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Household Net Worth, Income, and Credit Limits*

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Wealth affects credit limits in complex ways, partly due to challenges in measuring net worth and accounting for endogeneity. To address these issues, we use household-level data from the Survey of Consumer Finances (2004–2022) and conduct two-stage least squares (2SLS) regression analysis. In our two-step generalized method of moments (GMM) 2SLS model, bequests serve as instrumental variables for net worth, with controls for demographic characteristics and credit history. We find that both income and net worth significantly increase credit limits. These results are robust in models with alternative measures of credit access, different econometric specifications, and subsamples. We also examine the life-cycle effects of net worth on credit limits–particularly among young adults with entry-level jobs and mortgages–highlighting how limited savings and lower early-career income constrain credit access.

JEL Classification: D15, E51
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I. Introduction

Credit cards have become a highly convenient payment method, especially with the rise of e-commerce and contactless transactions. Today, the vast majority of U.S. adults hold at least one credit card (Consumer Financial Protection Bureau, 2021), making it a preferred means of payment for both online and in-person purchases. Despite their widespread use, clear patterns in personal credit behavior are difficult to identify. One reason is that credit limits are endogenously linked to usage: greater use of credit, coupled with limit increases (Gross and Souleles, 2002; Narajabad, 2012), can expand purchasing power and improve credit scores by lowering utilization ratios. Moreover, even among individuals at similar stages of the income and wealth life cycle, credit use reflects diverse spending behaviors, further obscuring consistent patterns in credit behavior.

Two main strands exist in the literature. The first develops theoretical models of credit limits, typically within an equilibrium framework that values the incentive to participate in financial markets (Jaffee and Modigliani, 1969; Eaton et al., 1986; Azariadis and Kaas, 2008; Á braham and C árceles-Poveda, 2010; Choi et al., 2024; Choi, 2025). This line of research emphasizes that credit limits are imposed because of limited commitment–namely, the inability of debtors to fully commit to repay unsecured debt (Kehoe and Levine, 1993; Kocherlakota, 1996; Alvarez and Jermann, 2000). For example, Choi et al. (2024) highlight income as a key determinant of repayment capacity and willingness, making it central to the determination of credit limits.

The second strand focuses on the informational role of net worth. It argues that net worth provides signals about consumers' unobserved characteristics that are correlated with repayment incentives. This perspective often incorporates uninsurable income risk and asymmetric information in credit markets (Livshits et al., 2007; Chatterjee et al., 2007, 2011; Narajabad, 2012; Sánchez, 2012), emphasizing that access to credit depends in part on permanent income. Empirical work in this area is limited. For instance, Fulford (2014) briefly examine the relationship between net worth, housing, and house-hold credit limits, while Han et al. (2018) consider household financial variables in credit limit estimation, but primarily to explain cyclical aspects of credit supply rather than systematic differences across debtors.

In this paper, we examine which factors are most critical in explaining differences in credit limits among U.S. consumers, using household-level data. Our analysis focuses on the marginal effects of current income and net worth, considering both their association with attitudes toward creditworthiness and their life-cycle implications. We use the Survey of Consumer Finances (SCF) from 2004 to 2022, the most recent publicly available dataset that reports the maximum credit card limit, card terms and conditions, and other unsecured credit lines for U.S. households. Using repeated cross-sections of household-level data, we identify the demographic and credit-related characteristics of credit card borrowers and credit-constrained households (Jappelli, 1990; Crook, 1996; Stavins, 2000; Han et al., 2018; Beer et al., 2018). To measure current wealth as a determinant of unsecured credit limits, we compile both cost-based net worth and the value of transfers received from a debtor's parents. We also address conceptual and practical issues: for instance, how to treat unrealized capital gains[1], as well as how to interpret nondiscretionary rules in the credit and lending industry.

One major challenge in our analysis is endogeneity: a higher credit limit may itself contribute to an increase in household net worth. To address this issue, we review both theoretical arguments and statistical evidence, including identification tests. Our empirical strategy relies on a two-stage least squares (2SLS) approach, estimated using the efficient two-step generalized method of moments (GMM), which is robust to heteroskedasticity in the error variances. Following Meer et al. (2003), we use parental transfers–including cash gifts and bequests–as an instrumental variable (IV) for net worth. Parental transfers are a relevant and exogenous source of variation: they are determined outside the debtor's own credit history or contract terms, yet strongly correlated with household wealth. We examine their statistical properties in detail, focusing on both relevance and exclusion conditions.

Our 2SLS results suggest that net worth, alongside current income, is a significant determinant of borrowers' credit limits. The joint life-cycle evolution of income and wealth is critical for understanding the complex effects of wealth on household credit. Among older households with comparable levels of social security and secondary income, higher credit limits are offered to those holding valuable equity, reflecting lenders' expectations of greater financial stability from unrealized capital gains. On the other hand, net worth is largely insignificant for young adults with entry-level jobs and relatively little accumulated wealth. By contrast, high-skilled supervisory workers tend to receive higher credit limits, reflecting expectations of stable employment trajectories and greater job security, as discussed in Karahan, et al. (2017).

Additional tests on the effect of nonfinancial wealth on credit limit show that nonfinancial wealth has a limited role in shaping credit limits of homeowners. It is in contrast to our finding on significant credit history variables and net worth, but consistent

[1] Literature on wealth taxation highlights the challenges of assessing asset values net of liabilities, depending on valuation methods, administrative procedures, and compliance issues (Bricker et al., 2016; Li and Smith, 2020). The income capitalization approach, which maps observed income flows to household wealth, is highly sensitive to assumptions about capitalization factors. Even when public markets provide clear valuations for bonds, stocks, and bank accounts, questions remain about effective valuation dates and formulas (Kopczuk, 2019). Additional difficulties arise when valuing ownership through trusts, privately held businesses, art collections, and farm assets, especially given widespread estate tax avoidance and evasion.

with theoretical models that link household net worth to the probability of bankruptcy (Chatterjee et al., 2011; Sánchez, 2012; Narajabad, 2012). In their bankruptcy models, homeownership is viewed as a signal of financial stability when it represents a long-term committed investment. Our analysis highlights the role of net worth according to its impact on household liquidity. A large mortgage along with an expensive estate creates a significant, long-term responsibility that can severely impact a household's liquidity, or access to ready cash. This occurs by locking up a substantial portion of income into a fixed, high-priority expense for many years. According to Kaplan, Violante, and Weidner (2014), the wealthy hand-to-mouth households with little or no liquid wealth (cash, checking, and savings accounts), owning sizable amounts of illiquid assets (assets that carry a transaction cost, such as housing or retirement accounts) tend to have high marginal propensity to consume out of transitory income changes. In this case, housing wealth is limited in providing lenders with a borrower's financial health and capacity to withstand income shocks. We discuss the broader implications of these findings for the systemic link between wealth inequality, human capital, and their valuation in credit markets.

The paper proceeds as follows. We explain our data and present stylized facts about US household credit limits in Section 2. Our empirical model and methodologies are discussed in Section 3, entailed by discussion on main results in Section 4. In Section 5, we evaluate our IV strategy by testing whether our IV satisfies exclusion and relevance restrictions. Section 6 concludes the paper.

II. Data

The SCF is conducted by the Board of Governors of the Federal Reserve System and aims to help the public understand financial conditions of US households as well as to study the effects of changes in the economy. Participation is strictly voluntary with 6,500 families interviewed in the most recent study. To maintain the scientific validity of the study, interviewers are not allowed to substitute respondents for families that do not participate. The Federal Reserve System ensures the representativeness of the study by selecting respondents randomly using procedures suggested in technical working papers including Montalto and Sung (1996)[2]. It is a cross-sectional survey, with a sample of voluntary family participants drawn anew every three years. To the best of our knowledge,

[2] https://www.federalreserve.gov/econres/scf workingpapers.htm

the SCF is the sole publicly[3] available source of information on the financial status and credit limits of families in the US.

2.1. Credit Access Data

According to data released by the Federal Reserve Bank of Atlanta in August 2019, credit cards are the most commonly used unsecured credit line, with 75.5% of consumers holding at least one credit card.[4] From the SCF of 2004 – 2022, we find that 78.4% of sample household heads are credit card holders. Our household-level credit data comprise multiple accounts including credit limit, monthly payment, outstanding amount, terms and conditions like credit card APR rates. Particularly, the maximum borrowing limit is available in household-level by collecting responses to Question x414 in the SCF:

> "[Question x414] The maximum amount you could borrow on all of these credit card accounts; that is, what is your total credit limit? (Visa, Mastercard, Discover, or American Express); Total amount of high credit on all credit cards held by the consumer."

A household's total credit limit may increase in two ways: automatically, through periodic adjustments made by the card issuer, or upon approval of a limit increase request. The SCF data provide a cardholder's reasons and background of application. For example, if a person applied for a new card or higher limit in the last 12 months, he/she was asked for the reason. If not, reasons of not applying for credit are asked. Credit approval status per request is also available from data and used for alternatively specifying credit access in our test of wealth's impact on credit limit. Finally, if the request is declined, an applicant is asked to suggest a reason for decline based on individual perspectives and experiences.

Privately compiled credit reports and scores provide important information in determining credit limits (Chandler and Parker, 1989; Arya et al., 2013; Han et al., 2018). In the absence of credit score data, we rely on variables commonly used in credit-underwriting policies and credit-scoring models (Consumer Financial Protection Bureau,

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[3] Individual-level data on credit can also be obtained from the Italian Survey of Household Income and Wealth, the Dutch DNB Household Survey, the German Economic Panel, and the British Household Panel Study.

[4] According to Durkin (2000), 74% of American families had at least one credit card in 1995, while 44% had a positive balance after the most recent payment. Data from the American Bankers Association, released on Nov. 1, 2019, show that there were 374 million open credit card accounts in the US as of the middle of 2019. The number includes 197 million accounts held by superprime consumers, 103 million held by prime consumers, and 74 million held by subprime consumers.

2021; Equifax, 2021; FICO, 2021).[5] These include repayment status indicators (e.g., whether payments on car loans, consumer loans, or mortgages are more than 90 days delinquent), the number of credit cards, total outstanding credit card balances, and the debt-service ratio. Following Han et al. (2018), we also include a bankruptcy flag (equal to 1 if an individual has filed for Chapter 7 or 13 bankruptcy within the past five years) as a control variable.

Table 1 reports the mean and median values of several household financial variables, including credit card limits over time. Each variable is inflation-adjusted to 2016 dollars using the consumer price index (for all urban consumers and for all items) published by the Federal Reserve Bank of St. Louis. To deal with sampling weights and five multiple imputations[6], we follow the steps suggested in the SCF codebooks and Montalto and Sung (1996).

The net worth statistics in Table 1 report annual values of financial and non-financial assets net of related debt. All asset-related values are marked to the market cost-based value of the survey year. Non-financial assets include the market values of vehicles, primary residence, other residential properties, and equity in non-residential property. In financial assets, we include balances on checking and saving accounts, and the current values of the investments in both risk-free (government bonds) and risky (corporate bonds, equity, and mutual funds) assets. We exclude cash values of IRA and insurance accounts. For equity values, we include stocks, royalties, and some capital gains from risky assets, while including the net worth of a business owned by a household through partnership, sole proprietorship, or through some other arrangements. To calculate net worth, we follow the definition suggested by the Federal Reserve, aggregating the values of financial and non-financial assets net of the current outstanding debt.

Income includes wage earnings as well as supplementary income from pensions and social security. Our main specification focuses on nonfinancial, nonbusiness income, thereby excluding capital gains, dividends, and rental income that may be generated from net worth. This measure of nonfinancial, nonbusiness income is similar to labor and social

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[5] Equifax, an American multinational consumer credit reporting agency and one of the three largest consumer credit reporting agencies, along with Experian and TransUnion, explains how credit scores are calculated. Equifax highlights i) Everybody has multiple credit score; ii) Credit scores may vary because of several reasons; iii) Payment history, the number and type of credit accounts, used vs. available credit and length of credit history are factors frequently used to calculate credit scores. FICO scores are calculated using various pieces of credit data in a credit report, which are grouped into five categories: payment history (35%), amounts owed (30%), length of credit history (15%), new credit (10%) and credit mix (10%) For more information, refer to the the Federal Reserve Bank of St.Louis “Understanding how a FICO Credit Score is Determined” at https://www.stlouisfed.org/education/continuing-feducation-video-series/episode-1-understanding-how-a-fico-credit-score-is-determined.

[6] The Fed provides the survey data with five imputations in treating their missing variables.

security income, employed by De Nardi (2004) and Hurst and Lusardi (2004), which discuss the intergenerational link as a critical factor to explain current business entry and large estates. If inheritances capture more than simply household liquidity as suggested by Hurst and Lusardi (2004), wage income is a more relevant measure of income as a predictor of human capital value. As a robustness check, however, we also use gross income, which includes capital gains, dividends, and all financial and business income. We use business ownership as an additional variable.

[Table 1] Average Household Financial Variables over Survey Years (in thousands of US dollars)

	2004	2007	2010	2013	2016	2019	2022
Credit card limit	21.4	23.4	18.4	16.9	17.5	20.4	21.7
	[8.99]	[10.4]	[5.5]	[5.15]	[6]	[8.45]	[101]
Outstanding debt	107.8	130.3	114.5	102.6	106.6	128.5	114.7
	[30.2]	[32.2]	[28.6]	[23.7]	[27.7]	[26.3]	[30.3]
Outstanding credit card balance	3.1	3.9	3.0	2.3	2.5	2.75	2.4
	[0]	[0]	[0]	[0]	[0]	[0]	[0]
Card approval rate[a]	0.69	0.70	0.66	0.68	0.77	0.76	0.77
Net worth[b]	318.3	321.3	162.0	297.2	353.6	370.0	523.2
	[73.9]	[79.0]	[25.8]	[49.8]	[55.0]	[70.4]	[117.9]
Financial asset[b]	186.5	188.9	71.9	195.1	242.8	257.7	329.8
	[8.35]	[9.26]	[1.11]	[5.67]	[6.5]	[7.13]	10.9
Nonfinancial asset[b]	239.6	263.4	215.4	202.4	215.1	239.6	301.1
	[148.8]	[159.8]	[128.7]	[115.7]	[114.2]	[143.0]	[189.6]
Gross income	87.7	94.1	83.7	88.2	99.9	97.3	109.9
	[53.9]	[52.1]	[49.5]	[47.4]	[51.0]	[51.6]	[55.5]
Nonfinancial/nonbusiness income	73.5	72.6	69.7	70.4	78.8	75.8	81.0
	[50.1]	[46.3]	[44.0]	[43.3]	[47.0]	[46.9]	[48.8]
Wages and salaries	61.7	61.0	57.0	56.1	62.2	61.6	65.9
	[38.6]	[35.9]	[31.9]	[30.9]	[32.0]	[34.7]	[33.6]
Number of observations[c]	22,270	21,715	24,735	28,990	30,030	27,725	21,560

Source: The Survey of Consumer Finances 2004 – 2020.

Note: All values are inflation-adjusted to 2016 dollars. Numbers in brackets indicate median values.

[a] in decimal points.

[b] The asset values are cost-based values for the current year.

[c] The number of observations is based on sampling weight provided by the SCF including five imputations.

We find notable changes in credit limits over the years. The credit limit increased from 2001 to 2007, entailed by a decrease from 2010. Along with the decrease, outstanding debt balance decreased from $130,300 in 2007 to $114,500 in 2010. The outstanding credit card balance shows the same pattern from 2007($3,900) to 2010($3,000). The lower credit limit in 2010 also corresponds to the decrease in average income and net worth. The change in wages and salaries was -7.17% from $61,000 in 2007 to $57,000 in 2010. Part of the observed contraction in assets, income, and credit reflects the recessionary economic conditions following the Subprime Mortgage Crisis of 2008–2009, as the 2010 survey was conducted between late 2009 and early 2010. In contrast, from 2022 data we find the average net worth of $523,000, gross income of $109,900 and credit limit of $21,700, showing significant increases in net worth and credit limit during the recent economic recession caused by the COVID pandemic (Board of Governors of the Federal Reserve System, 2019). To understand the 2010 trend, we remark the CARD Act of 2009, which has introduced a series of reforms to prevent abusive practices in the credit card industry, and placed significant restrictions on credit card issuers. Although the Act did not significantly alter existing credit limits (Jambulapati and Stavins, 2014), it did change the terms and fees of credit card plans, as documented by Pew (2011) and Bar-Gill and Bubb (2012).

2.2. Net worth, Income, and Credit Limit

In this section, we look into cross-sectional correlation between selected household financial and credit variables to understand details. In Table 2, we summarize pairwise correlation of credit limit with wealth and income per wealth percentile. Overall, as predicted by credit-rationing practice provided by FICO (2021) and Consumer Financial Protection Bureau (2021), income has stronger correlation with credit limit. For households in the second quintile, credit limits are highly correlated with both net worth and income. In Figure 1, we show a simple regression line of log credit limits on log net worth on the top. Its positive relationship maintains with a lesser degree when we use log of residual credit limits from its fitting on log income (in bottom panel of Figure 1).

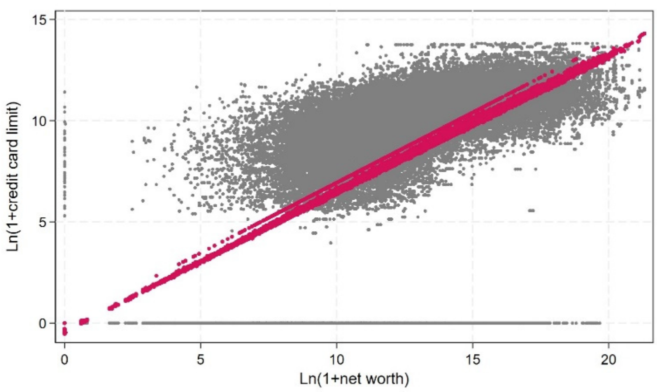
[Table 2] Pairwise Correlation of Credit Limit by Wealth Percentiles

Variables Wealth percentiles	Q1 (～, 20%]	Q2 (20%, 40%]	Q3 (40%, 60%]	Q4 (60%, 80%]	Q5 (80% ～]
Net worth	-0.0645	0.2088	0.1048	0.1501	0.0964
Nonfinancial/nonbusiness income	0.4078	0.3690	0.2333	0.2725	0.1365
Gross income	0.2518	0.3824	0.2453	0.2615	0.1231
Wages & salaries	0.3960	0.3380	0.2033	0.2694	0.1407

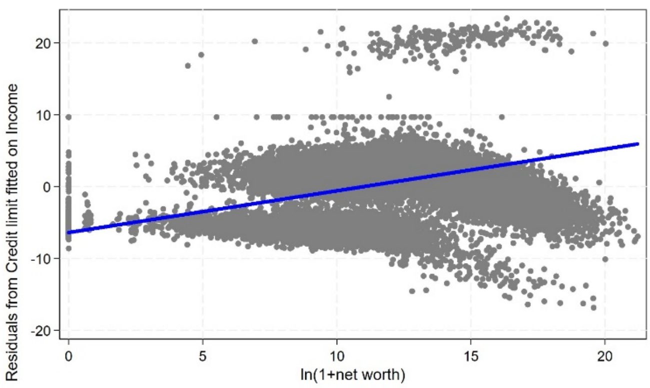
Source: The Survey of Consumer Finances 2004 – 2020.
Note: All values are inflation-adjusted to 2016 dollars.

Considering age as a primer of one's net worth and income, we extract life cycle trends of non-financial income including wages, salaries, and social security income (Figure 2(a)), credit limits (Figure 2(b)), and net worth (Figure 2(c)). The plots are based on individuals born between 1915 and 1995, with each age–cohort cell containing about 306 observations per year. The life-cycle profile of income closely parallels that of credit limits, as shown in Figure 2(a). Consistent with real-world credit-offering practices, correlation of credit limit with wealth and income per wealth percentile. Overall, as current income provides direct information about a borrower's willingness and ability to borrow. From this perspective, the mean growth rate and volatility of income serve as conventional predictors of credit limits by approximating the value of human capital.

[Figure 1] Credit Limit Scatter Plot on Net worth



(a) Credit limit on net worth

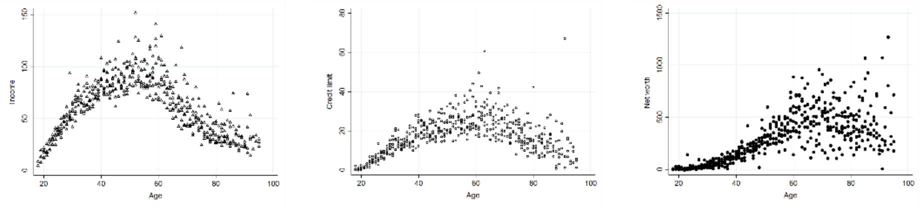


(b) Residual credit limit on net worth

Source: The SCF 2004 – 2022

However, because no explicit guidelines on the role of wealth exist in credit-rationing practices, the wide dispersion of wealth near retirement shown in Figure 2(c) has limited explanatory power for predicting the life-cycle component of credit limits. In Section 3, we introduce a model that analyzes the effect of net worth by identifying individuals with high credit limits due to large net worth among those with similar income and characteristics.

[Figure 2] Cohort-level Data over a Household Head's Age



(a) Non-financial Income (b) Credit Limit (c) Net Worth

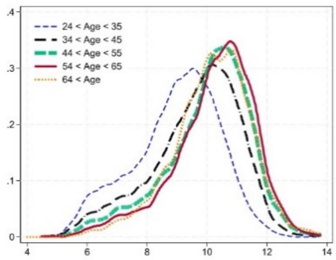
Note: Values are in thousands of US dollars. All imputed data are included in each year's data.
Source: Author's cohort-level data tabulated from the SCF 2004 – 2022

2.3. Covariates

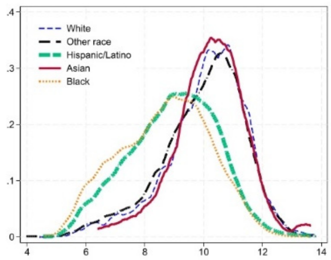
Following Hurst, Luoh, and Stafford (1998), Bricker et al. (2016) and Beer et al. (2018), we include age, age-squared, education (1 if postsecondary education), ethnicity (African-American, Hispanic, and Anglo-Saxon), and marital status (1 if married, and 0 otherwise) of a household head in a model. The number of individuals is also considered to control its influence on a household's saving/spending propensity. To separate the effect of income and wealth from job and demographic characteristics on credit limit, we control a household head's job industry and title. Job industries cover six sectors from mining and construction (job industry 1) to public administration and the armed forces (job industry 6). The effects of different job skills and experiences are measured by using two job title dummies: the manager and entry level, respectively.

From our data, we find that job and demographic characteristics carry meaningful information about credit limits. Figures 3(a) and 3(b) present smoothed kernel densities of the log unsecured credit limits for various demographic groups from 2004 to 2022, using the Epanechnikov kernel with a bandwidth of 5. Figure 3(a) shows that young households aged 24–35 are much more likely to receive lower credit limits than other age groups. Figure 3(b) illustrates notable ethnic differences, with African-Americans tending to have lower credit limits than other groups. However, such disparities do not necessarily imply discrimination by lenders. In the following sections, we examine whether the patterns observed in Figure 3(b) can be explained by differences in net worth, income, or other economically significant variables across ethnic groups.

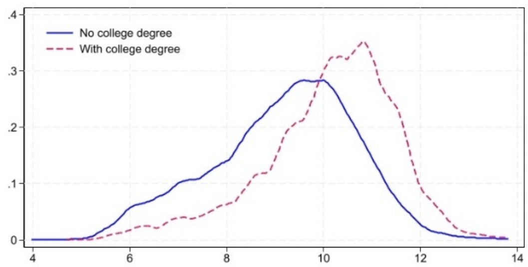
[Figure 3] Kernel density of log credit card limit by demographic characteristics



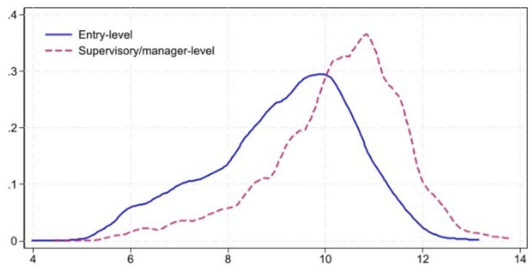
(a) Density by Age



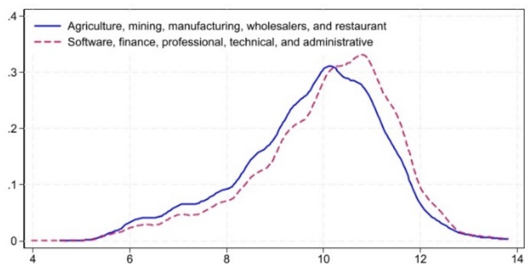
(b) Density by Ethnicity



(c) Density by Education



(d) Density by Title



(e) Density by Industry

Source: The Survey of Consumer Finance published 2004 – 2022

Figures 3(c)–3(e) present kernel densities across proxies for human capital, ranging from education level to job skills. Figure 3(c) shows that individuals with more years of education are more likely to receive higher credit limits. Consistent with positive returns to human capital investment, better-educated individuals expect higher wage growth and thus tend to borrow larger amounts earlier in life. Figure 3(d) indicates that those in management or supervisory positions receive higher credit limits than workers in other occupations. Figure 3(e) reveals only small differences in credit limits between individuals employed in construction, manufacturing, and wholesale industries compared with those in software, finance, technical and administrative industries. In our regression analysis, we control for these demographic characteristics in order to isolate the effects of current income and net worth on credit limits.

III. Econometric Model

In this section, we explain our regression model to study the determination of credit limits. The discussion includes an instrumental variables (IV) approach as a means of dealing with the endogeneity problem. We briefly review the literature on parental transfer to discuss its role as an instrumental variable of net worth. Finally, we explain our 2SLS model estimated by the two-step GMM method.

3.1. IV-2SLS Regression Model

Similar to Han and Li (2011), we consider the following cross-sectional regression equation with fixed year dummies:

$$Y_{it} = \beta_N \mathrm{N}_{it} + \beta_W \mathrm{W}_{it} + \mathrm{X}_{it}^{'}\beta_X + \mathrm{T} + \mathrm{e}_{it} \quad \text{for} \quad \mathrm{i} = 1,\cdots,\mathrm{I} \quad \text{and} \quad \mathrm{t} = 2007, \ \cdots, 2022, \quad (1)$$

where Y_{it} denotes the outcome variable (credit limit) for household head i in year t. The variables N_{it} and W_{it} represent net worth and income, respectively, with corresponding coefficients β_N and β_W. The covariate matrix X_{it} includes K control variables, with coefficients collected in β_X. Fixed year effects are captured by T, which consists of a vector of ones and year dummies for survey years 2007 to 2022, accounting for changes in the macroeconomic environment that may affect credit supply. Finally, e_{it} denotes the error term. We estimate the coefficients using the two-step generalized method of moments (GMM) estimator (Hansen, 1982; Baum et al., 2003), which is robust to heteroskedasticity.

The OLS estimate of the coefficient on net worth is consistent only if net worth is exogenous to credit limits, an assumption that does not always hold in practice. On the one hand, high-net-worth individuals are able to obtain higher credit limits based on their presumed repayment capacity; on the other hand, credit limits can influence households' desired debt levels and thereby affect their net worth (Cox and Jappelli, 1993; Crook, 2001; Duca and Rosenthal, 1993; Gropp et al., 1997; Gross and Souleles, 2002). Moreover, unexpected increases in credit limits may contribute to asset accumulation, particularly through the purchase of durable goods (Aydin, 2018). The issue of endogeneity also arises in corporate finance: Jaffee and Stiglitz (1990), for example, show how a firm's capital structure becomes endogenous when it finances projects with fixed investment scales.

One solution to the endogeneity problem and to improve causal inference is to use an instrumental variables (IV) regression model. Following Meer et al. (2003), we consider parental transfers as an IV for net worth, and Cox and Jappelli (1990) highlight the link between transfers, net worth, and credit limits. Much of the related literature examines these links at an aggregate level, focusing on the wealth distribution in the U.S. by using models with bequests and stochastic labor earnings shocks to quantify the extent of wealth inequality in a life-cycle framework (Huggett, 1996). Bequest motives have also been developed to analyze the transmission of financial transfers and earnings ability in self-insured economies facing labor income shocks and uncertain lifespans (De Nardi, 2004).

Empirical evidence from the SCF and the Health and Retirement Survey shows that bequest motives help explain the concentration of wealth at the upper tail of the distribution, particularly the large asset holdings near death that often appear in trust funds and transfer accounts (De Nardi and Yang, 2014). As emphasized in the literature on the role of bequests in asset accumulation (Cagetti and De Nardi, 2008), if changes in wealth are correlated with parental transfers, then substituting transfers into the credit limit equation allows us to evaluate the significance and magnitude of their effect.

3.2. Instrumental Variable Data

Unlike other personal credit-related datasets–such as panel data from multiple card issuers used by Gross and Souleles (2002) or administrative records from credit bureaus (e.g., Teletrack, Equifax, and the Federal Reserve Bank of New York) used by Agarwal et al. (2009) and Fulford and Schuh (2019)–the SCF provides information on intergenerational transfers. The SCF offers several advantages for studying the effects of parental transfers on credit limits as suggested by Felver and Yoo (2023). It allows us to identify household heads who have received bequests and gifts. Although parental spending on children's education or medical expenses cannot be perfectly measured, the SCF does identify parental involvement in children's student debt. By distinguishing between gifts as regular or intermittent transfers from living parents and realized bequests, we can separate the effects of anticipated transfers on credit limits from those of realized gains. Leveraging the SCF's large, nationally representative sample of households, we test the validity of parental transfers as an instrumental variable.

[Table 3] Summary Statistics by Transfer-type (Average, in percent or thousand dollars)

Variables	Have you received transfer?	
	No (No.obs = 127,425)	Yes (No.obs = 45,350)
Yearly dining-out expenses	7.376	8.574
Outstanding debt	112.3	125.1
Financial assets, current value	154.3	425.7
Nonfinancial assets, current value	211.8	342.4
Current home value	189.7	305.7
In own student debts	20.6%	13.2%
Debt service ratio	18.9%	12.4%
Outstanding card balance	2.757	3.148
Outstanding consumer loan	1.41	2.118
Outstanding vehicle loan	5.885	5.150
Outstanding mortgage	72.55	76.18
Gross income	87.23	121.9
Wage income	59.86	64.37
Credit card limit	17.94	27.36

From the SCF data, we find that approximately 21.4% of individuals over age 20 have ever received a "financial transfer" from a parent living in a separate household. About 4.3% report having received lifetime gifts, a smaller share than those who report receiving bequests. Gifts are often given in conjunction with bequests and may occur multiple times. The mean transfer amount is $193,822, composed of an average bequest of $191,625 and an average gift of $269,608.

We summarize statistics on household assets, income, and debt by group – never received vs. ever received – in Table 3. On average, recipients of transfers have higher net worth than non-recipients, a pattern consistently observed in financial asset comparisons. Trust funds, cash transfers, and family-owned business equity (through stock holdings) appear to play prominent roles in explaining these differences. Recipients also hold greater values of nonfinancial assets and housing. At the same time, they carry larger outstanding debts and equity-loan balances, primarily through mortgages. More interestingly, children who receive bequests exhibit higher wages and incomes on average. Since wage income reflects personal human capital, the link between transfers and human capital is key to understanding why households with transfers are offered higher credit limits, even after controlling for their higher credit card balances.

[Table 4] Frequency of Intergenerational Transfer (Average, in percentage)

Case	Bequest	Gift
Received	17.95 [0.39]	4.3 [0.20]
Received from parents	13.6 [0.34]	3.3 [0.18]
Received from parents within a survey year	12.6 [0.33]	0.29 [0.17]
First received from parents within a survey year	1.6 [0.13]	0.03 [0.05]
Received from parents within a survey year & younger than 45	0.3 [0.06]	0.1 [0.03]
First received from parents within a survey year & younger than 45	0.3 [0.06]	0.001 [0.03]

Note: Numbers in brackets are standard deviations.

In Table 4, we summarize the share of the population that has participated in intergenerational transfers, broken down by timing. The timing of receipt is determined using three survey questions: (i) Have you ever received a financial transfer in your lifetime? (ii) Have you received a transfer from your parents within the survey year? (iii) Was this transfer the only transfer ever received, or one of multiple transfers received within the survey year?

From Table 4, we find that most transfers are made by parents and occur within the survey year. However, such transfers are not necessarily the first ever received. When transfers occur for the first time, recipients are most often younger than 45 years of age. Transfer-timing information is critical for ensuring the validity of our IV, as discussed in Meer et al. (2003). Because most large transfers–such as bequests–are reported within the survey year, we interpret them as immediate and exogenous increases in household wealth. Nevertheless, we acknowledge the possibility of overestimating their effect, given that many households report receiving multiple transfers prior to the survey year.

In subsequent analysis, we examine the statistical properties of parental transfers, both in dollar amounts ($transfer) and in logarithmic form (log(1 + $*transfer*)),[7] as relevant IVs for net worth, based on residuals from a baseline two-step GMM 2SLS regression model.

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[7] We use log(1 + $*transfer*) to ensure that households with zero transfers are included.

IV. Results

Our baseline results are summarized in Table 5. Under IV-OLS 1 and IV-OLS 2 of Table 5, we present the OLS regression results using log transfer with a small and large set of covariates, respectively.

Results from the two-stage least squares (2SLS) models are summarized in specifications 2SLS (1) – 2SLS (4). In 2SLS (1) and 2SLS (2), log net worth is instrumented by transfers measured in dollars, while in 2SLS (3) and 2SLS (4), the instrument is log transfers. Specifications 2SLS (2) and 2SLS (4), along with the IV-OLS 2, include controls for education, job industry and title, ethnicity, age, and gender. These variables, which approximate human capital and financial literacy, are added to estimate the marginal roles of income and net worth. We compare the estimated coefficients on income and net worth in models with and without these controls, which–although not officially reviewed by credit-rating agencies (Equifax, 2021; FICO, 2021)–serve as proxies for human capital and thus help isolate the effect of instrumented net worth on credit limits. Finally, 2SLS (2f) reports the first-stage regression results corresponding to specification (2).

The marginal effect of nonfinancial, nonbusiness income is significant across all models. Results also remain consistent when gross income is used instead of nonfinancial, nonbusiness income[8]. This finding is consistent with large-scale empirical studies on corporate credit lines and sustainable government debt (e.g., Sufi (2009); Collard et al. (2015)). More broadly, the literature emphasizes the role of credit channels in the transmission of income shocks (Bernanke and Blinder, 1988), the effect of credit constraints in contracting frameworks (Stiglitz and Weiss, 1981), and the importance of consumption smoothing (Hall, 1978).

[Table 5] Regression Model Results

Variable	IV-OLS 1	IV-OLS 2	IV: transfer in dollars		IV: transfer log transformed		First-stage for net worth
			2SLS (1)	2SLS (2)	2SLS (3)	2SLS (4)	2SLS (2f)
Log net worth (Instrumented)			0.438*** [0.0707]	0.210*** [0.0803]	0.486*** [0.0685]	0.0714 [0.106]	
Log gifts & bequests	0.0316*** [0.00379]	0.00176 [0.00369]					0.0002** [0.0001]
Log Income	0.260*** [0.0107]	0.169*** [0.0105]	0.193*** [0.0197]	0.144*** [0.0180]	0.184*** [0.0192]	0.163*** [0.0207]	0.1374*** [0.0086]
Debt-service ratio	0.000971 [0.00299]	0.00102 [0.00285]	-0.00213*** [0.000445]	-0.00106** [0.000467]	-0.00225*** [0.000461]	-0.00062 [0.000516]	0.0032*** [0.0002]
Job industry 1 (=1, if mining or construction)		-0.0248 [0.122]		-0.0792 [0.156]		-0.0554 [0.158]	0.1683 [0.1267]
Job industry 2 (=1, if food manufacturing, publishing, or entertainment)		0.0708 [0.0784]		0.0615 [0.103]		0.06 [0.104]	-0.0083 [0.0590]

[8] Results are available upon request.

Variable	IV-OLS 1	IV-OLS 2	IV: transfer in dollars		IV: transfer log transformed		First-stage for net worth
			2SLS (1)	2SLS (2)	2SLS (3)	2SLS (4)	2SLS (2f)
Job industry 3		0.00912		-0.00901		-0.0078	0.0113
(=1, if wholesaler or restaurants)		[0.0719]		[0.0924]		[0.0935]	[0.0502]
Job industry 4		-0.131**		-0.167**		-0.174**	-0.0417
(=1, if industrial, or maintenance)		[0.0642]		[0.0822]		[0.0831]	[0.0524]
Job industry 5		0.165***		0.112*		0.120*	0.0615
(=1, if technical, other administrative and personal services)		[0.0517]		[0.0676]		[0.0687]	[0.0419]
Job industry 6		0.570***		0.484***		0.495***	0.0880
(=1, if public administration or the armed forces)		[0.0818]		[0.106]		[0.107]	[0.0536]
Job title 1		0.0758		0.0286		0.0635	0.2571***
(=1, if farmer, manufacturer, or entry-level worker)		[0.0608]		[0.0839]		[0.0864]	[0.0493]
Job title 2		0.784***		0.703***		0.768***	0.4708***
(=1, if supervisor or technician)		[0.0505]		[0.0771]		[0.0838]	[0.0399]
Marital status	0.239***	0.512***	0.211***	0.473***	0.190***	0.503***	0.2116***
(=1, if married household head)	[0.0438]	[0.0459]	[0.0587]	[0.0648]	[0.0578]	[0.0669]	[0.0362]
Sex		0.392***		0.286***		0.353***	0.4826***
(=1, if male household head)		[0.0458]		[0.0749]		[0.0830]	[0.0430]
Number of persons in a household		-0.228***		-0.218***		-0.219***	-0.0116
		[0.0142]		[0.0180]		[0.0182]	[0.0118]
Ethnicity 1		-1.153***		-1.029***		-1.153***	-0.8908***
(=1, if African-American)		[0.0479]		[0.0981]		[0.115]	[0.0457]
Ethnicity 2		-0.679***		-0.621***		-0.668***	-0.3328***
(=1, if Hispanic)		[0.0547]		[0.0766]		[0.0803]	[0.0479]
Age		-0.0206***		-0.0163*		-0.0152*	0.0080
		[0.006]		[0.0088]		[0.0089]	[0.0054]
Age-squared		0.0003***		0.0002**		0.0002**	0.0002***
		[0.0001]		[0.0001]		[0.0001]	[0.0000]
Postsecondary education		1.177***		1.029***		1.136***	0.7593***
(=1, if college-educated)		[0.0365]		[0.0815]		[0.0972]	[0.0275]
Homeownership	1.564***	1.308***	0.422*	0.885***	0.267	1.273***	2.7849***
(=1, if yes)	[0.0387]	[0.0392]	[0.233]	[0.230]	[0.225]	[0.301]	[0.0365]
Business ownership	0.845***	0.461***	0.453***	0.294***	0.402***	0.402***	0.7620***
(=1, if yes)	[0.0533]	[0.0528]	[0.0974]	[0.0906]	[0.0948]	[0.105]	[0.0339]
Number of credit cards	0.714***	0.649***	0.651***	0.623***	0.644***	0.637***	0.1009***
	[0.00586]	[0.00571]	[0.0137]	[0.0121]	[0.0138]	[0.0144]	[0.0036]
Outstanding credit card balance	0.0317***	0.0321***	0.0457***	0.0403***	0.0471***	0.0366***	-0.0268***
	[0.00218]	[0.00208]	[0.00502]	[0.00482]	[0.00509]	[0.00514]	[0.0018]
Delinquency in mortgage repayment	-1.483***	-1.222***	-1.436***	-1.255***	-1.416***	-1.275***	-0.1425**
	[0.0700]	[0.0674]	[0.115]	[0.111]	[0.114]	[0.112]	[0.0564]
Delinquency in vehicle-loan repayment	0.315***	0.339***	0.412***	0.365***	0.425***	0.344***	-0.1445***
	[0.0369]	[0.0360]	[0.0510]	[0.0479]	[0.0504]	[0.0494]	[0.0228]
Delinquency in consumer loan	-0.513***	-0.401***	-0.427***	-0.395***	-0.407***	-0.432***	-0.2615***
	[0.0790]	[0.0754]	[0.114]	[0.111]	[0.114]	[0.114]	[0.0531]
Have you ever filed for bankruptcy?	-0.0493***	0.0444 ***	-0.0374***	-0.0383***	-0.0363***	-0.0421***	-0.0274***
(=1, if yes)	[0.00332]	[0.00323]	[0.00476]	[0.00509]	[0.00472]	[0.00549]	[0.0024]
Fixed year effects:							
2007	-0.0449	-0.049	0.00623	0.00877	0.00108	0.0184	0.0679
	[0.0636]	[0.0606]	[0.0861]	[0.0841]	[0.0860]	[0.0850]	[0.0479]
2010	-0.328***	-0.358***	-0.454***	0.443***	-0.439***	-0.482***	-0.2837***
	[0.0634]	[0.0605]	[0.0855]	[0.0839]	[0.0857]	[0.0871]	[0.0480]
2013	-0.386***	-0.424***	-0.291***	-0.334***	-0.292***	-0.348***	-0.1050***
	[0.0630]	[0.0602]	[0.0792]	[0.0780]	[0.0792]	[0.0793]	[0.0439]

Variable	IV-OLS 1	IV-OLS 2	IV: transfer in dollars		IV: transfer log transformed		First-stage for net worth
			2SLS (1)	2SLS (2)	2SLS (3)	2SLS (4)	2SLS (2f)
2016	-0.154**	-0.217***	-0.116	-0.157**	-0.118	-0.164**	-0.0588
	[0.0627]	[0.0599]	[0.0768]	[0.0754]	[0.0766]	[0.0765]	[0.0442]
2019	0.128**	0.0198	0.115	0.043	0.108	0.0418	-0.0110
	[0.0626]	[0.0599]	[0.0801]	[0.0778]	[0.0798]	[0.0787]	[0.0446]
2022	0.483***	0.302***	0.341***	0.279***	0.318***	0.316***	0.2616***
	[0.0628]	[0.0603]	[0.0923]	[0.0874]	[0.0902]	[0.0893]	[0.0480]
Constant	0.341***	1.450***	-2.590***	-0.0159	-2.883***	0.714	5.2599***
	[0.119]	[0.185]	[0.453]	[0.495]	[0.441]	[0.617]	[0.1635]
Test of weak identification							
Anderson-Rubin Wald test (p-value)			0.0152	0.0865	0.0000	0.5052	
Stock-Wright LM S statistic (p-value)			0.0000	0.0089	0.0000	0.5050	
Test of underidentification							
Kleibergen-Paap rk LM statistic (p-value)			0.000	0.000	0.000	0.000	
First-stage regression results							
SW† Chi-squared (Underid)			5.11	4.28	883.75	409.47	
SW† F statistics (Weak id)			5.10	4.28	883.19	409.00	
Number of Observations	36,390	36,390	29,709	29,709	29,709	29,709	29,709
Adj R-squared	0.497	0.543	0.5662	0.5662	0.5429	0.5554	005467

Source: Survey of Consumer Finances 2004 to 2022.

Note: We use the two-step efficient generalized method of moments (GMM) estimator with robust standard errors in brackets. *** p-value < .01, ** p-value < .05, * p-value < .1

† The Sanderson-Windmeijer first-stage chi-squared and F statistics are tests of underidentification and weak identification, respectively, of individual endogenous regressors. First-stage test statistics heteroskedasticity-robust.

Our baseline results also reveal significant demographic patterns. On average, households headed by women tend to receive lower credit limits. From the SCF data, we find that among single-parent households, the 55% are female-headed, while 99% of male-headed found among the married. This suggests that the observed gender effect is closely tied to the role of income in determining credit limits. Marital status also matters: although it is difficult to separate spousal income from household income in the baseline specification, additional spousal income may reduce household income volatility and thereby influence credit limits.

The coefficient on instrumented net worth is larger than that on income in most models, with the exception of 2SLS (4). The effect of net worth also exceeds the marginal effects of log gifts and bequests in the IV-OLS specifications (IV-OLS 1 and 2). However, the estimated impact of net worth declines once additional demographic characteristics are directly controlled for, as in 2SLS (2). We view the results from 2SLS (2) as more consistent than those from 2SLS (4) with the evidence on wealth inequality and the role of intergenerational transfers in shaping wealth at the top quintile of the U.S. distribution (De Nardi, 2004; Cagetti and De Nardi, 2008). Moreover, when the coefficient on log net worth is sensitive to households receiving large transfers (measured in dollar amounts), credit limits remain significantly dependent on the percentage change in net worth, even after controlling for the mean and volatility of income growth by age, occupation, and education.

From Table 5, we also draw several implications regarding credit history in the credit market. First, delinquency in consumer loan repayment has a significantly negative effect on credit limits. Second, timely mortgage repayment is important for maintaining access to credit. By contrast, vehicle-loan delinquency is associated with a positive effect on credit limits, even though such delinquency reduces net worth. This juxtaposition may arise because credit card limits influence the amount and interest rate of approved car loans. Similarly, large outstanding credit card balances and a greater number of credit cards are positively related to credit limits, likely reflecting the same mechanism. Finally, personal bankruptcy filings reduce credit limits in a manner similar to delinquencies.

From the comparison of life-cycle components of net worth, income, and credit limits in Section 2.2, we find that a household head's age is a key variable in explaining current levels of income and net worth. Older individuals tend to have longer work experience, higher wage income, and a greater likelihood of holding supervisory or managerial positions. Their net worth, however, varies considerably depending on demographic and financial conditions. Moreover, because net worth is instrumented by parental transfers in our baseline regression model, wealth is closely related to age: older individuals have a higher probability of receiving larger bequests.

[Table 6] Marginal Effect from log Net Worth per Demographic Group

Variable	Age			Education		Job title	
	Young 20 ≤ Age <41	Middle 41 ≤ Age <61	Old 61 ≤ Age <81	No College degree	With college degree	Entry level	Manager level
Log net worth	0.16	0.18*	0.361*	0.260*	0.328*	-0.0075	0.199**
	[0.142]	[0.0995]	[0.203]	[0.086]	[0.172]	[0.212]	[0.096]
Log income	0.144***	0.112***	0.364***	0.118***	0.150***	0.160***	0.099**
	[0.0378]	[0.0188]	[0.0990]	[0.0201]	[0.034]	[0.039]	[0.0203]
Observations	6,736	15,976	7,583	19,104	10,605	4,877	14,366
Adj R-squared	0.605	0.574	0.506	0.472	0.579	0.548	0.482

Note: Robust standard errors in brackets. The marginal effects are based on the 2SLS (2) model.
*** p-value < .01, ** p-value < .05, * p-value < .1

We conduct the 2SLS (2) regression separately by age group and summarize the effects of income and net worth in Table 6. Income and net worth have substantially larger effects on credit limits for older household heads compared with younger ones. With supplemental social security income as a primary source of total income, additional income and net worth among older borrowers are especially effective in increasing credit limits.

Additional subsample analyses by education and job title further show that the effects of net worth are robust and consistent with implications of permanent income: households with college-educated or managerial heads are more likely to receive higher credit limits. Having established the notable role of net worth, we next conduct regression analyses to examine which components of wealth–home equity and non-financial net worth–explain credit limits in Section 5.3.

Although ethnicity is not directly related to the life-cycle components of credit limits, the dummy variables for African-American and Hispanic households in Table 5 are statistically significant in explaining credit limits. Prior studies document systematic disadvantages faced by minority borrowers. Traub and Ruetschlin (2012) and Freeman (2017) report that credit card companies impose heavier burdens on African-American and Hispanic customers, who often face the most unfavorable terms. For example, Traub and Ruetschlin (2012) find that African-American borrowers carried lower balances but nonetheless paid higher interest rates, resulting in average annual interest payments at least $100 greater than those of white borrowers. Additional evidence suggests that some banks restricted credit to customers living in predominantly African-American neighborhoods, even when credit scores were similar. These patterns of credit card red-lining imply that Black borrowers may be more credit-constrained than their observable financial characteristics suggest (Cohen-Cole, 2011).

V. Evaluating IV Strategy

In this section, we discuss the quality of the instrumental variable and the two-stage regression models. In the identification test results reported in Table 5, the first two rows present the p-values of the Anderson-Rubin (1949) test and the Stock-Wright (2000) LM S statistic for weak-instrument robust inference. The null hypothesis in both tests is that the coefficient of net worth in the equation is equal to zero. The results indicate that the instrument is valid: p-values for all models reject the null hypothesis, except for 2SLS (4) at the 10% significance level.

We also report weak identification test results without the i.i.d. assumption. Specifically, we present the Cragg-Donald Wald *F* statistic (with degrees of freedom adjusted) and the Kleibergen-Paap Wald *F* statistic. Both statistics are robust to heteroskedasticity. According to these tests, the baseline results remain valid under the assumption that parental transfers are exogenous to the error term in the credit limit equation.

The first-stage regression results are summarized by the Sanderson-Windmeijer (SW) first-stage chi-squared and F statistics. In the case of a single endogenous regressor, the SW statistic coincides with the underidentification statistic from the weak identification tests, namely the Kleibergen-Paap rk Wald statistic with cluster-robust standard errors. Across all four models, the results confirm the statistical significance of the instrumental variable.

Although our 2SLS models demonstrate the joint significance of the endogenous regressors in the main equation under the orthogonality condition, we further examine the exclusion and relevance conditions of the IV to provide weak-instrument-robust inference. Section 5.1 reports the results of tests for the exclusion restriction, while Section 5.2 examines relevance conditions. In Section 5.3, we present regression analyses with alternative specifications of variables and econometric models. Specifically, we assess the robustness of our results by testing the significance of net worth using different measures of credit limits, alternative samples, and various econometric models. Section 5.4 provides additional analysis using panel data from 2007-2009.

5.1. Exclusion Restrictions

In two-stage least squares (2SLS) estimation, the exclusion restriction requires that the instrumental variables affect only the endogenous variable–in our case, net worth–and not the outcome variable, credit limit, except through their effect on net worth. Thus, transfers should influence credit limits solely through their impact on net worth in order to serve as valid instruments. We consider two cases in which the exclusion restriction may be violated. First, transfers may be internalized directly into net worth, weakening the exclusion restriction. Second, background factors related to transfers may simultaneously affect both net worth and the probability or amount of parental transfers.

Hypothetically, if a creditor could fully anticipate the exact timing and amount of gifts and bequests, he or she would authorize more credit to the borrower. In this case, transfers would function as an additional source of income or wealth, thereby violating the exclusion restriction. To assess the validity of transfers as an instrument for net worth, marginal effect of instrumented net worth differs if a borrower can foresee receiving a transfer from parents in a particular year. Such foreseen transfers are more common among parents who have made multiple gifts prior to the survey year. In practice, under the U.S. estate and gift tax system, it is less costly to pay gift taxes on multiple small gifts than to pay estate taxes on a large bequest. If a transfer is made earlier and deposited into a child's account, the child may generate capital gains from it or use the information to extend credit limits. In such cases, transfers are limited in their ability to represent an exogenous increase in net worth.

[Table 7] Results from models with transfer-timing specification

	Log net worth	Log income	KP rk LM test†	SW Chi-sq‡
Model (1)	0.270***	0.143***	0.0000	0.1082
(Received within this year)	[0.107]	[0.038]		
Model (2)	0.312***	0.155***	0.0000	0.0000
(Repeated transfer within this year)	[0.094]	[0.034]		
Model (3)	0.697***	-0.125	0.0708	0.0007
(First transfer within this year)	[0.277]	[0.180]		
Model (4)	0.210***	0.144***	0.0000	0.0385
(Old transfers made many years ago)	[0.0803]	[0.018]		

Note: All results are obtained from IV-2SLS (2) in Table 5. Numbers in brackets are robust standard errors.

† Kleibergen-Paap rk LM statistic (p-value)

‡ The Sanderson-Windmeijer first-stage F statistics (p-value)

Using detailed information on expected transfers, we conduct regression analysis with the IV-2SLS specification (2). We distinguish two cases: transfers received within the survey year and transfers received many years prior to the survey year. Model (1) in Table 7 summarizes results using immediate transfers made only within the survey year. Although instrumented net worth is significant, the SW statistic yields a high p-value, raising concerns about instrument strength. Model (2) presents results using repeatedly made transfers, which are more likely to be anticipated. Here, log net worth remains a significant predictor of credit limits, with a similar magnitude of effect.

Model (3) instruments net worth using the first immediate transfer and shows a larger effect than in Models (1) and (2), consistent with the exclusion restriction. This result confirms that sudden, unexpected transfers–representing a purely exogenous increase in net worth–explain the significant role of net worth in raising credit limits. This contrasts with Model (4), which uses old transfers received many years earlier and shows only a small effect. Nevertheless, exogeneity test results indicate that old transfers remain significant, with capital gains from these transfers also contributing to higher credit limits.

Moving on to the second potential issue, unobserved variables may drive both parental transfers and credit limits. Although our data do not allow us to control directly for the economic status of respondents' parents, we use demographic variables as proxies for privileged family background. Individuals from such backgrounds are more likely to receive inheritances and to have benefited from early-life conditions–such as better care and education–that enhance human capital and support favorable debt-repayment schedules. This type of background can bias the coefficient on instrumented net worth upward. Demographic variables such as post-secondary education may play a similar role in capturing familial privilege. The impact of these controls is evident in the smaller coefficients on log gifts and bequests or instrumented log net worth in IV-OLS (2) and 2SLS (2) compared with IV-OLS (1) and 2SLS (1), respectively. Nevertheless, even after accounting for these influences, net worth remains a significant determinant of credit limits.

5.2. Relevance Condition

Based on the baseline 2SLS (2) model, we investigate the causal effect of parental transfers on net worth to assess the relevance of the IV. The average treatment effect on the treated (ATET) is estimated using propensity score matching in combination with the linear regression framework of 2SLS (2). Results in Table 8 show that bequests and gifts increase recipients' net worth by altering their investment behavior: household heads are more likely to hold stocks after receiving transfers from parents. This effect appears to operate through (i) lower risk aversion and (ii) a greater willingness to take financial risks, both of which are associated with parental transfers. Such risk-taking behaviors are especially pronounced among younger cohorts. This is an important finding, since a higher probability of taking risks in investment often leads to realizing sizable gains from risky assets.

Interestingly, parental transfers also reduce recipients' active search for financial information on saving and investment planning. If transfers provide both direct benefits (through an increase in wealth) and indirect benefits (through changes in habits and attitudes), then children may enjoy relatively easier access to credit and savings without the need for intensive information-gathering.

[Table 8] Parental Transfer's Average Treatment Effect on Stockholding Probability & Attitude toward Risks

Outcome Variable	Whole sample *Household heads aged between 25 and 85*	Young sample *Household heads aged between 25 and 41*
	(No.obs = 29,770)	*(No.obs = 6,745)*
(1) Stockholding	0.0853***	0.0511***
(=1, if holding a public stock)	[0.000]	[0.0001]
Population Outcome Mean	0.3179***	0.2629***
	[0.0000]	[0.0001]
	(No.obs = 30,647)	*(No.obs = 6,809)*
(2) Risk-averseness	-0.0069***	-0.0774***
(From 0 (lowest) to 4 (highest))	[0.0001]	[0.0002]
Population Outcome Mean	3.1726***	2.937***
	[0.0001]	[0.0001]

Outcome Variable	Whole sample *Household heads aged between 25 and 85*	Young sample *Household heads aged between 25 and 41*
	(No.obs = 13,797)	*(No.obs = 2,689)*
(3) Willingness to take risks	0.1335***	0.2662***
(From 0 (lowest) to 10 (highest))	[0.0004]	[0.0009]
Population Outcome Mean	4.2663***	4.8***
	[0.0002]	[0.0005]
	(No.obs = 30,647)	*(No.obs = 6,809)*
(4) How intensively shopping for information	-0.0877***	-0.0232***
in saving and investment planning?	[0.0003]	[0.0007]
(From 0 (lowest) to 10 (highest))		
Population Outcome Mean	4.564***	4.6413***
	[0.0001]	[0.0003]

Note: Standard errors are in brackets. *** p<0.01, ** p<0.05, * p<0.1. The ATET is estimated on propensity score matching by logit regression.

The effect of bequests on children's attitudes toward risk has been examined by Hurst and Lusardi (2004) and Cagetti and De Nardi (2009), who explore the relationship between inheritances and entrepreneurship. Hurst and Lusardi (2004) argue that receiving an inheritance is not a random event but a strong predictor of current business entry and future business gains. SCF data also indicate that ownership of a parent's company or the sharing of a family business between parents and children constitutes a form of bequeathed financial wealth, which helps secure a child's income.

Furthermore, De Nardi (2004) demonstrates an intergenerational link in asset over-accumulation by modeling the productivity connection between parent and child. This framework explains entrepreneurship as a natural family outcome. Although the educational aspects of parental transfers–particularly their role in promoting financial literacy and shaping risk-taking attitudes–require further study, our relevance test results support parental transfers as a valid and relevant IV for net worth.

5.3. Alternative Specification

The potential endogeneity of using past or expected inheritances as instruments for changes in household liquidity is addressed in the estimation of entrepreneurship by wealth in Hurst and Lusardi (2004). The issue is important because households influenced by inheritances may display a greater propensity to start businesses, which in turn increases their borrowing needs. Since broader use of credit requires higher credit limits, it is crucial to determine whether such increases are made upon request. If credit limits are instead automatically updated by lenders based on low utilization rates and high credit scores, then limits are not necessarily determined by business entry following a bequest, as argued in Hurst and Lusardi (2004).

To examine the supply-side effect of credit limits, we employ alternative measures of credit access beyond credit limits and estimate different econometric models to test robustness. Later in this section, we also report results using housing equity as an alternative measure of net worth, in order to assess the role of non-financial wealth in shaping unsecured credit limits.

We summarize results from different econometric models using various measures of credit access, including the probability of card application acceptance, in Table 9. We focus on a 2SLS probit model, where the dependent variable is an indicator equal to one if an applicant's card application is approved by a creditor and zero otherwise. In this specification, net worth is not statistically significant. To investigate why net worth plays a limited role in explaining acceptance rates, we conduct additional regression analyses on applicants' application behavior and motivation.

[Table 9] Marginal Effects of log Net Worth from Alternative Models

Regression Model	Sample Description (Number of observations)	Dependent variable	Coefficient of Log net worth
2SLS Probit	2004-2022 SCFs *(17,127)*	Card application approved	0.0406 [0.145]
2SLS Probit	(i) Applied for some credit *(4,990)*	Card application approved	-0.015 [0.169]
2SLS GMM	(i) Applied for some credit *(4,988)*	Log credit limit	0.377 [0.310]
2SLS GMM	(ii+iii) Not applied for any credit from 2016-2022 SCFs *(8,433)*	Log credit limit	0.405*** [0.087]
2SLS Probit	(ii) 2004-2022 SCFs *(23,252)*	Not applied for credit, worried to be denied	-0.493*** [0.130]
2SLS GMM	(ii) Not applied for any credit worried to be denied *(734)*	Log credit limit	0.76 [0.586]
2SLS LIML	(ii) Not applied for any credit worried to be denied *(734)*	Log credit limit	0.73 [0.454]
2SLS GMM	(iii) Not applied for any credit unnecessary *(5,781)*	Log credit limit	0.386*** [0.112]
2SLS LIML	(iii) Not applied for any credit unnecessary *(5,781)*	Log credit limit	0.717*** [0.434]

Note: Robust standard errors in brackets. We use 2016-2022 SCFs in regression models. All results are obtained from the corresponding model with same covariates of IV-2SLS (2) in Table 5.
*** p-value < .01, ** p-value < .05, * p-value < .1

Using the 2016–2022 SCFs, we construct additional variables capturing household credit attitudes. By employing a dependent variable that indicates whether a household applied for more credit for any reason, we distinguish demand-driven increases in credit limits and examine the role of net worth in shaping the limits of "credit shoppers." If higher limits are granted to active shoppers facing liquidity constraints, such increases have different implications from limits extended automatically to households that did not apply but received higher limits based on their repayment capacity.

We test the role of net worth in determining credit limits across several subsamples of potential applicants. Group (i) includes households that applied for additional credit in a survey year. Households that did not apply are divided into two subgroups: Group (ii), those who refrained from applying because they feared being declined, and Group (iii), those who did not apply because they had no need.

Results from the various specifications in Table 9 support the view that net worth is an important factor in determining credit limits. For Group (i) households that applied for additional credit, net worth is not relevant in explaining approval rates, although credit limits themselves remain correlated with net worth. In both the 2SLS probit model of card application approval and the GMM model of credit limits, net worth is not statistically significant. This finding is consistent with real-world cases such as credit cards marketed to college students or foreigners who lack wealth but hold large cash deposits.

For Group (ii), we find that reluctance to apply for credit is associated with negative changes in net worth. For Group (iii), creditors appear willing to extend higher limits to households that did not request additional credit. These offers are positively related to increases in net worth in both the 2SLS GMM and limited-information maximum likelihood (LIML) models, providing evidence that the exclusion restriction for our IV is satisfied.

We also test the robustness of our baseline results by using nonfinancial asset values to measure household net worth. Housing equity is the largest component of net worth, as suggested by Hurst, Luoh, and Stafford (1998), and Hurst and Lusardi (2004) argue that capital gains from housing are a more relevant instrument of household liquidity than bequests. We measure nonfinancial net worth as the sum of housing, farm property, and car values, net of the secured debts associated with these assets.

[Table 10] Results from 2SLS Regression Models using Nonfinancial Net Worth

Variable	IV: log transfer Whole sample 2SLS (i)	IV: log transfer		IV: transfer in dollars	
		Home-owners 2SLS (ii)	No home 2SLS (iii)	Home-owners 2SLS (iv)	No home 2SLS (v)
Log nonfinancial net worth (Instrumented) (Nonfinancial assets - home and miscellaneous mortgage, other property loans, and car loans)	0.0552 [0.136]	-0.448 [0.298]	0.474** [0.185]	0.272** [0.138]	0.369** [0.153]
Log income	0.163*** [0.0202]	0.197*** [0.0271]	0.0643 [0.0448]	0.147*** [0.0195]	0.0856** [0.0390]
Debt-service ratio	0.0006 [0.0018]	0.0017 [0.0016]	-0.538 [0.331]	0.0011 [0.0016]	-0.484 [0.310]
Job industry 1 (=1, if mining or construction)	-0.0994 [0.166]	-0.508** [0.237]	-0.0762 [0.262]	-0.436* [0.231]	0.0192 [0.235]
Job industry 2 (=1, if food manufacturing, publishing, or entertainment)	0.0506 [0.0982]	-0.0441 [0.128]	0.11 [0.171]	-0.0198 [0.125]	0.141 [0.161]
Job industry 3 (=1, if wholesaler or restaurants)	-0.00145 [0.0885]	-0.181 [0.117]	-0.118 [0.183]	-0.104 [0.111]	-0.0665 [0.170]
Job industry 4 (=1, if industrial or maintenance)	-0.150* [0.0783]	-0.207* [0.115]	-0.312** [0.150]	-0.114 [0.108]	-0.261* [0.136]
Job industry 5 (=1, if technical or other administrative and personal services)	0.147** [0.0651]	-0.0199 [0.0890]	0.089 [0.142]	0.0534 [0.0835]	0.143 [0.128]
Job industry 6 (=1, if public administration or the armed forces)	0.530*** [0.112]	0.274** [0.125]	0.189 [0.332]	0.360*** [0.119]	0.343 [0.292]
Job title 1 (=1, if farmer, manufacturer, or entry-level worker)	0.0605 [0.0941]	0.0555 [0.110]	-0.503** [0.217]	0.101 [0.107]	-0.402** [0.188]
Job title 2 (=1, if supervisor or technician)	0.759*** [0.0747]	0.753*** [0.0988]	0.515*** [0.140]	0.635*** [0.0871]	0.564*** [0.127]
Marital status (=1, if married household head)	0.512*** [0.0643]	0.655*** [0.0981]	0.0119 [0.152]	0.521*** [0.0833]	0.0769 [0.133]
Sex (=1, if male household head)	0.357*** [0.0844]	0.445*** [0.102]	0.102 [0.147]	0.329*** [0.0917]	0.175 [0.127]
Number of persons in a household	-0.243*** [0.0228]	-0.173*** [0.0262]	-0.364*** [0.0567]	-0.199*** [0.0240]	-0.336*** [0.0485]
Ethnicity 1 (=1, if African-American)	-1.104*** [0.129]	-1.412*** [0.136]	-0.162 [0.254]	-1.184*** [0.105]	-0.298 [0.215]

Variable	IV: log transfer Whole sample 2SLS (i)	IV: log transfer		IV: transfer in dollars	
		Home-owners 2SLS (ii)	No home 2SLS (iii)	Home-owners 2SLS (iv)	No home 2SLS (v)
Ethnicity 2 (=1, if Hispanic)	-0.659*** [0.0728]	-0.747*** [0.104]	-0.219 [0.133]	-0.760*** [0.102]	-0.272** [0.120]
Age	-0.0253*** [0.00882]	0.0578** [0.0264]	-0.0879*** [0.0156]	0.000585 [0.0160]	-0.0825*** [0.0143]
Age-squared	0.0003*** [7.72e-05]	-0.0003* [0.0002]	0.0009*** [0.0002]	0.0001 [0.0001]	0.0009*** [0.0001]
Postsecondary education (=1, if college-educated)	1.166*** [0.0799]	1.269*** [0.126]	0.888*** [0.127]	1.006*** [0.0813]	0.945*** [0.112]
Homeownership (=1, if yes)	1.106* [0.611]				
Business ownership (=1, if yes)	0.401*** [0.110]	0.526*** [0.138]	-0.0423 [0.363]	0.235*** [0.0874]	0.139 [0.312]
Number of credit cards	0.652*** [0.0121]	0.560*** [0.0155]	1.013*** [0.0333]	0.529*** [0.0107]	1.026*** [0.0307]
Outstanding credit card balance	0.0332*** [0.00391]	0.0257*** [0.00442]	0.0467*** [0.0139]	0.0336*** [0.00336]	0.0434*** [0.0133]
Delinquency in mortgage repayment	-1.213*** [0.0852]	-2.198*** [0.185]	-0.576*** [0.118]	-1.905*** [0.147]	-0.576*** [0.112]
Delinquency in car loan repayment	0.330*** [0.0575]	0.0872 [0.0973]	-0.194 [0.305]	0.286*** [0.0643]	-0.0282 [0.256]
Delinquency in consumer loan repayment	-0.395*** [0.0950]	-0.595*** [0.155]	-0.440*** [0.165]	-0.380*** [0.129]	-0.412*** [0.156]
Have you ever filed for bankruptcy? (=1, if yes)	-0.0453*** [0.00470]	-0.0583*** [0.00993]	-0.0541*** [0.00911]	-0.0382*** [0.00660]	-0.0512*** [0.00845]
Fixed year effects:					
2007	-0.0157 [0.0815]	0.0662 [0.108]	0.0463 [0.150]	-0.0134 [0.102]	0.0318 [0.142]
2010	-0.348*** [0.0734]	-0.402*** [0.108]	-0.319** [0.128]	-0.278*** [0.0962]	-0.307** [0.120]
2013	-0.402*** [0.0755]	-0.550*** [0.119]	-0.361*** [0.136]	-0.379*** [0.100]	-0.344*** [0.128]
2016	-0.184** [0.0734]	-0.318*** [0.101]	0.00206 [0.128]	-0.220** [0.0928]	-0.0099 [0.121]
2019	0.0163 [0.0752]	-0.0793 [0.0951]	0.251* [0.137]	-0.075 [0.0935]	0.229* [0.129]
2022	0.300*** [0.0920]	0.363*** [0.141]	0.272* [0.158]	0.138 [0.111]	0.292** [0.149]

Variable	IV: log transfer Whole sample 2SLS (i)	IV: log transfer		IV: transfer in dollars	
		Home-owners 2SLS (ii)	No home 2SLS (iii)	Home-owners 2SLS (iv)	No home 2SLS (v)
Constant	1.323***	5.767**	1.190***	0.268	1.257***
	[0.476]	[2.304]	[0.402]	[1.108]	[0.380]
Weak-instrument-robust inference					
Anderson-Rubin Wald test (p-value)	0.6859	0.1222	0.0047	0.1229	0.5837
Stock-Wright LM S statistic (p-value)	0.6847	0.1219	0.0047	0.1226	0.5831
Test of underidentification					
Kleinbergen-Paap rk LM statistic (p-value)	0.0000	0.0000	0.0000	0.000	0.0274
Test of weak identification					
Cragg-Donald Wald F statistic	114.41	150.10	32.33	73.00	5.30
Kleinbergen-Paap Wald F statistic	140.17	108.86	26.36	4.40	3.29
First-stage regression results					
Robust F statistic	140.17	108.86	26.36	4.40	3.29
SW† Chi-squared (Underid)	140.31	109.01	26.44	4.41	3.30
SW† F statistics (Weak id)	140.17	108.86	26.36	4.40	3.29
Observations	34,048	22,978	11,070	22,978	11,070
R-squared	0.55	0.395	0.471	0.447	0.523

Source: Survey of Consumer Finances 2004 to 2022.

Note: We use the two-step efficient generalized method of moments (GMM) estimator with robust standard errors in brackets. *** p-value<0.01, ** p-value <0.05, * p-value <0.1

† The Sanderson-Windmeijer first-stage chi-squared and F statistics. First-stage test statistics are heteroskedasticity-robust.

From Table 10, we find that nonfinancial net worth is a significant determinant of credit limits. In particular, it is significant for households who do not own homes (2SLS (iii) and (v)), where nonfinancial wealth other than housing has a statistically significant marginal effect, especially when large bequests are considered (2SLS (v)). By contrast, when wealth gains are measured in dollar terms, including expensive bequests (2SLS (iv)), homeowners' nonfinancial wealth also becomes significant in explaining credit limits.

Since identification conditions are not satisfied in most 2SLS models with nonfinancial net worth, except for 2SLS (iii), we rely on 2SLS (iii) to conclude that housing wealth plays only a limited role in explaining credit limits. First, large or expensive housing wealth does not necessarily imply better creditworthiness. As noted by Chatterjee et al. (2011) and Albanesi et al. (2019), increases in housing net worth can raise the probability of bankruptcy, as cash flows related to homeownership make liquidity highly sensitive to fluctuations in home equity values, mortgage rates, and repayment obligations.

Second, when creditors determine a borrower's credit limit, durable consumption such as car ownership and additional property holdings becomes a critical factor. For example, young borrowers–many of whom rent and do not receive bequests–are likely to have credit limits tied closely to their current income, job characteristics, and education. In such cases, ownership of additional property provides an appreciated signal that can raise their credit limits.

5.4. Panel Regression

In this section, we present results from a panel data regression using the 2007-09 panel of the Survey of Consumer Finances. This dataset covers household financial information during the Great Recession, spanning 2007 and 2008, the first half of 2009, and the second half of 2009–a period in which real GDP began to recover and equity markets realized gains. The panel regression allows us to identify factors associated with changes in household credit limits while controlling for cross-sectional differences in demographic haracteristics across household heads. Compared with our baseline specification, the panel model uses a smaller set of covariates to reflect the more limited set of variables available in the 2007-09 panel relative to the regularly published SCFs.

Our fixed-effects panel regression results are reported in Table 11. We present two models: a fixed-effects regression of log credit limits and a panel probit model of card application approval. In both models, parental transfers are used as an IV, and robust variance-covariance estimates are obtained by clustering at the household level across the two years. The panel analysis results consistently show that percentage changes in net worth significantly increase credit limits. Credit card-related variables are also significant: a larger number of credit cards and higher outstanding balances are positively correlated with increases in credit limits, while delinquency and bankruptcy significantly reduce approval rates.

On the other hand, income, job industry, and education are insignificant. Because many proxies for human capital are absorbed by fixed effects in this panel regression, income effectively serves as the sole proxy for an individual's human capital and repayment capacity. The insignificance of income in explaining changes in credit limits is therefore notable, especially in contrast to the significant role of net worth. Furthermore, despite the additional income or capital gains that might be expected from starting a new business, our results show no evidence that business entry raises credit limits. Overall, the panel regression analysis highlights that changes in wealth are critical in explaining changes in credit limits and access, underscoring the central role of net worth—a factor largely neglected in the prior literature on (optimal) credit limits.

[Table 11] Panel Regression Models

Variable	Fixed-effects Model Log credit limit	Fixed-effects Probit Model Approval Rate
Log net worth	0.106***	0.132***
	[0.0337]	[0.0440]
Log income	-0.0323	0.0437
	[0.0350]	[0.0505]
Job industry 1	0.262	0.436
(=1, if mining or construction)	[0.178]	[0.361]
Job industry 2	0.481*	0.137
(=1, if food manufacturing, publishing, or entertainment)	[0.248]	[0.236]
Job industry 3	0.085	0.0282
(=1, if wholesaler or restaurants)	[0.102]	[0.210]
Job industry 4	0.182	0.0403
(=1, if software, finance, industrial, or maintenance)	[0.120]	[0.209]
Job industry 5	0.151	0.315*
(=1, if data processing, technical, entertainment, other administrative and personal services)	[0.0946]	[0.162]
Job industry 6	-0.0421	0.0688
(=1, if public administration or the armed forces)	[0.181]	[0.273]
Job title 1	-0.19	-0.137
(=1, if farmer, manufacturer, or entry-level worker)	[0.128]	[0.243]
Job title 2	-0.209*	0.0745
(=1, if supervisor, manager, or technician)	[0.107]	[0.187]
Postsecondary education		-0.206
(=1, if college-educated)		[0.158]
Number of persons in a household	0.0188	-0.0933**
	[0.0422]	[0.0433]
Age	0.115**	0.110***
	[0.0570]	[0.0288]
Age-squared	-0.0007	-0.001***
	[0.0005]	[0.0003]
Homeownership	-0.0275	0.390**
(=1, if yes)	[0.0898]	[0.178]
Business ownership	0.0764	-0.166
(=1, if yes)	[0.0821]	[0.131]
Number of credit cards	0.0411***	0.0224
	[0.00982]	[0.0209]
Outstanding credit card balance	0.0111***	-0.0008
	[0.0011]	[0.0007]

Variable	Fixed-effects Model Log credit limit	Fixed-effects Probit Model Approval Rate
Delinquency in credit card balance repayment	0.0449	-0.490***
	[0.0695]	[0.139]
Have you ever filed for bankruptcy?	0.0224	-0.517**
	[0.118]	[0.242]
Constant	5.337***	-3.846***
	[1.950]	[0.986]
Number of Observations	2,195	
Number of id	1,291	
R-squared	0.528	

Source: 2007-2009 SCF panel data.
Note: Robust standard errors, clustered by id in brackets. *** p<0.01, ** p<0.05, * p<0.1

VI. Conclusion

In this study, we use SCF data to investigate the determinants of unsecured credit limits for U.S. households. By addressing endogeneity with instrumental variables, our findings clarify the relationship between net worth and credit limits. We show that net worth plays a crucial role in determining credit limits. Income, by contrast, is significant only for households with small housing net worth, particularly for those under age 40. We also find that increases in nonfinancial wealth are associated with higher credit limits among households without housing wealth. Additional analyses using alternative regression models, variables, and datasets confirm the significant role of net worth in setting credit limits, even after controlling for income and demographic characteristics.

The SCF data have limitations, such as the lack of credit scores and income dynamics. To improve our understanding of credit limit determination, future research should incorporate richer data sources. Nevertheless, the empirical evidence from this study offers insights into households' saving and portfolio decisions in relation to credit limits. In particular, given the significant relationship between income, net worth, and credit limits, an optimal portfolio selection model could be developed by incorporating variation in credit limits over the life cycle and across business cycles.

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가계의 자산, 소득 및 신용한도에 대한 연구*

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초 록 자산은 신용한도를 결정하는 중요한 변수임에도 불구하고 변수 간 내생성과 통계적 추정의 한계로 인하여 엄밀한 영향 분석이 어렵다. 본고에서는 2004년~2022년 미국 소비자재무조사 (Survey of Consumer Finance)를 바탕으로 가계의 인구학적 특성과 신용 거래 및 상환 이력을 고려한 신용한도 결정 요인을 분석하였다. 상속 및 증여 금액을 도구변수로 활용하여 일반화적률법(General Method of Moments) 2단계 최소 자승 회귀(Two-stage Least Squares)모형을 적용한 결과 큰 규모의 자산을 가진 가계일수록 높은 신용한도를 할당받는 경향을 보였다. 이 경향성은 노동소득의 효과를 고려한 후에도 유지되며 대체 계량 분석 기법 및 자료를 사용한 강건성 검증 결과에서도 일관적으로 나타났다. 나아가 학력, 종사 분야, 직급 별 재무 자료 분석을 바탕으로 순자산의 효과의 생애주기적 변화를 밝혀 분석의 엄밀성을 더했다.

핵심 주제어: 무담보 신용 한도, 순자산, 소득, 주택, 내생성, 도구변수
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