $\theta_{al} < 0$. Unsurprisingly, Panel D shows that the decline in labor supply for high indebtedness (> 0.4) is less prominent under complementarity ($\theta_{al} < 0$) than the solid line ($\theta_{al} = 0$). This pattern reflects that supplying labor now partially offsets the cost of accumulating more valuable human capital, thereby making the household less averse to providing labor than the baseline case. Accordingly, the anticipated ample labor supply makes boosting hourly wages more fruitful, encouraging the household to acquire labor skills ex ante – the reverse of the back-propagation effect. Indeed, we see that in Panel C, the dotted line lies above the solid line, in contrast to Panel A. In Online Appendix A.4, we provide further nuances of this back-propagation effect in the expanded parameter space.

2.5 Comparative statics

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

2.5.1 Comparative statics with respect to ρ.

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

Panel B illustrates this intuition. The dashed (resp. solid) line represents skills acquisition as a function of household indebtedness when ρ is high (resp. low).[19] We observe that when ρ is high, the decline in skills acquisition due to debt overhang emerges relatively

[19]For the case of high ρ, we lower the cost of skills acquisition θ_a as a compensating variation to keep the payoff to the household unchanged when evaluated at $d = 0$. This adjustment helps neutralize any income effects (whereby the higher depreciation rate leads to lower income levels), and thus isolate the impact of human capital depreciation on skills acquisition incentives.

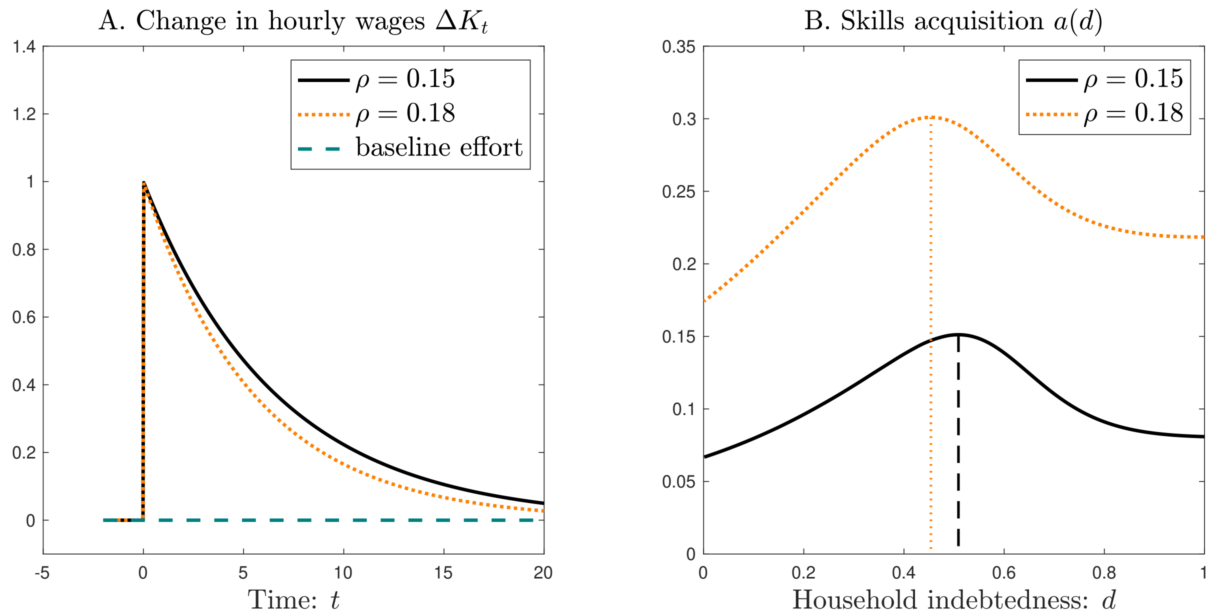

Figure IV: **Comparative statics with respect to the depreciation rate of labor skills parameter ρ.** Other parameter values follow those of Figure I.

early (at $d = 0.45$), as indicated by the dotted vertical line. It is similar to the switching point of labor supply shown in Figure II (at $d = 0.43$). Such similarity reflects that skills acquisition under high depreciation is not as resilient to debt overhang, due to the partial loss of skills' inseparability attribute. In contrast, when ρ is low, the switching point of training is postponed to $d = 0.51$ (the dashed vertical line), farther away from that of the labor supply. In our later empirical analyses (see Section 4.3), we confirm such a pattern with respect to ρ in the data.

2.5.2 Comparative statics with respect to σ.

Figure V depicts comparative statics with respect to the volatility of hourly wages σ. It shows that households facing greater hourly wage volatility engage in higher skills acquisition uniformly across all levels of household indebtedness – a pattern that we confirm in empirical analysis (see Section 4.4). This pattern stems from two sources. First, higher volatility is welfare-reducing for a risk averse household because uncertainty in earnings limits its ability to smooth consumption. In response, the household adjusts 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

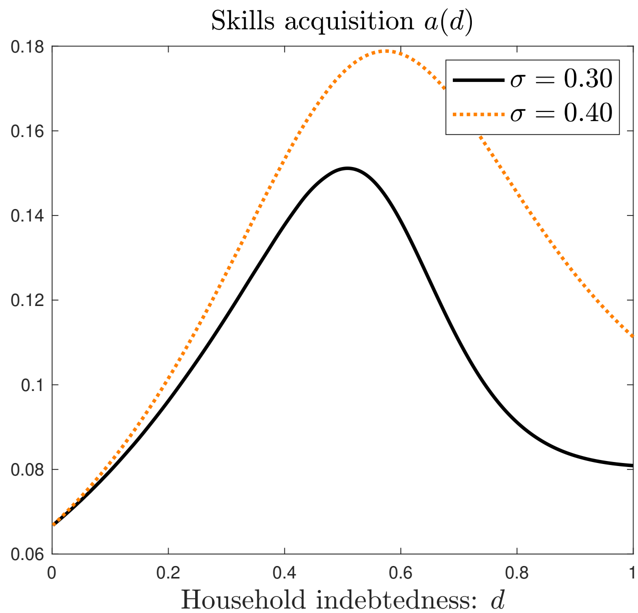

Figure V: **Comparative statics with respect to hourly wage volatility σ.** Other parameter values follow those of Figure I.

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 precautionary incentives, but also increases households' labor supply for a similar reason, as shown in Online Appendix A.7. Such an increase in labor supply in turn feeds back into the ex-ante skills acquisition decision, further raising the effort to acquire labor skills.

3 Data, variable construction, and summary statistics

3.1 The 1979 National Longitudinal Survey Youth

Our main data source is the 1979 National Longitudinal Survey Youth (NLSY79), a program run by the U.S. Bureau of Labor Statistics. NLSY79 surveys a sample of Americans born between 1957 and 1964, and follows their lives through multiple rounds of interviews. The first interview was conducted in 1979, when the respondents aged between 14 and 22. Follow-up interviews were conducted annually from 1979 to 1994 (round 1 to round 16), and biennially since 1996 (round 17). 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-survey-year panel (hereafter, respondent-year panel). The detailed description of the survey and survey questions are available on the website of the National Longitudinal Surveys (https://www.nlsinfo.org/).

3.2 Information on skills acquisition

Several sets of information from NLSY79 are important for testing the model predictions: individuals' on-career training participation, labor supply, and household balance sheets.

We employ individuals' training participation after the start of their careers to capture labor skills acquisition, and thus, human capital investments. This measurement is inspired by Acemoglu (1997), who posits that "*in modern economics, a large portion of human capital investments takes place within firms in the form of training.*" In each survey, respondents are asked to provide information about the training programs that they have taken since the last survey, including whether they have enrolled in any vocational or technical training designed to learn or improve job-related skills,[20] 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),[21] the starting and completion date of each training program, and the average number of hours per week respondents spend on training.

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

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

[21] 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).

training participation, our empirical analyses speak to how household indebtedness affects skills acquisition through shaping individuals' incentives.[22]

The NLSY79 begins to collect basic questions about training participation since the 1979 survey (round 1), and supplements these questions over time. Since 1991 (round 13), most information needed for our study (such as which party initiates the training) becomes available. We therefore construct the main outcome variables from 1991. Independent variables (including control variables) are constructed with a one-year lag starting from 1990.

3.3 Proxying for the state variable d

NLSY79 collects detailed household balance sheet information. On the asset side, NLSY79 surveys each respondent's estimated market value of residential and non-residential property, market value of vehicles, and the amount of savings and various financial assets (e.g., stocks and bonds). On the debt side, NLSY79 surveys the amount of mortgage loans, auto loans, student loans, credit card loans, and money owed to other individuals or entities. See Online Appendix B.7 Table B4 and Table B5 for the list of surveyed items.

Our model characterizes optimal policies as a function of the state variable d (household indebtedness), which economically captures the probability of a household entering default (Figure I). To find an empirical counterpart of the state variable, we need a measure that analogously captures this default probability. To this end, we use household net debt scaled by the total assets – namely, the net debt-to-asset ratio. Net debt equals the household's total debt minus cash and cash equivalents including (i) money assets such as savings accounts and (ii) liquid investments such as stocks, bonds, or mutual funds (Online Appendix B.7 Table B5). Different from total debt, net debt can take negative values – an attribute shared with the state variable d. This happens when the household has abundant cash (or cash equivalents) that exceeds the amount of debt, corresponding to the negative region of d as shown by equation (11). We scale net debt by total assets to control for the overall size of household wealth, following the corporate finance literature. For an easier exposition, we

[22] In complementary studies, Ji (2021) and Hampole (2024) show that financial frictions related to student debt borrowing affects individuals' choice of major in college as well as job search decisions, driven by the trade off between initial earnings and lifetime earnings.

refer to this net debt-to-asset measure simply as household leverage.[23]

Economically, this leverage measure is similar in spirit as Melzer (2017), who documents that the ratio of household mortgage to property value – the largest components of debt and assets among U.S. households – are highly indicative of their default likelihood. In Figure 1, we verify that such an indication continues to hold using our measure of household leverage.[24]

Specifically, in Figure 1 Panel A, we plot the average household default probability for various leverage bins. Default is identified by whether a household has ever missed any bill payment as of a given year.[25] Overall, default probability increases with leverage: it remains relatively flat when leverage is at a low level, and accelerates once leverage surpasses 40-50% – a pattern largely resembling that in Figure I of Section 2.1. In Panel B, we alternatively identify default by whether a household has filed for bankruptcy as of a given year. By nature, bankruptcy reflects more persistent and extreme financial hardships. The level of default probability therefore becomes lower than that captured by missed payments.[26] Nevertheless, we continue to observe that leverage strongly predicts default.

Taken together, Figure 1 verifies that our leverage measure is a reasonable empirical counterpart of the state variable d in the model.

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).[27] Because delinquent student borrowers are expected to eventually make up

[23] In the 1991, 2002, 2006, and 2010 surveys, the balance sheet information is entirely missing. In this case, we take the average of a respondent's leverage from two adjacent surveys to estimate the leverage of the missing year. In addition, we assign the leverage as missing if the items determining its calculation are missing.

[24] An alternative measure to capture household default probability is the debt-to-income ratio, defined as the monthly debt payment to gross income. This measure, however, is a less suitable proxy for the state variable d. The existing literature often uses household income to capture labor supply (e.g., Bernstein 2021; Zator 2025). Therefore, the denominator of the debt-to-income ratio would mechanically embed one of our outcome variables: labor supply.

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

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

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

missed payments (through, e.g., wage garnishment), non-dischargeability would discourage households from reducing effort in skills acquisition or labor supply, thereby mitigating the debt overhang force that we study. In a companion paper, Manso, Rivera, Wang, and Xia (2024) formally derive such an effect of student loans.

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. Our sample consists of individuals born between 1957 and 1964, and we track their life activities until 2014. Therefore, for a large proportion of this period, student debt is not different from other consumer debt in terms of dischargeability. Second and importantly, student loans only became a prominent part of household debt over the past two decades. For the generation of our sample individuals (who likely went to college in the early 1980s), merely about 10% of them reported outstanding student loans and the unconditional average student loan amount is about $1,444. 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.[28]

3.5 Information on labor supply

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

[28] As a robustness test, we repeat our main analyses in Table 2 – excluding individuals that have outstanding student debt in a given year. We confirm our findings in this subsample. That is, both actions exhibit a hump-shaped relation with household indebtedness; the switching points for skills acquisition and labor supply are 0.571 and 0.341, significantly different from each other at the 5% level.

3.6 Sample and variable construction

Our main outcome variables on training and labor supply are constructed from 1991 to 2014. The independent variables are constructed with a one-year lag starting from 1990. We exclude respondent-years when the respondents are younger than 25 or older than 57 (about 10 years before retirement). This filter ensures that our sample individuals are in the labor force and thus, the decision of on-career training participation is relevant. In addition, we exclude individuals without employers in a given year because by definition, they do not have opportunities to participate in on-career training programs. Our analyses sample consists of 52,016 respondent-year observations representing 6,867 respondents. They constitute the basis for our analyses. In untabulated analysis, we verify that this sample shares similar household characteristics as the initial NLSY79 sample.

As described in Section 3.2, we identify skills acquisition as an individual's training participation that is requested by the individual and is not self-paid. This identification not only differentiates voluntary decisions from employer requirements, but also helps mute the confounding effect of financial constraints on training. In each survey year, we generate an indicator, $Training$, which equals one if the respondent has requested and participated in non-self paid training programs since the last survey, and zero if the respondent does not take any voluntary training in this period.[29] To capture an individual's labor supply, we generate $LaborSupply$ as the total number of hours the individual has worked since the last survey. The key independent variable is $Leverage$, which corresponds to the modeled state variable d (household indebtedness) and is defined as the ratio of net debt to assets (Section 3.3).

We construct a host of control variables. $Male$ and $White$ indicate a respondent's gender and ethnicity. $MaritalStatus$ indicates whether the respondent is married and $College$ indicates whether the respondent has attended college as of the previous survey year. To measure a respondent's family education background, we include $FatherEdu$, which equals the number of years of schooling that a respondent's father has completed. To control for factors related to the life cycle of households, we include the respondent's age and its

[29] Alternatively, we generate $TrainingTime$, defined as the total number of hours a respondent spends on voluntary and non-self paid training programs since the last survey. By definition, $TrainingTime$ equals zero if $Training$ is zero. In Online Appendix B.7 Table B8, we show that our main findings are robust to this alternative measure.

quadratic form, *Age* and Age^2. In addition, we include various fixed effects to control for macro (state or county), industry, and occupation factors (see more discussion in Section 4.2). We winsorize all continuous variables at the 2.5th and 97.5th percentile to eliminate undue effects of outliers.

The geographic location of each respondent is obtained from the restricted-use NLSY79 Geocode files supplementing the main NLSY79 survey. The Geocode files track each respondent's location in a survey. We obtain a license to use this information from the Bureau of Labor Statistics.

3.7 Summary statistics

Table 1 reports summary statistics of the sample at the respondent-year level. *Training* has a mean of 0.088 and a standard deviation of 0.283. Conditioning on participating in training (i.e., *Training*=1), the variable *TrainingTime* indicates that on average, an individual spends approximately 49 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 16 weeks per semester). *LaborSupply* (in hours) has a mean of 3,400 and a standard deviation of 1,562.[30] These working hours represent, on average, 33% of available hours (based on 24 hours a day and 5 days a week). The main independent variable *Leverage* has a mean of 0.296 (29.6%) and a standard deviation of 0.456. As discussed in Section 3.3, *Leverage* can take negative values when a household's cash and cash equivalents exceeds the amount of debt, as shown by the 5th percentile.

4 Empirical findings

4.1 The hump-shaped relation

Figure 2 presents a univariate analysis to visually examine whether skills acquisition exhibits a hump-shaped function with respect to household indebtedness, and how this shape differs from that of labor supply. Following Section 3.3, household indebtedness (leverage) is proxied

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

by the net debt-to-asset ratio. Panel A plots skills acquisition for different leverage groups. The x-axis denotes household leverage by quintiles, where the numbers denote the range of household leverage (in percentage) within each quintile. For example, the bottom quantile consists of households with negative leverage – representing those that have more cash and cash equivalent than debt. The third quantile consists of households with leverage between 21% and 39%. The y-axis denotes the percentage of individuals who participate in self-requested and non-self-paid training (i.e., the mean of $Training$).

Consistent with the model prediction in Panel A of Figure II, skills acquisition exhibits a hump shape in household leverage. Individuals are more likely to participate in training as leverage initially rises, but become less likely to do so once leverage is above the range of 39-64%.

Panel B plots the relation between labor supply and leverage. The y-axis denotes the average hours of labor supply (i.e., the mean of $LaborSupply$). We observe a similar hump-shaped relation. However, labor supply exhibits an earlier manifestation of debt overhang, in line with the model prediction. Specifically, the switching point of the hump shape occurs as early as 21-39%, compared to 39-64% for skills acquisition. In addition, the decline in labor supply appears sharper: by the highest leverage quintile (>64%), labor supply has decreased by over half of the previous run-up (during the first three quintiles of leverage), whereas in Panel A, skills acquisition remains at a relatively high level at the top leverage quintile.

4.2 Regression analyses

To formalize the graphical evidence, we next estimate a quadratic regression model, separately for training and labor supply. We then contrast the switching points of the hump shapes between the two actions. The regression specification for training participation takes the following form:

$$Training_{i,t} = \alpha + \beta_1 Leverage_{i,t-1} + \beta_2 Leverage_{i,t-1}^2 + \gamma_1 Z_{i,t-1} + \gamma_2 X_i + FE + \epsilon_{i,t}. \quad (14)$$

The dependent variable is the indicator $Training$, which takes the value of one if respondent i reports in survey year t that he/she has participated in training programs since the last survey. $Leverage$ is the net debt-to-asset ratio of respondent i at the last survey year,

$t-1$, defined in Section 3.3. The quadratic function aims to capture the hump-shaped relation between training participation and leverage, as shown in Figure 2. The vectors Z and X include time-varying and time-invariant respondent characteristics. Time-varying characteristics include respondent age, college enrollment, and marital status. Time-invariant characteristics include gender, race, and father's education.

We include various fixed effects, such as survey year fixed effects, respondent's employer industry and occupation or industry×occupation fixed effects, as well as state, state×year or county×year fixed effects. These fixed effects help us control for industry/occupation shocks or state and county level economic conditions, which might affect both household leverage and training participation.

It is worth noting that generally, on-career training participation is not a frequent decision – and in fact, the vast majority (about 85%) of households in our sample participate in training programs no more than once. As a result, our estimation mainly compares the training participation across households with varying leverage (ceteris paribus), rather than a household's continuous training decisions over leverage cycles. Given this caveat, our results should be interpreted as an average effect from the cross-section, and they have limited power in speaking to the time-series variation.[31]

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 skills acquisition and leverage. We estimate OLS regressions because they generate more precise estimates of the marginal effects when high-dimensional fixed effects are employed (Angrist and Pischke, 2008). Standard errors are clustered at the state-year level.

Table 2 presents the regression results. In column (1), we include household characteristics, as well as fixed effects for industry, occupation and state×year.[32] We observe that while parental education and college enrollment can significantly affect training decisions, neither Age or Age^2 is statistically significant. It indicates that factors associated with the life cycle

[31]In Online Appendix B.1 Table B1, we repeat the main analyses including individual fixed effects. We confirm our results.

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

of households are unlikely to drive the humped-shape relation between training and leverage.[33] This lack of significance is likely because in our sample, the majority (almost 90%) of individuals are between 28 and 50 years old, and are relatively distant from designated retirement. Thus life-cycle considerations are less relevant in our setting.

In column (2), 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). In column (3), we include county×year fixed effects, which subsume state×year fixed effects.[34] Overall, the results consistently show that households are more likely to participate in training when leverage initially increases, but this relation reverses when leverage reaches a higher level. Based on the coefficient estimations of β_1 and β_2, we calculate the switching point separating the two regimes (i.e., the peak of the hump shape): $-\frac{\beta_1}{2\beta_2}$. The switching points range from 0.540 to 0.592 (i.e., 54% to 59.2% of leverage), as reported below the coefficient estimates in the row *Switching point*.

In columns (3) to (6), we repeat the estimation using labor supply as the dependent variable. We find that labor supply similarly exhibits a hump shape with respect to household leverage, as indicated by the positive β_1 and negative β_2. The switching points of the hump shape are from 30.8% to 33.1%.

To test the differences in the switching points between training and labor supply, we employ the Delta method (e.g., Rao, 1973; Oehlert, 1992; Haans, Pieters, and He, 2016) – which uses the Taylor approximation to estimate the standard errors of the function of fitted model parameters (in our case, the function of $-\frac{\beta_1}{2\beta_2}$ to obtain the switching points). These differences are reported in the row *Switching point diff.* Based on columns (3) and (6), the switching point difference between training and labor supply is 0.261 (26.1%), and it is significant at the 5% level. This observation suggests that labor supply exhibits an earlier manifestation of debt overhang than skills acquisition, in line with the model prediction. We obtain a similar interpretation from other columns.

[33] For instance, one may be concerned that training participation is more prevalent for mid-aged individuals than either fresh college graduates or soon-to-be retirees – rendering a hump-shaped relation between training and age. To the extent that households accumulate debt over time, leverage may simply pick up the effect of age in generating the hump shape.

[34] We benchmark the regression samples to that of column (3) in order to keep the number of observations across specifications constant.

Taken together, the regression analyses support the non-monotonic effect of household leverage on skills acquisition, and importantly, the significant differences between skills acquisition and labor supply due to the inseparability of human capital.[35]

4.3 Heterogeneity with respect to ρ

We next examine cross-sectional variations of the hump shape relation 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 proxy for skills depreciation, first based on the skills' exposure to technology inspired by the recent literature (e.g., Kogan, Papanikolaou, Schmidt, and Seegmiller, 2024), and second based on changes in the wage path as modeled in Section 2.5.1.

4.3.1 Exposure to technology

Recent work by Kogan, Papanikolaou, Schmidt, and Seegmiller (2024) 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 becomes obsolete as technology evolves into a new vintage, rendering faster skills depreciation. This channel is particularly germane in our setting because the sample individuals – aged in their twenties or thirties during the 1980s – underwent an information technology revolution thanks to the rapid development of the internet. Therefore, we capture the degree of skills depreciation based on their exposure to the computer and information technology (CIT).

Specifically, for each training program, the NLSY79 specifies the type of skills acquired. We flag a training program as being exposed to CIT if the acquired skills include computer skills.[36] We then aggregate the training level CIT exposure to the occupation level by calculating the percentage of CIT-exposed training programs taken by the sample individuals working in a given occupation, where occupation is provided by the NLSY79 and based on

[35] In Online Appendix B.2, we supplement the quadratic regression model with a piece-wise linear model. We confirm the results in this section and find a sharper manifestation of debt overhang for labor supply – a secondary prediction of the model.

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

the classifications of the Bureau of Labor Statistics (BLS). We perform this occupation level aggregation because (i) it reduces idiosyncratic factors that drive individuals' choice of training programs and CIT exposure, and (ii) we expect that variation in skills depreciation largely arises across occupations.

In Online Appendix B.7, Table B6 Panel A, we provide example occupations with the highest and lowest CIT exposure, as well as 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 are considered to have a low degree of skills depreciation. It is consistent with the finding that occupations associated with interpersonal tasks are less subject to disruption from technological innovation (Kogan, Papanikolaou, Schmidt, and Seegmiller, 2024). On the other hand, *Architecture and Engineering* is among the occupations with the highest CIT exposure and skills depreciation, consistent with MacDonald and Weisbach (2004).

According to Section 2.5.1, high depreciation (a larger ρ) implies that the returns of skills acquisition are more front-loaded in time, and thus, the total benefit from acquiring labor skills (via training) is materialized mostly in the shorter term. In such a case, training "loses" part of the inalienability attribute, making them resemble labor supply. Empirically, this result predicts that training programs associated with high skills depreciation should exhibit a similar hump shape as labor supply with respect to household indebtedness – and their switching points should be relatively close to each other. On the other hand, low depreciation (a smaller ρ) preserves skills' inalienability and their resilience to debt overhang. Training of such skills should therefore exhibit a significantly different switching point from labor supply. We find support for these predictions.

In Table 3, we re-estimate equation (14) in columns (1) and (2) – separately for individuals working in occupations with a CIT exposure in the top tercile (i.e., high skills depreciation ρ) and for those working in the rest occupations (i.e., low skills depreciation ρ). We then contrast the switching points of these two subsamples, respectively, with the switching point of labor supply (column (5)). Columns (1) and (2) follow the specification in column (3) of Table 2. Column (5) of Table 3 replicates column (6) of Table 2, and is reported here for easier comparison.[37]

[37]The numbers of observations in columns (1) and (2) do not add up to that in Table 2 because the two

Consistent with the model prediction, we find that the switching point of training with low depreciation is notably larger than that of labor supply (67.3% versus 33.1%), as shown by columns (2) and (5). The difference – 34.3% is statistically significant. In contrast, the switching point of training with high depreciation is smaller (49.5%), as shown in column (1). It is insignificantly different from that of labor supply.

4.3.2 Changes in the wage path

Our second approach to proxy for skills depreciation is based on Section 2.5.1. Specifically, we capture changes in the path of each individual's wage after training completion. The intuition of this approach follows the illustration in Panel A of Figure IV. 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 after training experience smaller declines. Online Appendix B.3 details the steps of measuring such a wage path.

In Table 3 columns (3) and (4), we repeat the analyses using this alternative measure of skills depreciation. That is, we examine individuals working in occupations with high depreciation (whose post-training wage decay is relatively high) versus low depreciation. We then respectively compare the switching points of these two groups with that of labor supply in column (5). We obtain the same conclusion as before. The switching point difference between low depreciation training and labor supply stands at 30.1% (significant at the 5% level), whereas that between high depreciation training and labor supply shrinks to 18.7% (insignificant at the 10% level). Taken together, these findings provide support to our model predictions in Section 2.5.1.

4.4 Heterogeneity with respect to σ

In Online Appendix B.4, we examine variation of the hump shape relation with respect to σ – the degree of labor income uncertainty. Our model (Section 2.5.2 and Figure V) predicts that households facing higher σ engage in more skills acquisition in order to counter the reduced utility due to greater labor income uncertainty. We present the detailed empirical

columns share the same control group, i.e., individuals without taking training programs.

approach and results in support of this prediction.

4.5 Alternative theories

The hump-shaped relation between household leverage and skills acquisition stems from the interplay of diminishing marginal utility and debt overhang forces. This non-monotonic relation complements the growing literature that finds a negative effect of household leverage on individual decisions, positing that indebtedness reduces labor income and mobility, residential home improvements, and innovation. Besides debt overhang, these studies discuss several alternative explanations for the negative effect of household leverage, including "housing lock", "mental distress", "inattentiveness." As an additional contribution, we examine these alternative theories by taking advantage of the rich records provided in NLSY79. We discuss these theories in detail and provide empirical results in Online Appendix B.5.

4.6 Instrumental variable analysis

The inclusion of industry×occupation and county×year fixed effects helps control for industry and occupation conditions, as well as county-level economic conditions that might affect both household leverage and training participation (or labor supply). However, one might still be concerned about confounding factors occurring at the household level. As discussed in the *Introduction*, in order for these factors to explain the documented hump shape, they must correlate with household leverage in such a way that they differentially affect training participation (or labor supply) depending on the level of leverage. For instance, 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 unable to capture the full extent of household incentives in skills acquisition. To the extent that individuals' connectedness is correlated with household indebtedness, the "opportunity cap" may bias our estimates.

To filter out this potential bias, we perform an instrumental variable analysis based on the interaction of individuals' home purchasing location and timing. The design of the instrumental variable analysis follows Bernstein (2021) and Gopalan, Hamilton, Kalda, and Sovich (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 evolution of households' mortgage loan-to-value ratios (LTV) – the largest part of household leverage (i.e., the inclusion criterion). On the other hand, because this variation comes from the interaction of home purchasing timing and location (instead of simply an earlier or later time overall, or simply different regions), it is plausibly exogenous to local shocks that might be correlated with training participation or labor supply (i.e., the exclusion criterion). In Online Appendix B.6, we describe the detailed procedures for constructing the instrument variable, i.e., the synthetic loan-to-value ratio ($SLTV$) following Bernstein (2021), and the regression specifications for the two-stage least square (2SLS) IV analysis.[38]

One limitation of our IV analysis is the relatively small sample, which arises because we require a household to have purchased a home by a given point in time – the necessary condition for constructing the instrument. In light of this limitation, we estimate the IV models with sample weights provided by NLSY79, following Kuhnen and Melzer (2018) who similarly use the NLSY79 data. Sample weights account for the representativeness of each surveyed respondent. Adjusting for these weights therefore allows us to obtain estimates closer to those from a broader population. Nevertheless, we interpret the IV analysis with caution.

Table 4 reports the second-stage regressions, using the instrumented LTV as the independent variable of interest.[39] Columns (1) and (2) pertain to training participation and

[38]Following Bernstein (2021), here we replace *Leverage* by LTV as the variable of interest, based on the assumption that mortgages and home value constitute a significant proportion of household leverage. To ensure the validity of this assumption, we require a household's LTV ratio in a given year to be at least 5%. We obtain qualitatively similar results using 10% for this requirement.

[39]The first-stage regressions are presented in Online Appendix B.7 Table B7, in which we include the corresponding control variables as the second-stage regressions. We see that 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 over 16, greater than the

columns (3) to (4) pertain to labor supply. Columns (1) and (3) report the specifications without individual characteristics as controls. Two findings are worth noting. First, both training and labor supply exhibit a hump shape with respect to the instrumented LTV. Second and importantly, the switching point for training is 79.8%, and that for labor supply is 45.6%. The difference (34.2%) is both economically and statistically significant. We obtain a similar interpretation from columns (2) and (4), which include additional control variables as in Table 2. The magnitude of the switching point difference is generally comparable with those estimated in Table 2. These results assure that our baseline findings are unlikely to be driven by confounding unobservable factors.[40]

5 Implications for debt forgiveness

In this section, we derive implications regarding debt forgiveness based on the two extensions of our model relative to Donaldson, Piacentino, and Thakor (2019): (i) household risk aversion and (ii) skills acquisition. Intuitively, the first extension renders the hump-shaped relation that we have theoretically and empirically documented, that is, increasing household indebtedness starts out by encouraging skills acquisition and labor supply (i.e., the diminishing marginal utility force) before it switches to suppressing them (i.e., the debt overhang force). Therefore, while debt forgiveness may initially promote skills acquisition and labor supply – due to the mitigation of debt overhang, excessive debt forgiveness undermines the beneficial effects of moderate indebtedness – due to the diminishing marginal utility. Hence, an optimal level of debt forgiveness obtains for both actions. The second extension, on the other hand, implies that the effect of household indebtedness switches (from beneficial to detrimental) at different levels for the two actions, reflecting the greater resilience of skills acquisition to debt overhang than labor supply (due to the inalienability of human capital). The optimal debt forgiveness varies accordingly across the two actions. In the sequel, we

10% critical values.

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

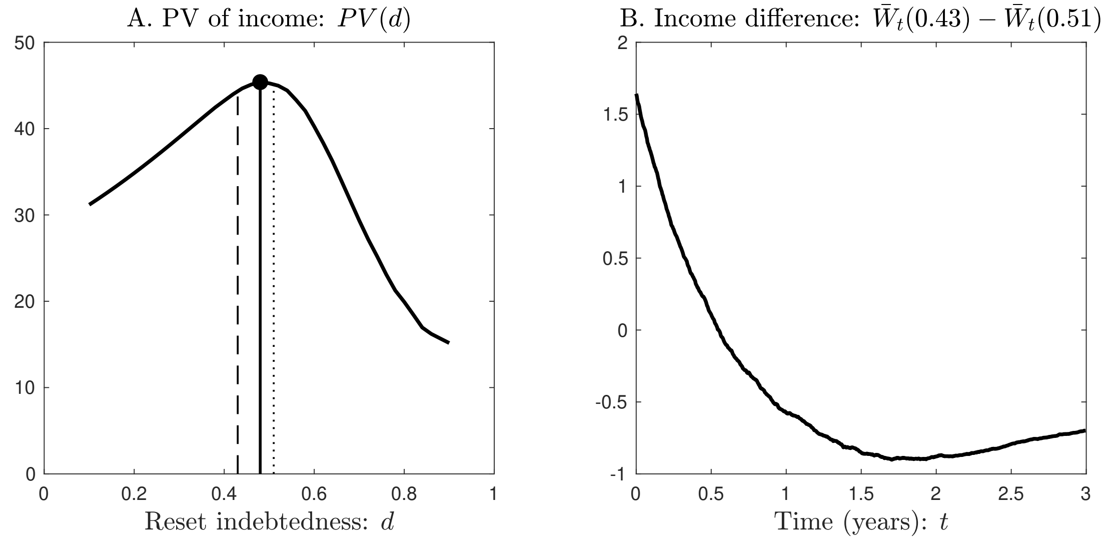

Figure VI: **Present value of household income for different reset values of indebtedness d and expected income difference path.** In Panel A, the present value of income is maximized at $d = 0.47$ (vertical solid line). The dashed line corresponds to the value $d = 0.43$ that maximizes labor supply. The dotted line corresponds to the value $d = 0.51$ that maximizes skills acquisition. Panel B depicts the difference in expected income paths between resetting indebtedness to $d = 0.43$ and $d = 0.51$. Other parameter values follow those of Figure I.

demonstrate these nuances around debt forgiveness.[41]

Specifically, denote d_0 as the level of household indebtedness that a debt forgiveness policy resets to. We simulate the paths of skills acquisition (a), labor supply (l), hourly wage (K), and total income ($W = lK$) for households starting at different d_0, and then take the average of these quantities as:

$$\bar{a}_t(d) = \mathbb{E}\Big[a_t | d_0 = d\Big], \qquad \bar{l}_t(d) = \mathbb{E}\Big[l_t | d_0 = d\Big], \tag{15}$$

$$\bar{W}_t(d) = \mathbb{E}\Big[W_t | d_0 = d\Big], \qquad \bar{K}_t(d) = \mathbb{E}\Big[K_t | d_0 = d\Big]. \tag{16}$$

We perform the simulation for 5,000 households over a three year period.[42] We then compute the expected present value (PV) of the total income generated by households for a

[41] To remain focused on our model framework, we assume away moral hazard considerations from ex-post debt forgiveness – that is, households' anticipation of debt forgiveness may foster ex-ante reluctance in spending effort, even in the absence of diminishing marginal utility and debt overhang.

[42] Parameter values follow those in Figure I.

given value of d_0. That is:

$$PV(d) = \mathbb{E}\left[\int_0^T e^{-r_B t} W_t | d_0 = d\right], \tag{17}$$

where $T = 3$ years.[43] This computation allows us to explore how the PV of household income varies with the reset indebtedness levels and thus, the effectiveness of a debt forgiveness policy in optimizing household income.

Panel A of Figure VI depicts the PV of household income as a function of the reset indebtedness. The pattern inherits the hump shape from skills acquisition and labor supply depicted in our baseline result (Figure II). Moving from the right end of the x-axis to the left – i.e., resetting the household debt to a lower level – initially increases the PV of income. This increase occurs because, in this region, the debt overhang force dominates; thus more aggressively forgiving debt revives households' incentives to acquire skills and supply labor. Because total income is the product of labor supply and hourly wage ($W = lK$), and because skills acquisition impacts the dynamics of hourly wage (via equation (3)), a boost in both actions increases household income. However, when debt is reset too aggressively – to the region where the diminishing marginal utility force dominates – debt forgiveness suppresses households' efforts in the two actions and the income.

Therefore, our first takeaway is that for households deeply in debt, there exists an interior optimum of debt forgiveness that maximizes the PV of income. Debt forgiveness should be large enough to mitigate debt overhang, but not too large to interfere with the diminishing marginal utility force. In the context of Figure VI, we find that such optimal debt forgiveness is to reset indebtedness level to $d_0 = 0.47$ (solid vertical line) – corresponding to the "peak" of the hump shape.

Interestingly, the value $d_0 = 0.47$ is between the peak of the hump shape for labor supply $l(d)$ at $d = 0.43$ (dashed vertical line) and the peak for skills acquisition $a(d)$ at $d = 0.51$ (dotted vertical line), obtained from Figure II. The intuition is as follows. Both skills acquisition and labor supply are subject to debt overhang. However, because skills acquisition is more resilient to debt overhang, the peak of its hump shape does not appear until a higher level of indebtedness. Skills acquisition thus requires less aggressive debt

[43] Setting the horizon to $T = 5$ or $T = 10$ does not qualitatively change the takeaways.

forgiveness – resetting debt "only" to 0.51 – to reach its maximum. Further reducing debt beyond this point would result in "over-forgiveness." By contrast, labor supply is more sensitive to debt overhang. It requires resetting debt "all the way" to 0.43 to reach its maximum. Because $l(d)$ and $a(d)$ jointly determine income generation, forgiveness policies resetting household debt to levels between those maximizing $l(d)$ and $a(d)$ (i.e., between the peaks of the two actions) would induce the highest PV of total income. This result constitutes the second takeaway from our analysis.

This takeaway suggests an interesting trade-off regarding optimal debt forgiveness. For values of $d > 0.51$, an additional dollar of debt forgiveness mitigates debt overhang for both $a(d)$ and $l(d)$ and is unambiguously beneficial for income generation. For values of $d < 0.43$, the diminishing marginal utility force is dominant for both actions, and additional debt forgiveness unambiguously discourages income generation. However, for values of $0.43 < d < 0.51$, a trade-off emerges: additional debt forgiveness encourages households to supply more labor (since labor supply is still dominated by debt overhang), but discourages households from acquiring skills (since skill acquisition is now dominated by the diminishing marginal utility force).

Discouraging skills acquisition negatively impacts household income – especially over the long term. Different from labor supply, skills acquisition determines the growth of household productivity (via equation (3)) and its effect accumulates in the long run. To see this intuition, we calculate the difference in the expected income paths when household debt is reset to $d_0 = 0.43$ versus $d_0 = 0.51$. Panel B of Figure VI depicts how this difference (i.e., $\bar{W}_t(0.43) - \bar{W}_t(0.51)$) evolves from the time of debt reset ($t = 0$) to three years later.

Following the previous discussion, resetting debt to $d_0 = 0.43$ is considered "over-forgiving" with respect to skills acquisition, but not so with respect to labor supply. Thus, while this policy promotes labor supply (relative to $d_0 = 0.51$), it impedes skills acquisition. We observe that even though in the short term, $d_0 = 0.43$ generates a higher income than $d_0 = 0.51$ (i.e., $\bar{W}_0(0.43) - \bar{W}_0(0.51) > 0$), in the longer term, impeded skills acquisition depresses income and $\bar{W}_t(0.43) - \bar{W}_t(0.51)$ turns negative. The more modest debt forgiveness (resetting $d_0 = 0.51$) would therefore benefit the household over time. It follows that in the region between the two "peaks," there is a trade-off between maximizing skills acquisition versus supplying labor.[44]

This trade-off has various practical applications. For instance, it speaks to the optimal debt forgiveness for high- versus low-skilled workers. To the extent that low-skilled workers primarily seek to expand their working hours to generate short-term income, policymakers may consider prioritizing skills acquisition (i.e., longer-term income generation) for this group. Such a policy can help mitigate income inequality and foster social mobility (e.g., Goldin and Katz, 2010; Chetty, Hendren, Kline, and Saez, 2014). Interestingly, this objective would entail a more modest debt forgiveness policy for low-skilled workers than for high-skilled workers – to avoid "over-forgiving" with respect to skills acquisition.[45] Another, more time-targeted application is motivated by the "Great Resignation" during 2021 and 2022 (Gittleman, 2022) – a period characterized by many workers voluntarily leaving their jobs.[46] In similar cases, policymakers could prioritize restoring labor supply; accordingly, a more aggressive debt forgiveness policy (that mitigates debt overhang all the way until the maximum of labor supply is reached) may help combat the shrinking labor pool and climbing wages in the near term.

6 Conclusion

In this paper, we study how household indebtedness affects human capital investment, and its interaction with labor supply. We develop a dynamic model featuring a risk-averse household investing in acquiring skills – which, unlike labor income, are largely inalienable from the household and do not accrue to creditors even at default. This attribute makes skills acquisition more resilient to debt overhang as household indebtedness rises. We show that skills acquisition is hump-shaped with respect to the level of household indebtedness, reflecting the interplay of two forces: diminishing marginal utility and debt overhang. Although labor

[44]Following Section 2.4, we repeat the analysis in this section separately for $\theta_{al} = +8$ (when the two actions are substitutes) and $\theta_{al} = -8$ (when the two actions are complements). We obtain the same takeaways as in the baseline case ($\theta_{al} = 0$).

[45]Relatedly, workers in sectors going through the clean energy transition – such as fossil fuel employees (Aklin and Urpelainen, 2022) – may face an emerging need to update their skill sets. For these workers, a modest debt forgiveness policy would be more effective in enhancing skills acquisition and employment resilience in the long term.

[46]It is believed that the COVID-19 pandemic and its aftermath led workers to reconsider their jobs and priorities. Many workers sought better work-life balance, resulting in them quitting their jobs.

supply exhibits a similar hump shape, it begins to tail off at an earlier stage as indebtedness builds up, reflecting its lower resilience to debt overhang. Moreover, the two actions interact with each other. Because skills acquisition is only valuable when the household expects to supply labor in the future, the response of labor supply to indebtedness propagates back in time, distorting the skills acquisition decision ex ante.

We test our model using longitudinal data from the NLSY79 survey and find empirical support for the model. When individuals face a relatively low level of indebtedness, increasing indebtedness initially encourages them to acquire labor skills, but this relation reverses after indebtedness reaches a certain level. Labor supply exhibits a similar hump shape but debt overhang emerges at a significantly lower level of household indebtedness. Further, we find that the hump-shaped relation between indebtedness and skills acquisition exhibits cross-sectional variation as predicted by the model. We derive implications regarding debt forgiveness based on the theoretical and empirical findings.

In the wake of the recent skilled labor shortage and historically high level of household indebtedness, our study provides a unified theoretical framework, supplemented by empirical evidence, to study the relation and the interaction between these household decisions.

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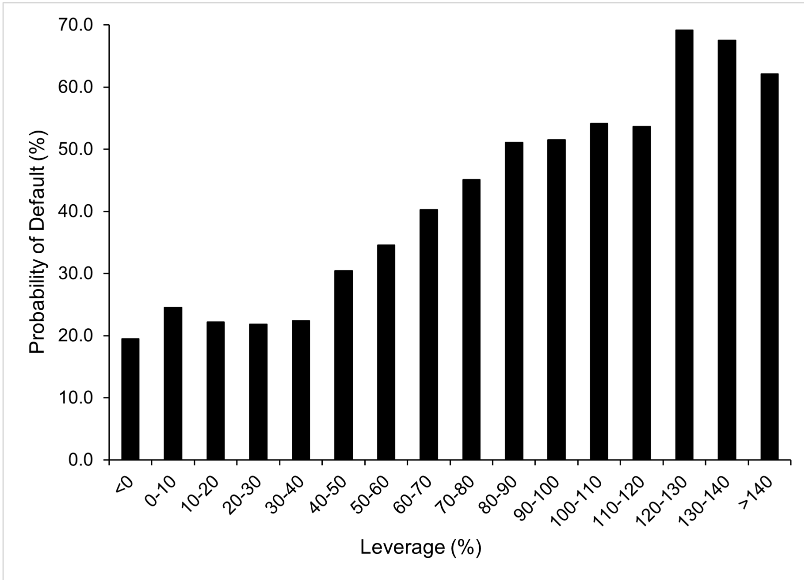
A. Late payments



B. Bankruptcy

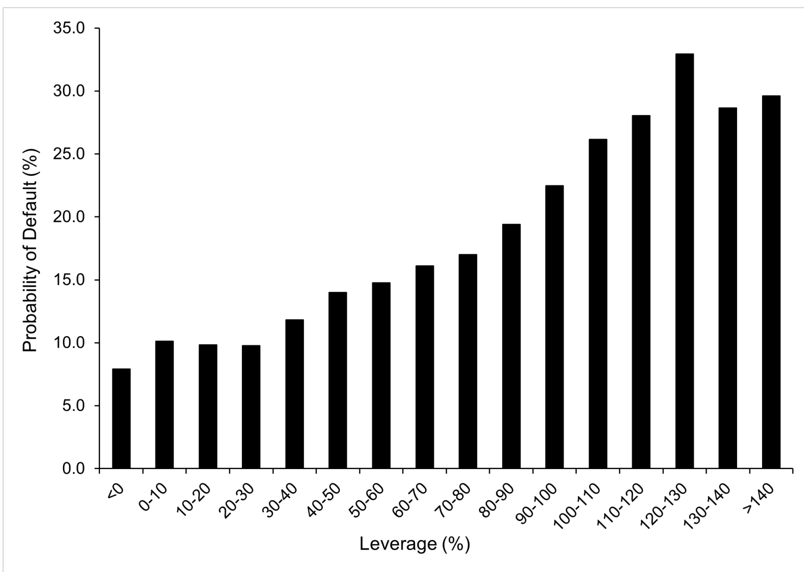
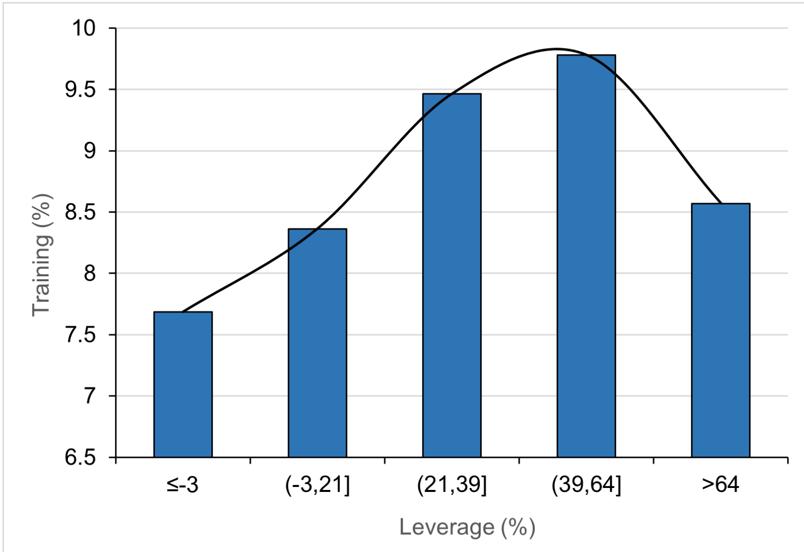


Figure 1: Default probability and household leverage

This figure plot the default probability for each household leverage bin based on data from the NLSY79. In Panel A, default is identified by whether a household has missed mortgage or rent payment as of a given year. Missed payments are those at least 60 days past due. The NLSY79 surveys whether an individual has missed payments in the past five years. In Panel B, default is identified by whether a household has filed for bankruptcy as of a given year. Household leverage (in percentage) is the ratio of net debt to asset, as defined in Section 3.3.

A. Skills acquisition



B. Labor supply

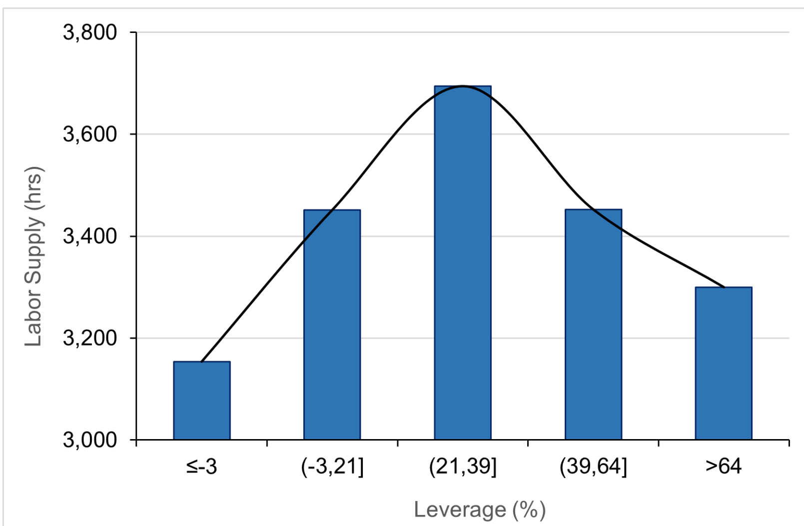


Figure 2: Skills acquisition and labor supply over leverage

Panel A reports percentage of individuals who have participated in self-requested training programs that are not self-paid since the previous survey among respondents from NLSY79. The first bin consists of respondents whose household leverage is in the lowest quintile of the sample distribution of household leverage. The second consists of respondents whose leverage is in the second quintile, and so forth. The numbers below each bin indicates the corresponding range of household leverage. Household leverage (in percentage) is the ratio of net debt to asset, as defined in Section 3.3. Panel B reports the average number of hours that individuals have worked since the previous survey across leverage bins.

Table 1: Summary Statistics

This table reports summary statistics of the sample. *Training* is an indicator variable that equals one if a respondent has participated in self-requested training programs that are not self-paid since the previous survey, and zero otherwise. *TrainingTime* is the number of hours a respondent spends on self-requested and non-self-paid training programs since the previous survey. *Labor Supply* is the total number of hours that a respondent has worked since the previous survey. *Leverage* is the ratio of net debt to asset, defined in Section 3.3 and measured as of the previous survey. *Age* is a respondent's age as of the current survey. *Male* and *White* are indicators of a respondent's gender and ethnicity. *MaritalStatus* is an indicator for whether a respondent is married, measured as of the previous survey. *College* is an indicator for whether a respondent has attended college as of the previous survey. *FatherEdu* is the number of years of schooling that a respondent's father has completed. Dummy variables are denoted by (d).

Variable	N	Mean	S.D.	p5	p50	p95
Training (d)	52,016	0.088	0.283	0	0	1
TrainingTime (hrs)	52,016	4.278	28.096	0	0	16
TrainingTime (hrs), Conditional on training	4,552	48.885	82.710	1	20.500	200
Labor Supply (hrs)	52,016	3,399.730	1,561.520	616	3,760	6,052
Leverage	52,016	0.296	0.456	-0.500	0.331	1.000
Age	52,016	39.301	7.790	28	38	52
Male (d)	52,016	0.504	0.500	0	1	1
White (d)	52,016	0.620	0.485	0	1	1
MaritalStatus(d)	52,016	0.623	0.485	0	1	1
College (d)	52,016	0.556	0.497	0	1	1
FatherEdu (years)	52,016	11.186	3.873	4	12	17

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

This table presents regression analyses of the effect of household leverage on skills acquisition (captured by training participation) and labor supply. Columns (1) to (3) pertain to training participation. The dependent variable, *Training*, is an indicator of whether the respondent has requested and participated in training programs that are not self-paid since the previous survey. Columns (4) to (6) pertain to labor supply. The dependent variable, *Labor Supply*, is the natural logarithm of one plus the number of hours that a respondent has worked since the previous survey. The quadratic regression model is specified in equation (14). *Leverage* is the ratio of net debt to asset, defined in Section 3.3. $Leverage^2$ is the square of *Leverage*. The control variables include a respondent's age, gender, ethnicity, marital status, college enrollment, and father's education. Definitions of control variables are in Table 1. For each estimated hump-shape relation between household leverage and training or labor supply, the switching point of this relation is calculated as $-\frac{\beta_1}{2\beta_2}$. The differences in the switching points of training versus labor supply are tested using the Delta method. Switching points, along with the respective differences, are reported below the coefficient estimates, in the rows *Switching point* and *Switching point diff.* 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 years. Industry FE and Occupation FE are indicators of the respondent's industry and occupation, respectively. Each regression includes a separate intercept. Standard errors are clustered at the state-year level and reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var.	*Training*			*Labor Supply*		
	(1)	(2)	(3)	(4)	(5)	(6)
Leverage (β_1)	0.017***	0.017***	0.019***	0.122***	0.122***	0.128***
	(0.003)	(0.003)	(0.004)	(0.020)	(0.020)	(0.021)
Leverage^2 (β_2)	-0.016***	-0.016***	-0.016***	-0.198***	-0.197***	-0.194***
	(0.003)	(0.003)	(0.003)	(0.025)	(0.025)	(0.025)
Male	-0.002	-0.002	-0.002	0.379***	0.382***	0.379***
	(0.003)	(0.003)	(0.003)	(0.017)	(0.017)	(0.018)
White	-0.001	-0.000	-0.007*	-0.035**	-0.033**	-0.030
	(0.003)	(0.003)	(0.004)	(0.017)	(0.016)	(0.020)
MaritalStatus	-0.004	-0.004	-0.004	-0.068***	-0.070***	-0.070***
	(0.003)	(0.003)	(0.003)	(0.015)	(0.015)	(0.015)
College	0.026***	0.026***	0.025***	0.126***	0.125***	0.125***
	(0.003)	(0.003)	(0.003)	(0.015)	(0.015)	(0.016)
FatherEdu	0.001**	0.001**	0.001**	-0.001	-0.001	-0.002
	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)	(0.002)
Age	0.001	0.001	-0.001	0.035*	0.035*	0.028
	(0.003)	(0.003)	(0.003)	(0.019)	(0.019)	(0.020)
Age^2	-0.000	-0.000	0.000	-0.001*	-0.001*	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Switching point	**0.540**	**0.549**	**0.592**	**0.310**	**0.308**	**0.331**
	(1)-(4)	**(2)-(5)**	**(3)-(6)**			
Switching point diff	**0.231****	**0.241****	**0.261****			
	(0.107)	**(0.112)**	**(0.118)**			
Industry FE	YES	NO	NO	YES	NO	NO
Occupation FE	YES	NO	NO	YES	NO	NO
State×Year FE	YES	YES	NO	YES	YES	NO
Industry×Occupation FE	NO	YES	YES	NO	YES	YES
County×Year FE	NO	NO	YES	NO	NO	YES
Observations	52,016	52,016	52,016	52,016	52,016	52,016
R-squared	0.038	0.040	0.150	0.089	0.092	0.202

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

This table presents analyses of the effect of household leverage on skills acquisition (captured by training participation), differentiating the degree of skills depreciation. In columns (1) to (4), the dependent variable is *Training*. For easier comparison, column (5) replicates Table 2 column (6), in which the dependent variable is *Labor Supply*. The degree of skills deprecation is measured using two complementary approaches. Columns (1) and (2) measure depreciation based on exposure to computer and information technology (Section 4.3.1). Column (1) consists of individuals facing low skills depreciation, identified as those working in occupations with less exposure to computer and information technology (CIT). Column (2) consists of individuals facing high skills depreciation, identified as those working in occupations with greater CIT exposure. The detailed classification is described in Section 4.3.1. Columns (3) and (4) measure the degree of skills deprecation based on individuals' changes in the wage path after training completion, and this approach is described in Section 4.3.2. Regression specifications follow equation (14). Switching points, along with their differences between training and labor supply, are obtained in the same manner as in Table 2 and are reported below the coefficient estimates, in the rows *Switching point* and *Switching point diff*. County FE are indicators of the respondent's residential county. Year FE are indicators of survey years. Industry FE and Occupation FE are indicators of the respondent's industry and occupation, respectively. Each regression includes a separate intercept. Standard errors are clustered at the state-year level and reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var.	*Training*		*Training*		*Labor Supply*
	Exposure to technology		Changes in the wage path		
	(1)	(2)	(3)	(4)	(5)
	High Depreciation	Low Depreciation	High Depreciation	Low Depreciation	
Leverage	0.008***	0.013***	0.006***	0.014***	0.128***
	(0.002)	(0.003)	(0.002)	(0.003)	(0.021)
Leverage^2	-0.008***	-0.009***	-0.006***	-0.011***	-0.194***
	(0.002)	(0.003)	(0.002)	(0.003)	(0.025)
Switching point	**0.495**	**0.673**	**0.517**	**0.632**	**0.331**
	(1)-(5)	**(2)-(5)**	**(3)-(5)**	**(4)-(5)**	
Switching point diff	**0.164**	**0.343***	**0.187**	**0.301****	
	(0.126)	**(0.194)**	**(0.182)**	**(0.146)**	
Controls	YES	YES	YES	YES	YES
Industry FE	NO	NO	NO	NO	NO
Occupation FE	NO	NO	NO	NO	NO
State×Year FE	NO	NO	NO	NO	NO
Industry×Occupation FE	YES	YES	YES	YES	YES
County×Year FE	YES	YES	YES	YES	YES
Observations	48,543	50,611	48,736	50,421	52,016
R-squared	0.161	0.156	0.198	0.149	0.202

Table 4: The instrumental variable analysis

This table reports the second-stage regressions of the two-stage least squares (2SLS) instrumental variable analysis for the effect of household leverage on labor skills acquisition and labor supply. Household leverage is proxied by the loan-to-value (LTV) ratio, which is instrumented using the synthetic loan-to-value ($SLTV$) ratio, following Bernstein (2021). The construction of $SLTV$, as well as the 2SLS specifications, are discussed in Section 4.6. $SLTV^2$ is the square of $SLTV$. Switching points, along with their differences between training and labor supply, are obtained in the same manner as in Table 2 and are reported below the coefficient estimates, in the rows *Switching point* and *Switching point diff*. Cohort FE are indicators of the survey year when the respondent becomes the owner of the house. Definitions of other variables are in Table 1 and Table 2. Standard errors are clustered at the state-year level and reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var.	*Training*		*Labor Supply*	
	(1)	(2)	(3)	(4)
Instrumented LTV	2.227**	1.946**	8.304*	8.655*
	(0.967)	(0.864)	(4.899)	(4.441)
Instrumented LTV^2	-1.395*	-1.250*	-9.110**	-8.856**
	(0.741)	(0.710)	(3.862)	(3.704)
Switching point	**0.798**	**0.778**	**0.456**	**0.489**
	(1)-(3)	**(2)-(4)**		
Switching point diff	**0.342****	**0.290***		
	(0.160)	**(0.168)**		
Controls	NO	YES	NO	YES
Industry×Occupation FE	NO	YES	NO	YES
Cohort FE	YES	YES	YES	YES
State×Year FE	YES	YES	YES	YES
Observations	13,358	13,358	13,358	13,358

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

$$\delta H(K) = \max_{a,l} \{ \log lK + \theta_a \frac{a^2}{2} + \theta_l \frac{l^2}{2} + H'(K)K(a-\rho) + \frac{1}{2} H''(K)K^2\sigma^2 \}. \tag{18}$$

We conjecture that the value function takes the form:

$$H_1 + \frac{1}{\delta} \log K, \tag{19}$$

where H_1 is a constant to be determined. Substituting (19) into (18) and collecting terms yields that:

$$H_1 = -\frac{\delta^2\theta_a \log\theta_l + \delta^2\theta_a + \delta\theta_a (2\rho+\sigma^2) - 1}{2\delta^3\theta_a}, \qquad a(K) = \frac{1}{\delta\theta_a}, \qquad l(K) = \frac{1}{\sqrt{\theta_l}}. \tag{20}$$

A.2 Proof of Lemma 1

Denote by C^*, a^*, l^*, τ_D^* the household's optimal consumption, skills acquisition, labor supply, and default policies. Suppose for a contradiction that there exist non-zero probability instances in which it is optimal for the household to default before reaching its borrowing limit (i.e., $\mathbb{P}(\tau_D < \tau) > 0$). Express the household's objective function (6) as:

$$\mathbb{P}(\tau_D < \tau)\mathbb{E}\left[\int_0^{\tau_D} e^{-\delta t} u(C_t^*, a_t^*, l_t^*)dt + e^{-\delta\tau_D} H(K_{\tau_D}) \middle| \tau_D < \tau\right] + \tag{21}$$

$$\mathbb{P}(\tau_D = \tau)\mathbb{E}\left[\int_0^{\tau_D} e^{-\delta t} u(C_t^*, a_t^*, l_t^*)dt + e^{-\delta\tau_D} H(K_{\tau_D}) \middle| \tau_D = \tau\right]. \tag{22}$$

Consider an alternative policy in which default is postponed by an interval Δt and consumption is set to $C^*_{\tau_D} + \Delta C$, where $\Delta C > 0$, while keeping $a = a^*_{\tau_D}$ and $l = l^*_{\tau_D}$. For a sufficiently short interval Δt, the increment in consumption can be set to an arbitrarily large value since the household has not reached yet its borrowing limit. Therefore, this alternative policy yields a higher value to the household since

$$\mathbb{E}\left[\int_0^{\tau_D} e^{-\delta t} u(C^*_t, a^*_t, l^*_t)dt + e^{-\delta \tau_D} H(K_{\tau_D}) \middle| \tau_D < \tau \right] <$$
$$\mathbb{E}\left[\int_0^{\tau_D} e^{-\delta t} u(C^*_t, a^*_t, l^*_t)dt + \int_{\tau_D}^{\tau_D+\Delta t} e^{-\delta t} u(C^*_{\tau_D} + \Delta C, a^*_{\tau_D}, l^*_{\tau_D})dt + e^{-\delta(\tau_D+\Delta t)} H(K_{\tau_D+\Delta t}) \middle| \tau_D < \tau \right],$$

which is a contradiction to the optimality of $\tau_D < \tau$. Therefore, it is optimal to set $\tau_D = \tau$.

A.3 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:

$$\begin{aligned}\delta F(S,K) = \max_{C,a,l} \Big\{ & \log C - g(a,l) + F_S(S,K)(r(S)S - C + lK) \\ & + F_K(S,K)K(a-\rho) + \frac{1}{2} F_{KK}(S,K)K^2\sigma^2 \Big\},\end{aligned} \tag{23}$$

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

$$\frac{1}{C(S,K)} = F_S(S,K), \qquad \theta_a a(S,K) = F_K(S,K)K, \qquad \theta_l l(S,K) = F_S(S,K)K. \tag{24}$$

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:

$$f(s) + \frac{1}{\delta} \log K, \tag{25}$$

where $f(s)$ is a function to be determined that only depends on scaled savings $s = S/K$. Substituting (25) into (24), we obtain the optimal controls as functions of $f(s)$:

$$C(S,K) = \frac{K}{f'(s)}, \qquad a(S,K) = \frac{1 - s\delta f'(s)}{\delta\theta_a}, \qquad l(S,K) = \frac{f'(s)}{\theta_l}. \tag{26}$$

Next, we substitute (25) and (26) into the HJB (23) to obtain an ordinary differential equation (ODE) for $f(s)$:

$$\begin{aligned} 0 =& 2\delta s f'(s)\left(\delta\theta_a\left(\rho+\sigma^2\right) + \delta\theta_a r(s) - 1\right) + \frac{\delta^2 f'(s)^2\left(\theta_a + \theta_l s^2\right)}{\theta_l} + \delta^2\theta_a s^2\sigma^2 f''(s) + 1 \\ & - \delta\theta_a\left(2\delta + 2\delta\log\left(f'(s)\right) + 2\delta^2 f(s) + 2\rho + \sigma^2\right). \end{aligned} \tag{27}$$

Because equation (27) 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,

$$f(\underline{s}) = -\frac{\delta^2\theta_a\log\theta_l + \delta^2\theta_a + \delta\theta_a\left(2\rho+\sigma^2\right) - 1}{2\delta^3\theta_a} = H_1. \tag{28}$$

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

$$\lim_{K\to 0} C(S,K) = \delta S \iff \lim_{s\to\infty} s f'(s) = \frac{1}{\delta}. \tag{29}$$

Finally, we numerically solve ODE (27) subject to boundary conditions (28) and (29) using a standard ODE solver.

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

$$d_t = \frac{S_t}{l_{\tau_D}\underline{s}K_t} = \frac{S_t\sqrt{\theta}}{\underline{s}K_t}, \tag{30}$$

where the equality follows from substituting the labor supply at default from equation (8). Next, we note that $s = S/K$ and d are linearly related. Finally, it follows that one can

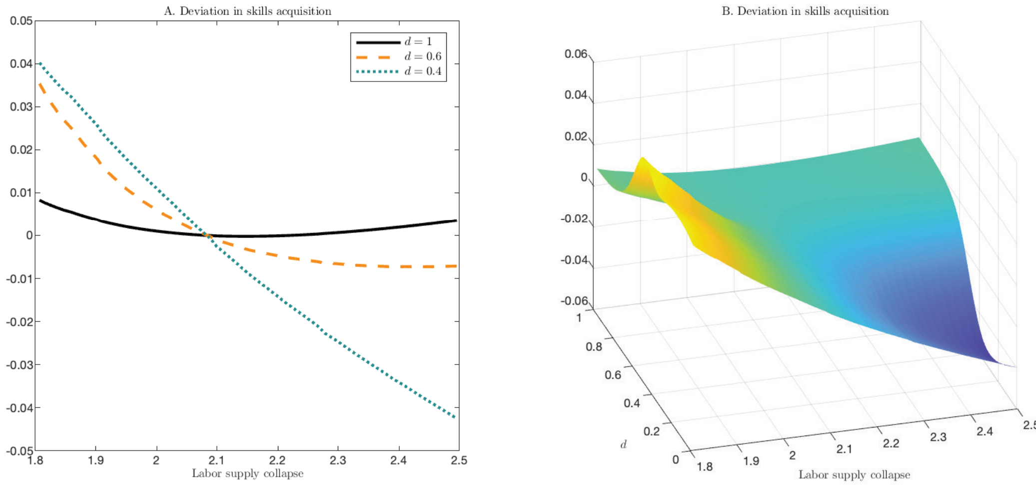


Figure AI: **Back-propagation illustration.** Other parameter values follow those of Figure I.

transition from the scaled savings s to the state variable d for all of the model's variables.

A.4 Further illustration of the back-propagation effect and policy implications

Figure AI provides further insights and nuances of the back-propagation effect. In Panel A, the x-axis denotes the extent of labor supply collapse in the regime of high default likelihood, defined as $\max_{[0,1]} l(d) - l(1)$ and obtained for each value of $\theta_{al} \in [-8, 8]$. For instance, the right end of the x-axis, 2.5, corresponds to the case of $\theta_{al} = 8$, in which the household's labor supply collapses – as seen in Panel B of Figure III – from the highest point 2.5 (when the household indebtedness is around 0.4) to the lowest point 0 (when the indebtedness is 1). On the other hand, the left end of the x-axis corresponds to the case of $\theta_{al} = -8$, in which case, labor supply collapses by about 1.8 – as seen in Panel D of Figure III. Intuitively, the higher θ_{al}, the more a household needs to pick one action over the other near default, and thus, the larger the collapse in labor supply.

The y-axis denotes, for each value of θ_{al}, the deviation of optimal skills acquisition from the benchmark case when $\theta_{al} = 0$ (i.e., $a(d; \theta_{al}) - a(d; 0)$). For example, given $\theta_{al} = 8$ (the right end of the x-axis), this deviation is the distance between the dotted and solid lines in Panel A of Figure III. This distance is calculated at three points of indebtedness: $d = 0.4$

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

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

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

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

A.5 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 show that the hump-shape relation between skills acquisition and leverage (resp. labor supply and leverage) is robust to a post-default decline in human capital. To this end, we extend the model to incorporate a parameter $\psi > 0$ that captures the fraction of human capital retained by the household upon default. That is, the value function post default for the household now becomes $H(\psi K)$. $1 - \psi > 0$ thus captures the magnitude of human capital decline after default.

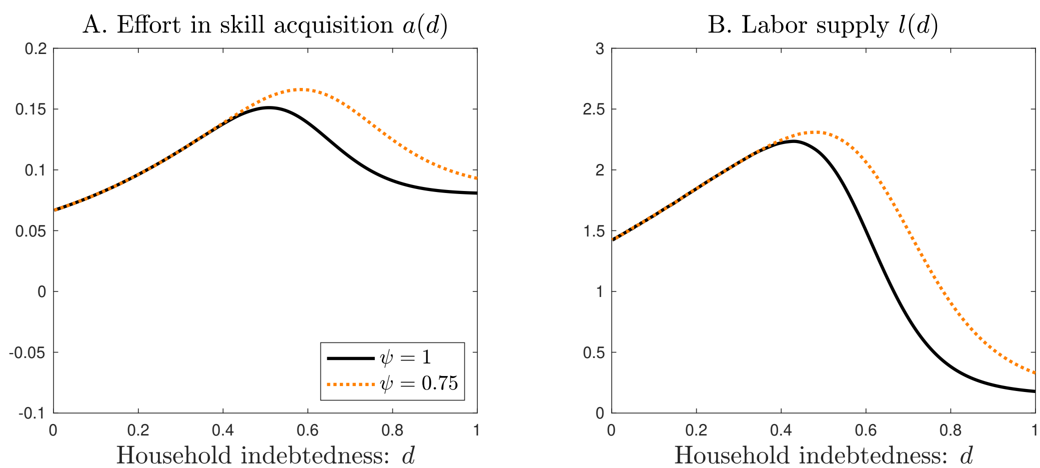


Figure AII: **Robustness with respect to ψ.** Other parameter values follow those of Figure I.

In Figure AII we depict the baseline case, in which human capital remains intact after default ($\psi = 1$), and the case in which there is a 25% human capital decline post default ($\psi = 0.75$). Bos, Breza, and Liberman (2018) estimate that bankruptcy is associated with 3% loss in subsequent employment and a wage earning reduction of $1,000. In addition, the U.S. federal laws allow wage garnishment of up to 25% of household disposable earnings

(Title III of Consumer Credit Protection Act). We therefore re-calibrate our model using the more conservative parameter, 25%, as the loss of human capital value. This parameter encompasses the magnitude of both wage reduction and garnishment after default in practice. Even so, we show that our patterns remain robust – that is, both actions exhibit a hump-shaped relation with household leverage, and importantly, labor supply exhibits an earlier manifestation of debt overhang than skills acquisition.

A.6 Default with less punitive outcomes

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

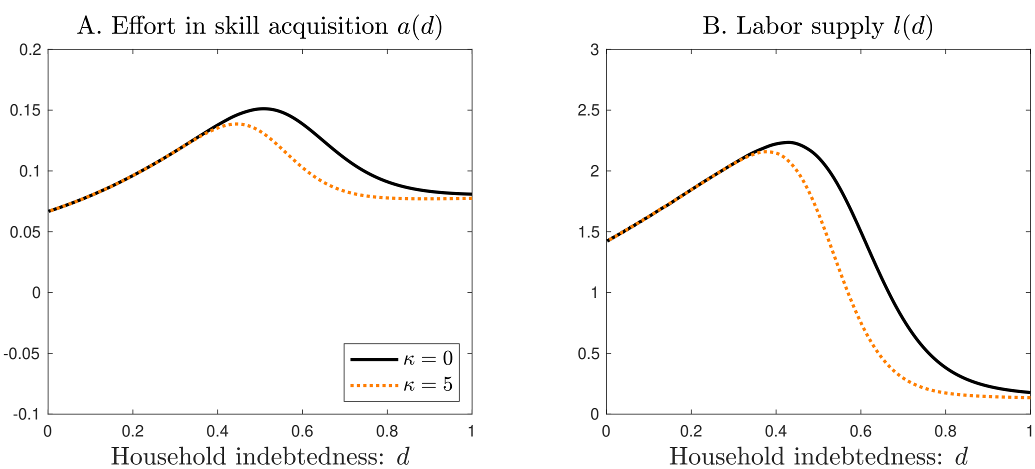


Figure AIII: **Robustness with respect to κ.** Other parameter values follow those of Figure I.

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

A.7 Labor supply comparative statics

Figure AIV depicts comparative statics of labor supply with respect to the volatility of hourly wages σ. As discussed in Section 2.5.2, the precautionary effect makes labor supply increasing in σ.

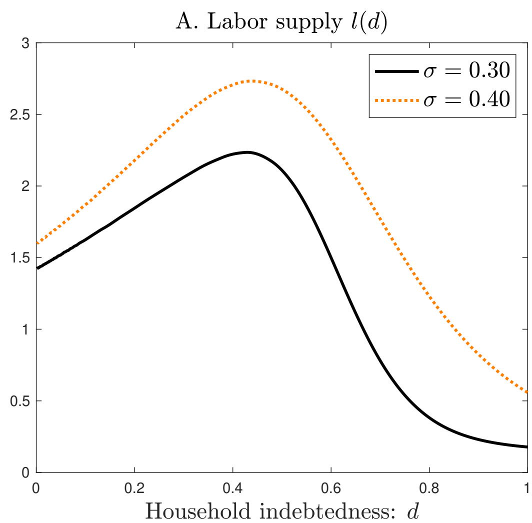


Figure AIV: **Comparative statics with respect to hourly wage volatility σ.** Other parameter values follow those of Figure I.

A.8 Illustration of main results using the expanded state space of d

Figure AV plots skills acquisition (Panel A) and labor supply (Panel B) as a function of household indebtedness d – including the negative region of the state space. As can be seen, our key insights remain unchanged from Figure II. This observation is intuitive because in the negative region of d (when the household has substantial savings and no debt), the diminishing marginal utility is the only active force. This region is not subject to the debt overhang force.

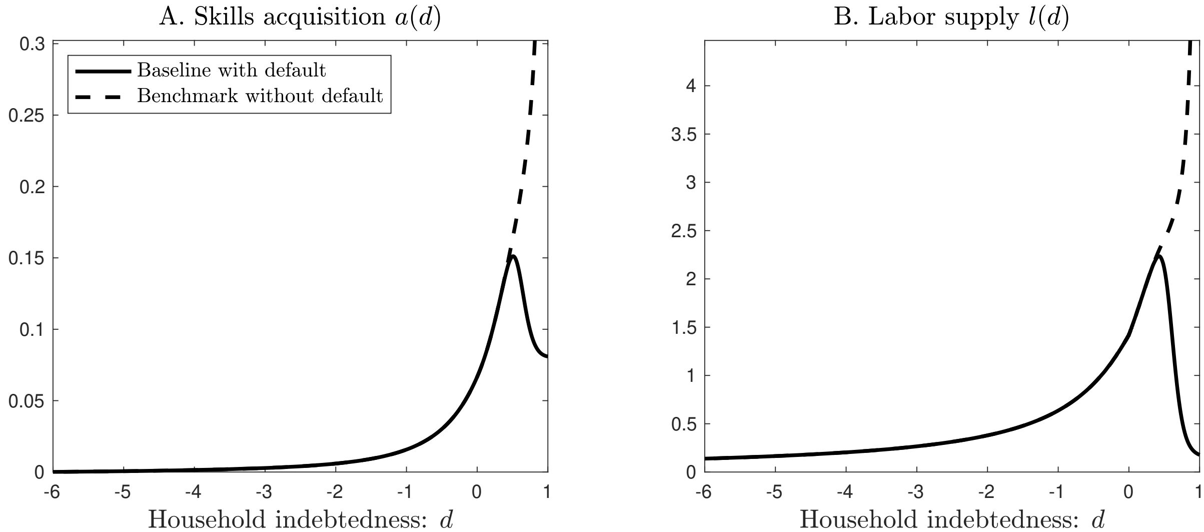


Figure AV: **Effort in skills acquisition and labor supply.** Parameter values follow those of Figure I.

B Online Appendix B

B.1 Individual fixed effects

In this appendix, we repeat the analyses in Table 2 including individual fixed effects. Because we aim to explore the time-series variation of a given individual's decision on training (and labor supply), we restrict our sample to those that have taken training programs at least once in our sample period.

Table B1 reports the results and confirms our main findings. Based on columns (1) and (2), the coefficient β_1 is significantly positive, while the coefficient β_2 becomes insignificant for training. This result indicates that with individual fixed effects, the decline in training during high leverage is trivial – or put it differently, the debt overhang force does not manifest in a significant manner any more. This observation is in line with the notion that skills acquisition is more resilient to debt overhang. In contrast, the hump shape preserves for labor supply, as shown by the significant coefficients β_1 and β_2 in columns (3) and (4). Accordingly, the difference in the switching points of the two actions becomes irrelevant, as the switching point of training may be regarded as infinitely positive.[47]

[47] We do not include State $\times$ Year FE, or County $\times$ Year FE in this table, following policies regarding the use of restricted Geocode data in models with individual fixed effects.

Table B1: Individual fixed effects

This table reports regression analyses of the effect of household leverage on skills acquisition and labor supply, including individual fixed effects. The sample consists of individuals that have taken training programs at least once in the sample period. Individual FE are indicators of each respondent in NLSY79. Year FE are indicators of survey years. Industry FE and Occupation FE are indicators of the respondent's industry and occupation, respectively. Definitions of other variables are in Table 1 and Table 2. Each regression includes a separate intercept. Standard errors are clustered at the state-year level and reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var.	*Training*		*Labor Supply*	
	(1)	(2)	(3)	(4)
Leverage	0.020**	0.022**	0.110***	0.119***
	(0.009)	(0.009)	(0.025)	(0.025)
Leverage^2	-0.007	-0.008	-0.112***	-0.122***
	(0.010)	(0.010)	(0.033)	(0.033)
Switching point	**N/A**	**N/A**	**0.489**	**0.485**
Controls	NO	YES	NO	YES
Individual FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry×Occupation FE	YES	YES	YES	YES
Observations	26,646	26,646	26,646	26,646
R-squared	0.114	0.114	0.328	0.328

B.2 Piece-wise regressions

To supplement the quadratic regression model in Section 4.2, we perform piece-wise linear regressions. The estimation for training takes the following form:

$$Training_{i,k,t} = \alpha + \beta_1 Leverage_{i,t-1} + \beta_3 X_{i,t-1}^{Leverage} + \gamma_1 Z_{i,t-1} + \gamma_2 X_i + FE + \epsilon_{i,k,t}. \quad (31)$$

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

$$X^{Leverage} = (Leverage - Switching\ point) \times D^{Leverage}, \quad (32)$$

where $D^{Leverage}$ is an indicator variable that equals one if *Leverage* is larger than the switching point – 59% as reported in Table 2 column (3), and zero otherwise. In this model, we expect the coefficient β_1 to be positive, the coefficient β_3 to be negative, and the summation of β_1 and β_3 to be significantly negative. A positive β_1 would indicate a positive relation between household leverage and training likelihood when leverage is relatively low (below 59%). A negative β_3 would indicate that such a relation reverses as leverage surpasses the the switching point. Accordingly, a negative and significant $\beta_1 + \beta_3$ would indicate that the reversal is sufficiently sizable such that in aggregate, leverage lowers the training likelihood in the high leverage regime (above 59%). These observations combined would indicate a hump-shaped relation between household leverage and training.

Columns (1) to (3) of Table B2 display the piece-wise regression estimates. With various controls, industry×occupation fixed effects, and county×year fixed effects in column (3), the coefficient of *Leverage* (β_1) is 0.024 and the coefficient of $X^{Leverage}(\beta_3)$ is -0.051. Both are statistically significant at 1% level. In addition, the F statistics reject the null hypothesis that $\beta_1 + \beta_3 = 0$ at the 1% significance level.

The economic significance of the piece-wise regression estimates is sizable. Based on column (3), a one-standard-deviation increase in household leverage is associated with a 1.1% increase in training likelihood when leverage is below 59%; when leverage is above 59%, a one-standard-deviation increase in leverage is associated with a 1.2% decrease in training likelihood. In comparison, the sample average of training participation is 8.8%, as shown in Table 1.

Columns (4) to (6) repeat the piece-wise regression for labor supply, and the results similarly indicate a hump shape, with approximately 33% of leverage as the switching point.

Section 4.2 shows that the switching points between training and labor supply are significantly different. Here, we additionally test whether the decline of labor supply (in the high leverage region) is sharper than that of training – a supplementary observation from Figure 2. Take labor supply as an example. We calculate the magnitude of drop in *Labor-Supply* during the high region of *Leverage* (i.e., from the switching point to the maximum of *Leverage*), divided by the magnitude of the increase in *LaborSupply* during the low region of *Leverage* (i.e., from the minimum of *Leverage* to the switching point). This ratio – namely, the *Drop ratio* – captures the sharpness of labor supply decline (due to debt overhang force) relative to its previous run-up (due to the diminishing marginal utility force).

The rows *Drop ratio* and *Drop ratio diff* in Table B2 reports the ratios for the two actions, respectively, and the statistical significance in their differences. We find that relative to training, the decline in labor supply (as a result of debt overhang) is sharper, as indicated by greater drop ratios. The drop ratio differences between the two actions are significant at the 5% level. This observation suggests that labor supply is associated with a sharper manifestation of debt overhang.

Table B2: Piece-wise regressions of skills acquisition and labor supply on household leverage

This table presents piece-wise linear regression analyses of the effect of household leverage on skills acquisition (captured by training participation) and labor supply. Columns (1) to (3) pertain to training participation. The dependent variable, *Training*, is an indicator of whether the respondent has requested and participated in training programs that are not self-paid since the previous survey. Columns (4) to (6) pertain to labor supply. The dependent variable, *Labor Supply*, is the natural logarithm of one plus the number of hours a respondent has worked since the previous survey. The piece-wise regression model is specified in equation (31). *Leverage* is the ratio of net debt to asset, defined in Section 3.3. $X^{Leverage}$ is an interaction term, defined in Online Appendix B.2. The F statistics testing $\beta_1 + \beta_3 = 0$ is reported. For each specification, we estimate the *Drop ratio*, which captures the extent of labor supply decline (due to debt overhang force) relative to its previous run-up (due to the diminishing marginal utility force). The detailed construction of this measure is in Online Appendix B.2. The drop ratios, along with their differences between training and labor supply, are reported below the coefficient estimates, in the rows *Drop ratio* and *Drop ratio diff*. Drop ratio differences are tested based on the Delta method. 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 years. Industry FE and Occupation FE are indicators of the respondent's industry and occupation, respectively. Each regression includes a separate intercept. Standard errors are clustered at the state-year level and reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var.	*Training*			*Labor Supply*		
	(1)	(2)	(3)	(4)	(5)	(6)
Leverage (β_1)	0.022***	0.021***	0.024***	0.238***	0.237***	0.243***
	(0.004)	(0.004)	(0.004)	(0.030)	(0.030)	(0.031)
$X^{Leverage}$ (β_3)	-0.050***	-0.048***	-0.051***	-0.477***	-0.477***	-0.471***
	(0.009)	(0.009)	(0.009)	(0.058)	(0.058)	(0.059)
Male	-0.002	-0.002	-0.002	0.379***	0.381***	0.378***
	(0.003)	(0.003)	(0.003)	(0.017)	(0.017)	(0.018)
White	-0.001	-0.000	-0.007*	-0.035**	-0.034**	-0.031
	(0.003)	(0.003)	(0.004)	(0.017)	(0.016)	(0.020)
MaritalStatus	-0.004	-0.004	-0.004	-0.072***	-0.074***	-0.074***
	(0.003)	(0.003)	(0.003)	(0.015)	(0.015)	(0.015)
College	0.026***	0.026***	0.025***	0.125***	0.124***	0.124***
	(0.003)	(0.003)	(0.003)	(0.015)	(0.015)	(0.016)
FatherEdu	0.001**	0.001**	0.001**	-0.001	-0.001	-0.002
	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)	(0.002)
Age	0.001	0.001	-0.001	0.034*	0.033*	0.026
	(0.003)	(0.003)	(0.003)	(0.019)	(0.019)	(0.020)
Age^2	-0.000	-0.000	0.000	-0.000*	-0.000*	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
F stat of (β_1+β_3=0)	**15.894*** **	**14.345*** **	**14.412*** **	**39.637*** **	**39.756*** **	**36.548*** **
Drop ratio	**2.175**	**2.073**	**1.654**	**3.725**	**3.762**	**3.201**
	(1)-(4)	**(2)-(5)**	**(3)-(6)**			
Drop ratio diff	**-1.550** **	**-1.689** **	**-1.546** **			
	(0.762)	**(0.765)**	**(0.669)**			
Industry FE	YES	NO	NO	YES	NO	NO
Occupation FE	YES	NO	NO	YES	NO	NO
State×Year FE	YES	YES	NO	YES	YES	NO
Industry×Occupation FE	NO	YES	YES	NO	YES	YES
County×Year FE	NO	NO	YES	NO	NO	YES
Observations	52,016	52,016	52,016	52,016	52,016	52,016
R-squared	0.038	0.040	0.150	0.089	0.092	0.202

B.3 Proxy for ρ based on changes in the wage path

In this appendix, we describe the steps of proxying for ρ based on individuals' changes in the wage path after training completion.

Following the intuition of Section 4.3.2, 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 measure the depreciation rates of skills acquired from a training program as follows. For each training, we first calculate the hourly 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 $R_3 = \frac{Wage_{y3} - Wage_{y2}}{wage_{y2}}$.[48]

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

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, and thus, the higher the depreciation. 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 training completion is then denoted as $G_{diffavg} = Mean(G_{diff2}, G_{diff3})$.

Lastly, as in Section 4.3.1, we aggregate the training level skills depreciation to occupation level by calculating the median of $G_{diffavg}$ associated with all training programs taken by individuals in a given occupation. If an occupation's post-training wage decay is in the top tercile, then we classify this occupation as facing high skills depreciation; otherwise, the occupation faces low depreciation. We provide examples of occupations with the highest and lowest CIT exposure based on approach, as well as example job titles, in Online Appendix B.7, Table B6 Panel B.

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

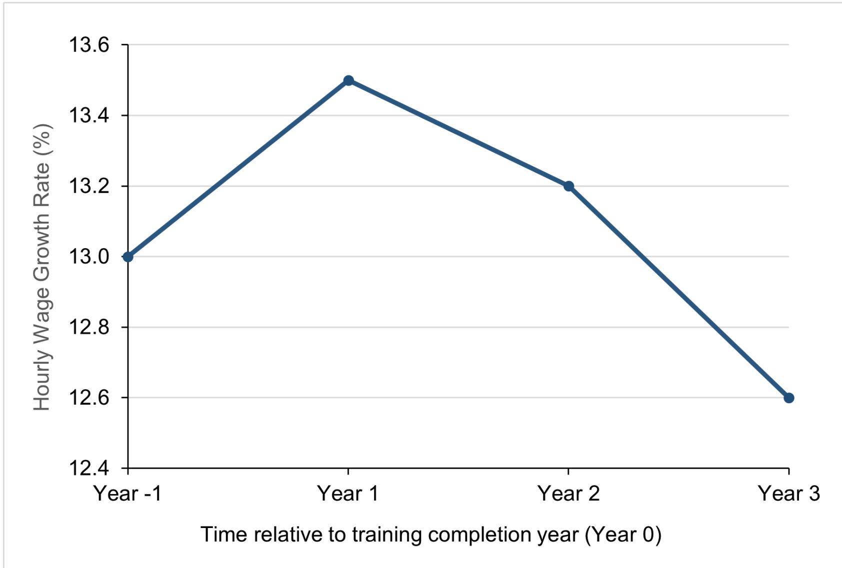


Figure B1: Hourly wage growth rate before and after training

This figure plots the growth rate of individuals' 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.

B.4 Heterogeneity with respect to σ

In this appendix, we examine variations of the hump shape relation between skills acquisition and household leverage with respect to σ – the degree of labor income uncertainty. The model (Section 2.5.2 and Figure V) predicts that households facing higher σ engage in more skills acquisition to counter the reduced utility due to greater labor income uncertainty.

For each year, we calculate the volatility of hourly wages across all sample individuals working in each occupation. As in Section 4.3, we then estimate the occupation level income volatility by taking the median of the wage volatility in a given occupation over the sample period. An individual is considered to face a higher σ if he/she works in an occupation exhibiting income volatility in the top tercile; otherwise, he/she faces a lower σ.

We repeat Table 2 regression analyses based on the degree of labor income uncertainty, and plot in Figure B2 the patterns of skills acquisition with respect to household leverage for high (the dashed line) versus low (the solid line) income uncertainty. The plot is based on the regression coefficients of the quadratic model in equation (14).

Figure B2 shows that in the presence of higher income uncertainty, the household exerts greater effort in skills acquisition. This is seen by the higher level of the dashed line relative to the solid line. These patterns are consistent with Figure V (Section 2.5.2).

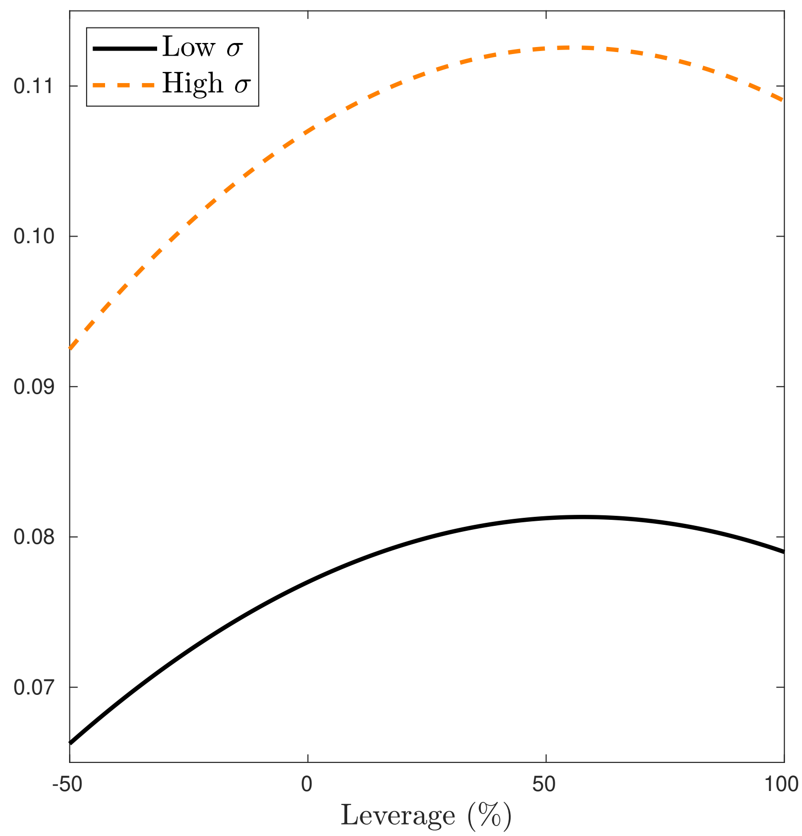


Figure B2: Heterogeneity with respect to labor income uncertainty

This figure plots the relation between household leverage and training participation for individuals with high (the dashed line) versus low (the solid line) income uncertainty. The classification of high and low income uncertainty is described in Online Appendix B.4. Coefficients are based on the quadratic regression model (equation (14)) without household characteristics controls. Household leverage (in percentage) is the ratio of net debt to asset as defined in Section 3.3.

B.5 Alternative theories

In this appendix, we explore a few alternative theories proposed in the existing literature that may explain the negative effect of household leverage on skills acquisition in the regime of high indebtedness, including "housing lock", "mental distress", and "inattentiveness."

First, we consider the "housing lock" theory, which posits that high 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; Gopalan, Hamilton, Kalda, and Sovich, 2021; Di Maggio, Kalda, and Yao, 2024). 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 exclude all respondent-year observations in which respondents report to own a residential property as of the previous survey year. We then repeat our analyses among these non-homeowners, which by design are not subject to "housing lock." Table B3 column (1) reports the results. The similar results as our baseline analyses suggest that "housing lock" is unlikely to drive our findings.

Second, we consider the "mental distress" theory, which posits that high 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 age 50. These individuals are therefore relatively less likely to experience intensive mental distress in the face of indebtedness. We repeat our analyses among this subsample. Table B3 column (2) reports the results. We again observe a significant hump-shaped relation between household leverage and skills acquisition. Therefore, "mental distress" is unlikely to drive our findings.

Third, we consider the "inattentiveness" theory, which posits that indebtedness compels financially burdened individuals to perform routine tasks (such as household chores) themselves instead of outsourcing, thereby preventing them from pursuing productive activities such as training (Becker, 1965; Baxter and Jermann, 1999; Aguiar, Hurst, and Karabarbounis, 2013). Bernstein, McQuade, and Townsend (2021) suggest that such inattentiveness may 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 face fewer daily chores and time constraints, they are less likely to be overwhelmed by housework. We repeat our analyses in this subsample, and again confirm our main findings. Table B3 column (3) reports the results.

Table B3: Alternative theories

This table reports regression analyses to examine alternative theories that may explain our findings. The dependent variable, *Training*, is an indicator of whether the respondent has requested and participated in training programs that are not self-paid since the previous survey. Column (1) consists the subsample of individuals who do not own a residential property of a given year. Column (2) consists of the subsample of individuals that have never been diagnosed with depression as of age 50. Column (3) consists of the subsample of individuals who do not have children. Definitions of all other 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 Distress	No Kids
	(1)	(2)	(3)
Leverage	0.013***	0.011***	0.014**
	(0.004)	(0.004)	(0.005)
Leverage^2	-0.012***	-0.011***	-0.013**
	(0.004)	(0.004)	(0.005)
Switching point	**0.563**	**0.504**	**0.516**
Controls	YES	YES	YES
Industry×Occupation FE	YES	YES	YES
County×Year FE	YES	YES	YES
Observations	26,961	40,141	18,513
R-squared	0.177	0.164	0.227

B.6 The construction of the instrumental variable

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

$$SLTV_{k,c,t} = LTV_c \times \frac{1 + \Delta Synthloan_{c,t}}{1 + \Delta HPI_{k,c,t}}, \tag{33}$$

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 properties during a given year. LTV_c is the loan-to-value ratio at mortgage origination for each cohort at the national level, obtained from the Federal Housing Finance Agency's National Mortgage Database (NMDB). This national loan-to-value ratio at origination is unlikely affected by household-specific factors. $\Delta HPI_{k,c,t}$ is the house price growth since the purchasing time of cohort c up to year t in a county k, calculated using Zillow home value index. The Zillow data are available since 1996 and the NMDB data are available since 1998. We extrapolate these data to the beginning of our sample period, 1990.[49] $\Delta Synthloan_{c,t}$ is the projected change in mortgage loan balance for each cohort at a given time:

$$\Delta Synthloan_{c,t} = -\frac{(1 + r/12)^{t-c} - 1}{(1 + r/12)^{T} - 1}, \tag{34}$$

where r is median of the national annual mortgage rate (7.2%) in our sample period, based on the historical record of U.S. mortgage rates. T equals 360 months by assuming that the mortgage is a 30-year fixed rate loan. $t - c$ is the number of months passed since loan origination (i.e., home purchasing). As seen in equations (33) and (34), the construction of $SLTV$ captures the variation from the interaction of purchase timing (represented by c) and

[49] Specifically, for Zillow, we first calculate the average annual growth rate of the home values in each county during the initial 5 years of available Zillow data (i.e., between 1996 and 2000). We then use a linear extrapolation to infer each county's home values prior to 1996. For instance, the home value in 1995 equals the home value in 1996 divided by one plus the growth rate obtained above in a given county. We perform a similar extrapolation for NMDB. Due to the limited time periods covered by Zillow and NMDB, we restrict our IV sample to households that purchased homes since 1990 in order to avoid excessive extrapolation. To elaborate, if a household purchased the home in the 1970s or 1980s, then its LTV at mortgage origination (i.e., at the time of purchase) and the subsequent home value growth – two components of the instrument – would rely heavily on the extrapolated NMDB and Zillow information. This approach would likely lead to noisy inferences.

home location (represented by k).[50]

With the constructed $SLTV$, we perform the two-stage least square (2SLS) IV analysis:

$$LTV_{i,k,t} = \alpha + \beta_1 SLTV_{k,c,t} + \beta_2 SLTV^2_{k,c,t} + \gamma_1 Z_{i,t-1} + \gamma_2 X_i + \kappa_c + \eta_{k,t} + OtherFE + \epsilon_{i,k,t}, \quad (35)$$

$$LTV^2_{i,k,t} = \alpha + \beta_1 SLTV_{k,c,t} + \beta_2 SLTV^2_{k,c,t} + \gamma_1 Z_{i,t-1} + \gamma_2 X_i + \kappa_c + \eta_{k,t} + OtherFE + \epsilon_{i,k,t}, \quad (36)$$

$$Training_{i,k,t} = \alpha + \beta_1 \widehat{LTV_{i,t-1}} + \beta_2 \widehat{LTV^2_{i,t-1}} + \gamma_1 Z_{i,t-1} + \gamma_2 X_i + \kappa_c + \eta_{k,t} + OtherFE + \epsilon_{i,k,t}. \quad (37)$$

Equations (35) and (36) are the first-stage regressions. Equation (37) is the second-stage regression. Here $\eta_{k,t}$ represents region×time fixed effects, and κ_c represents cohort fixed effects. The inclusion of cohort fixed effects ensures that the $SLTV$ does not simply captures an earlier or later home purchasing time – which may correlate with an individual's career or life stages and in turn, their decisions. Similarly, region (by time) fixed effects ensure that variation of the instrument does not simply stem from different regions, which may differ in the availability of training opportunities (at a given point in time).

[50]In our analysis, we focus on households purchasing homes prior to 2008 – five years before the end of available balance sheet information in our sample (i.e., 2012) – to ensure that there are sufficient time-series observations for the $SLTV$ to capture variation in loan-to-value ratios after home purchase.

B.7 Additional tables

Table B4: Surveyed components of debt

Components of 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
Credit card debt	TOTAL BALANCE OWED ON ALL CREDIT CARD ACCOUNTS TOGETHER	2004, 2008, 2010, 2012
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
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
Student loan for children	TOTAL AMOUNT OWED ON STUDENT LOANS FOR CHILDREN	2004, 2008, 2010, 2012

Table B5: Surveyed components of asset

Components of 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 B6: 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 computer and information technology, and Panel B is based on changes in individual wage path after training. The details of these approaches are described in Section 4.3.1 and Section 4.3.2.

Panel A: Exposure to technology

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

Panel B: Changes in the wage path

High Skills Depreciation Occupation	**Job Title Examples**	
Life, Physical, and Social Services	Economist	Biological scientist
Computer and Mathematical	Computer programmer	Statistician
Management, Business and Financial Operations	Accountant	Loan officer
Low Skills Depreciation Occupation	**Job Title Examples**	
Sales and Related	Retail salesperson	Insurance sales agent
Lawyers, Judges and Legal Support Workers	Lawyer	Judge
Healthcare Support	Medical assistant	Nursing aide

Table B7: The first stage regression of the instrumental variable analysis

This table reports the first stage of the two-stage least squares (2SLS) instrumental variable regressions, as reported in Table 4. LTV^2 is the square of LTV. Columns (1) and (2) correspond to column (1) of Table 4. Columns (3) and (4) correspond to column (2) of Table 4. Columns (5) and (6) correspond to column (3) of Table 4. Columns (7) and (8) correspond to column (4) of Table 4. The Cragg-Donald Wald F statistics are reported below coefficient estimates. Cohort FE are indicators of the survey year when the individual becomes the owner of the house. Definitions of other variables are in Table 1 and Table 2. Standard errors are clustered at the state-year level and reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var.	*Training*				*Labor Supply*			
	LTV	LTV^2	LTV	LTV^2	LTV	LTV^2	LTV	LTV^2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LTV	0.287***	0.226**	0.302***	0.228**	0.287***	0.226**	0.302***	0.228**
	(0.094)	(0.102)	(0.092)	(0.099)	(0.094)	(0.102)	(0.092)	(0.099)
LTV^2	-0.132*	-0.019	-0.156**	-0.039	-0.132*	-0.019	-0.156**	-0.039
	(0.080)	(0.090)	(0.078)	(0.088)	(0.080)	(0.090)	(0.078)	(0.088)
Cragg-Donald Wald F Statistics	16.759		16.404		16.759		16.404	
Controls	NO	NO	YES	YES	NO	NO	YES	YES
Industry×Occupation FE	NO	NO	YES	YES	NO	NO	YES	YES
Cohort FE	YES	YES	YES	YES	YES	YES	YES	YES
State×Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	13,358	13,358	13,358	13,358	13,358	13,358	13,358	13,358

Table B8: An alternative measure of human capital investment: Duration of training

This table presents regression analyses using an alternative measure of human capital investment, *TrainingTime* in columns (1) and (2), defined as the natural logarithm of one plus the number of hours the respondent has spent on training programs that are self-requested and are not self-paid since the last survey. Columns (3) and (4) replicate Table 2 columns (5) and (6) for comparison. Switching points, along with their differences between training and labor supply, are obtained in the same manner as in Table 2 and are reported below the coefficient estimates, in the rows *Switching point* and *Switching point diff*. All other variables and fixed effects are defined in Table 1 and Table 2. Each regression includes a separate intercept. Standard errors are clustered at the state-year level and reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dep. Var.	*TrainingTime*		*Labor Supply*	
	(1)	(2)	(3)	(4)
Leverage	0.053***	0.057***	0.122***	0.128***
	(0.012)	(0.012)	(0.020)	(0.021)
Leverage^2	-0.047***	-0.046***	-0.197***	-0.194***
	(0.011)	(0.011)	(0.025)	(0.025)
Switching point	**0.565**	**0.617**	**0.308**	**0.331**
	(1)-(3)	**(2)-(4)**		
Switching point diff	**0.257****	**0.286****		
	(0.120)	**(0.135)**		
Controls	YES	YES	YES	YES
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	52,016	52,016	52,016	52,016
R-squared	0.037	0.151	0.092	0.202