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ON THE MACROECONOMIC DETERMINANTS OF CREDIT DELINQUENCIES IN THE USA[1]

DETERMINANTES MACROECONÔMICOS DA INADIMPLÊNCIA DE CRÉDITO NOS EUA

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Abstract: This investigation focuses on studying the impact of unemployment and income on debt delinquency. Auto loans, credit cards, mortgages, and student loans were used in the United States of America (USA) to perform this analysis. Panel data was used in the District of Columbia and the 50 states of the USA, with annual data from 2003 to 2019. In addition, a panel ARDL model was used for each type of loan. The study's innovation is researching the spread of unemployment to study the effect of unemployment on debt delinquency. The major findings of this research are trifold, (i) the determinants of the delinquency and default rate revealed only to share a limited number of determinants, (ii) the delinquency and default rate vary in complexity, and (iii) there is evidence that debtors arbitrage between credits if they have to enter in default. Most determinants have opposite impacts on the delinquency and default of borrowers. This fact means that policymakers must use a mix of instruments to minimize the delinquency end default globally. Policymakers also have to be aware of temporal inconsistencies, with short- and long-run contrary signs.

Keywords: Auto loan delinquency, Credit card delinquency, Mortgage delinquency, Student delinquency and default, Spread of unemployment.

Resumo: Esta investigação tem como foco estudar o impacto do desemprego e da renda na inadimplência. Empréstimos para automóveis, cartões de crédito, hipotecas e empréstimos estudantis foram usados nos Estados Unidos da América (EUA) para realizar esta análise. Dados de painel foram usados no Distrito de Columbia e nos 50 estados dos EUA, com dados anuais de 2003 a 2019. Além disso, um modelo ARDL de painel foi usado para cada tipo de empréstimo. A inovação do estudo é pesquisar os hiatos do desemprego para estudar o efeito do desemprego na inadimplência da dívida. As principais conclusões desta pesquisa são triplas, (i) os determinantes da taxa de inadimplência e inadimplência revelaram apenas compartilhar um número limitado de determinantes, (ii) a taxa de inadimplência e inadimplência variam em complexidade e (iii) há evidências de que os devedores arbitram entre os créditos caso estes tenham de entrar em incumprimento. A maioria dos determinantes tem impactos opostos sobre a inadimplência e a inadimplência dos tomadores de empréstimos. Esse fato significa que os formuladores de políticas devem usar uma combinação de instrumentos para minimizar a inadimplência e a inadimplência globalmente. Os formuladores de políticas também devem estar atentos às inconsistências temporais, com sinais contrários de curto e longo prazo.

Palavras-Chave: Inadimplência nos empréstimos para automóveis, inadimplência nos cartões de crédito, inadimplência nos cartões de crédito hipotecas e inadimplência nos cartões de crédito empréstimos estudantis, hiato do desemprego.

Classificação JEL: C33, E24, G51.

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1. Introduction

In recent years household debt in the United States of America (USA) has increased dramatically. In March 2019, the total household debt reached $13.67 trillion, increasing by $124 billion since the last quarter of 2018 and 22.5% above the 2013 values (Federal Reserve Bank of New York, 2019). The growing mass of debt, delinquency and default can prove problematic for the stability of the American economy.

By the end of March 2019, 4.6% of all outstanding debt was in delinquency. Moreover, in many areas, such as credit card debt and auto loans, the delinquency rate has seen a rising tendency in the last few years. The increase in debt and delinquency, paired with the fact that the USA is a major economic power whose financial stability has important repercussions for the rest of the world (Kim et al., 2015), motivates the American economy's choice as the object of study.

It is important to distinguish the concepts of delinquency and default clearly. In most definitions, one stems from the other. Delinquency effectively occurs when a borrower fails to pay an installment. Where the line between delinquency and default is drawn is more contested. According to the Basel II agreements, a default is considered a 90-day delinquency period (Sy, 2014). The United States of America, in the Code of Federal Regulations, only recognizes a default on federal loans after 270 days of delinquency (Code of Federal Regulations, 2022). For the credit rating agency Moody's, the concept of default includes both delinquency and an expected loss to the lender (Moody's Rating Symbols and Definitions, 2022). For the purpose of this investigation, delinquency with 90 days or more in arrears will be considered to be severe delinquency.

The main objective of this study is to determine the factors that influence delinquency and default, with special attention given to unemployment and income. This study hopes to answer the main questions: (i) what is the impact of unemployment and income on delinquency and default? (ii) does an increase in unemployment always increase the probability of delinquency and default? (iii) does an increase in income decrease the probability of delinquency and default?

The scope of this study encompasses delinquency and default on car loans, credit cards, mortgages, and student loans. A panel ARDL approach was used to empirically assess loan delinquency and default relationship with other macroeconomic variables. The main contribution of this study literature is the use of the spread of unemployment, instead of merely unemployment, as most studies do, to explain debt delinquency (Fuinhas et al., 2019).

This investigation is organized into seven sections. Section 2 presents the literature review. Section 3 presents the methodology used, divided into three subsections, data, method, and diagnostic tests. Section 4 shows the results, and Section 5 presents the robustness analysis. In Section 6, the results are discussed. Finally, Section 7 concludes and presents policy implications.

2. Literature Review

Common factors and idiosyncratic factors influence different types of credit. Indeed, these factors can be as diverse as the borrowers' characteristics, spending behaviors, household life cycle, or even temperature and precipitation (e.g., Xiao and Yao, 2014; Quaye et al., 2017; Sun and Vasarhelyi, 2018). Therefore, we chose to describe, separately, the determinants for each of the types of credit for its delinquency. The explanations advanced in the literature for its impact are also identified. The determinants of credit delinquency of student loans, auto loans, credit cards, and mortgages will be exposed below.

2.1. Student Loans

The causes that influence the likelihood of students going into default can be separated into two broad groups. These are the causes related to the students' background and the causes related to the economic situation.

Gender is a determining factor, as women are more likely to default on student debt than their male counterparts. The fact that women are discriminated against in the labor market produces a gender wage gap that makes it harder for women to repay their student loans and increases the average volume of student debt that women accumulate compared to men. This situation is even more pronounced for women of color (Miller et al., 2017). Race influences the probability of default for much the same reasons as gender. It is an aggravating factor that people of color are more likely to come from a disadvantaged socioeconomic background and pursue higher education avenues that result in lower wages (Jackson and Reynolds, 2013; Herr and Burt, 2005). Older students are more likely to default, possibly due to the progressive weakening of family ties as people age (Woo, 2002).

The student's family background influences the chances of defaulting on student debts. For example, students from richer families are less likely to default on their student loans (Looney and Yanellis, 2015). Furthermore, students whose parents have attended higher education are less likely to default on their loans than students who are the first in their families to attend higher education (Choy and Li, 2006). Moreover, students who have already defaulted once are more likely to default again (Woo, 2002).

Academic success is an important factor in explaining delinquency and default on student debt through the channel of better wages. Better students are, on average, well paid because college grades are taken into consideration by future employers and because the same personal characteristics that lead a student to have an excellent academic performance may also contribute to better work performance (Steiner and Teszler, 2003). Therefore, higher wages after university decrease the likelihood of delinquency default. By the same logic, students who leave the university without graduating are more likely to default, as, on average, they are paid less than their counterparts who graduated. As a consequence of having, on average, higher wages, people who live in areas with a low unemployment rate have a lower likelihood of going into delinquency and default. (Looney and Yanellis, 2015).

The type of institution a student graduates from can influence the probability of default. Since courses are more expensive in for-profit universities, students attending them tend to accumulate a higher volume of student debt than those graduating from their not-for-profit counterparts. Consequently, students graduating from for-profit universities are more likely to default (Deming et al., 2012).

High debt levels tend to influence the students' choice of a major, particularly underachieving ones. As students with higher levels of debt notice how challenging it will be to pay off their loans, one part of them opts to change to a major where they can expect a higher future income (Schemeiser et al., 2016; Malgwi et al., 2005). In the same line of thinking, the need for students to pay off their loans may lead them to follow suboptimal career paths (Kamenetz, 2016; Rothstein and Rouse, 2011). Students also tend to prioritize the repayment of other types of debt, such as credit card debt, over student debt (Pinto and Mansfield, 2006).

If the government subsidizes tuition fees, the number of students that need to borrow and the volume of debt accumulated by students decreases. Consequently, government subsidies also decrease delinquency rates (Ionescu and Simpson, 2016). In addition, optimistic expectations about the future are measured by consumer sentiment. When people are optimistic, they tend to increase investment in education. However, when those expectations do not pan out, there is a good chance that the investment in further education does not pay off and, therefore, can increase delinquency (Fuinhas et al., 2019).

2.2. Auto Loans

For most Americans, automobiles are an essential asset, second only to their homes, so auto loans are an essential part of banks' portfolios (Aizcorbe et al., 2003). Like student debt, auto loan delinquency can be traced back to the debtor's background and economic situation.

Concerning the debtors' background, age, gender, and marital status influence the probability of delinquency on auto loans. Men tend to have a higher delinquency rate than women. This situation can be attributed to women being more risk-averse than men and being less likely to accept riskier loans (Borghans et al., 2009). Younger people have a higher chance of defaulting on their auto loans, as they tend to be subject to higher levels of financial instability than older population strata. Married people tend to have a lower rate of default as being married tends to imply more financial stability as there are potentially two sources of income in a household. Finally, education has a negative impact on the delinquency rate, as people who are more educated tend to receive higher wages and be in a generally more stable financial position (Duan et al., 2018).

Considering the economic situation, the higher the unemployment rate, the higher the loan delinquency rate. These issues can be explained on a macro level because high unemployment tends to coincide with economic downturns. At a micro-level, unemployment represents an income that can make meeting financial obligations harder. Effectively, shocks in household liquidity can be considered major drivers in increasing auto loan delinquency (Heitfield and Sabarwal, 2004). Consumer sentiment is a determining factor of delinquency rates for auto loans. Increased confidence tends to reduce auto loan default rates but increased expected consumer sentiment raises these rates (Wadud et al., 2020).

The length of the auto loan itself also has a connection with the delinquency rate. Auto loans with more than five years of maturity are more likely to default than those with a shorter maturity (Wu et al., 2018). Błaszczyński et al. (2021) advance that frauds are sometimes classified as credit delinquency or default, contributing to burgeoning the dimension of this phenomenon.

2.3. Credit Cards

Ausubel (1997) states that in the USA, (i) there was not a well-established association between credit card defaults and bankruptcy before the 1990s, (ii) the rise in credit card defaults and bankruptcies was strongly associated during the 1990s, (iii) there was a link between the economy's cyclical state and household debt burden, (iv) credit card defaults and personal bankruptcy have moved upward in recessions and downward in economic booms exhibiting a countercyclical pattern, (v) deregulation contributed to increasing credit card profitability, and it has impacted credit card defaults and bankruptcy because it has created incentives to lessen the credit standards.

Credit cards have seen an increasing trend in their use throughout the rich world, notably in the United States. (Chakravorti and To, 2007). The expansion of credit card usage can be attributed to their ease of use and the increase in the volume of online transactions (Wadud et al., 2020; Donou-Adonsou and Basnet, 2019). Consequently, the costs of credit cards are potentially higher than before.

The debtors' backgrounds and attributes influence the default and delinquency rates in several ways. First, people who have a higher income are less likely to default on their credit card debt (Kim et al., 2018). In the same line of reasoning, unexpected fluctuations in income also affect the probability of default (Li et al., 2019). Second, younger people are more likely to default, as they tend to be relatively weak financially compared to older people. Finally, women are less likely than men to default due to being, in general, more risk-averse (Borghans et al., 2009).

Furthermore, a person's number of credit cards strongly correlates with credit card debt delinquency. The more credit cards a person has, the higher the probability of delinquency (Wadud et al., 2020). The borrower's occupational situation is a determinant of credit card debt and delinquency. Debtors who are self-employed or unemployed have a lower probability of going into delinquency (Leow and Crook, 2014).

Unemployment tends to increase the rate of credit card debt delinquency due to the financial instability that high levels of unemployment tend to imply for household finances (Agarwal and Liu, 2003; Bellotti and Crook, 2013; Kim et al., 2018). Interest rate hikes also tend to increase the rate of credit card delinquency as they make existing debt harder to service or rollover. An increase in consumer sentiment typically implies riskier behavior. Therefore, it increases the delinquency rate (Wadud et al., 2020).

2.4. Mortgages

Mortgages are an essential part of banks' financial assets. Even though banks have a threshold on the volume of mortgage delinquency they can absorb, big surges can destabilize the entire financial system (Campbell, 2012).

Traditionally, the leading causes of mortgage default were interest rates and the underlying asset's value. The probability of default was often conceptualized analogously to Black-Scholes option pricing models (Black and Scholes, 1973; Kau et al., 1995). Subsequently, other factors, such as unemployment, illness, or divorce, started being considered potential default triggers. These were dubbed trigger events (Danis and Pennington-Cross, 2008).

Given that the asset's value underlying the mortgage can vary, there is a possibility of the borrower going into strategic default. This situation happens when the market value of the underlying asset is perceived as being less than the value of the mortgage, resulting in the borrower having negative equity (Foote et al., 2008). Therefore, when negative equity is paired with a trigger factor, the probability of default increases substantially (Gerardi et al., 2013). On the other hand, if the borrower's equity is not negative, trigger events have a smaller contribution to default probability. As a result, the borrower can use their property and pay off the mortgage (Foote et al., 2008).

Variables related to the borrowers' backgrounds can influence the probability of delinquency. For example, people of color have, on average, higher delinquency rates when compared with white people. This situation involves people of color who tend to earn less and generally have a weaker financial position than others. Thus, in turn, it leads to the prevalence of high-risk mortgage characteristics, making delinquency more likely (Li and Mayock, 2019). Undeniably, household income is an essential factor in the likelihood of default and delinquency. Households with higher incomes are less likely to default. In the same line of reasoning, households that have experienced financial troubles in the past, such as a default, are more likely to experience financial troubles in the future (Böheim and Taylor, 2000). Income is not only relevant in levels but also in the variance. Households with higher income volatility have a higher probability of delinquency (Diaz-Serrano, 2005).

Households with lower financial literacy are more likely to default than their financially literate counterparts (Klapper et al., 2013). This situation partly explains households' increased difficulty in forming correct expectations about the future. Indeed, this is partly due to financially illiterate households feeling the effects of macroeconomic shocks more intensely (Gerardi et al., 2013).

Job loss is one of the critical trigger events in mortgage default and delinquency as it directly reduces households' income (Gerardi et al., 2013). Consequently, unemployment is one of the most important macroeconomic factors affecting mortgage default and delinquency. Regional unemployment is of particular relevance as it is the one that most directly affects household income (Böheim and Taylor, 2000). Consumer sentiment has the effect of decreasing default rates in the short term, but high levels of optimism about the future can increase the probability of future defaults (Wadud et al., 2020).

Chart 1 shows some factors found in the literature that can influence credit delinquency and causes default.

Chart 1. Factors identified in the literature that can cause credit delinquency and default

Student loan	Auto loan	Credit cards	Mortgages
Graduation	Loan Maturity	Number of Credit Cards	House Value
Unemployment Rate	Unemployment Rate	Interest Rates	Divorce
Wages	Consumer Sentiment	Consumer Sentiment	Unemployment Rate
Income	Income	Unemployment Rate	Accidents
Gender	Marital Status	Inflation	Illness
Consumer Sentiment	Education	Gender	Strategic Default
Age	Age	Occupational Situation	Financial Literacy
Loan Amount	Gender	Income	Ethnicity
Ethnicity			Consumer Sentiment
Type of Institution			Income
Academic performance			Interest Rates

3. Methodology

This section is divided into three subsections. The first section presents the variables, data sources, and descriptive statistics used in this investigation. The second section presents the models used, and the last section provides the diagnostic tests of the variables.

3.1. Data

This investigation used panel data for the District of Columbia, the USA's federal district, and the 50 states. Annual data from 2003 to 2019 was used. This time horizon was chosen due to data availability. The USA was chosen due to being one of the world's biggest economies, and the subprime crisis of 2007-2009 began. The USA can exert a strong influence on other economies when it is suffering a shock. Another reason that also motivated the USA's choice was that the delinquency phenomenon is increasing. Also, it has more data available to research this phenomenon than any other developed economy. Chart 2 describes the variables used in this study.

Chart 2. The acronym, variable description, and source

Acronym	Variable description	Source
auto	Percent of auto debt balance ninety or more days delinquent	Federal Reserve Bank of New York and Equifax
credit	Percent of credit card debt balance ninety or more days delinquent	Federal Reserve Bank of New York and Equifax
mortgage	Percent of mortgage debt balance ninety or more days delinquent	Federal Reserve Bank of New York and Equifax
student	Percent of student loan debt balance ninety or more days delinquent and in default	Federal Reserve Bank of New York and Equifax
gdp	Real total gross domestic product in millions of dollars	Federal Reserve Economic Data
creditd	Credit card debt balance per capita	Federal Reserve Bank of New York and Equifax
mortgaged	Mortgage debt balance per capita	Federal Reserve Bank of New York and Equifax

(*Continuation)*

Acronym	Variable description	Source
studentd	Student loan debt balance per capita	Federal Reserve Bank of New York and Equifax
unem	The unemployment rate in percent, annual by state	U.S. Bureau of Statistics
mhousehold	Real median household income in U.S. dollars by the state	Federal Reserve Economic Data
finstress	St. Louis Fed Financial Stress Index, annual	Federal Reserve Economic Data
deflator	GDP deflator	World Bank
inflation	Inflation at consumer prices, annual, in percent	World Bank
sp500	S&P500 Index	Yahoo Finance
longt	Long-term government bond yields(10-year) for the United States in percent, annual	Federal Reserve Economic Data
csent	The index of Consumer Sentiment, annual	Surveys of Consumers - University of Michigan
unemusa	The unemployment rate in percent annually in the USA	Federal Reserve Economic Data
pop	The resident population, thousands of persons	Federal Reserve Economic Data
vix	CBOE Volatility Index: VIX, Index, Annual, Not Seasonally Adjusted	Federal Reserve Economic Data
sunem	Deviation of the unemployment rate in percent, annual by state from the unemployment rate in percent, annual in the USA	Author's calculation

To study car loan default (auto) was used the proportion of borrowers with ninety or more days. To study credit card default (credit) was used the proportion of borrowers with ninety or more days. To study mortgage default (mortgage) was used the proportion of borrowers with ninety or more days. Lastly, to study student loan default, including defaults (student) was used the proportion of borrowers with ninety or more days. These variables were retrieved from the Federal Reserve Bank of New York and Equifax

The state's unemployment rate (unem) was retrieved from the USA Bureau of Statistics. The real median household income by state (mhousehold), and the unemployment rate (unemusa) were retrieved from Federal Reserve Economic Data . It was used to calculate the spread of unemployment (sunem), i.e., the difference between the state and the USA unemployment rates, both in natural logarithms. The spread of unemployment represents the deviation of unemployment in each state concerning unemployment in the USA.

The Consumer Sentiment (csent) index for the USA was retrieved from Surveys of Consumers - University of Michigan, and it represents the consumer's sentiment. The S&P500 variable (sp500) was retrieved from Yahoo Finance. It is an index that tracks the stocks of the 500 biggest companies listed on the New York Stock Exchange, representing the financial market's stance. This variable was deflated by the Gross Domestic Product (gdp) deflator (deflator) retrieved from the World Bank. The Gross Domestic Product for each state represents the economic outlook. This variable will be divided by the population (pop) to become *per capita* (gdppc).

The USA's St. Louis Fed Financial Stress Index (finstress) was retrieved from the Federal Reserve Economic Data, representing financial stress. The long-term government bond yields for ten years (longt) were retrieved from Federal Reserve Economic Data and represent the long-run borrowing cost as a ten-year interest rate. Finally, we deflate the variable longt using the inflation, retrieved from the World Bank.

The average credit card debt balance per borrower (creditd) was used to study credit card delinquency. Next, the average mortgage debt balance per borrower (mortgaged) was used to study mortgage delinquency. Finally, the average student debt balance per borrower (student) was used to study student loan delinquency and default. These variables were retrieved from the Federal Reserve Bank of New York and

Equifax. All variables were transformed into natural logarithms (variables with the prefix "L"), except finstress and longt. Table 1 reveals the characteristics of the series through descriptive statistics.

Table 1. Descriptive statistics

Variable		Mean	Std. Dev.	Min	Max	Observations	
auto	overall	3.322013	1.490135	.83	9.791719	N =	867
	between		1.128081	1.67803	6.267256	n =	51
	within		.98562	.3647573	7.488354	T =	17
lautod	overall	8.145155	.2316573	7.59589	8.836374	N =	867
	between		.1468717	7.792833	8.513887	n =	51
	within		.1802564	7.762756	8.654568	T =	17
credit	overall	8.516655	2.367444	3.61	22.35	N =	867
	between		1.61979	5.394462	13.3943	n =	51
	within		1.74056	4.717853	17.47235	T =	17
lcredit	overall	7.993819	.1788746	7.408531	8.486734	N =	867
	between		.1567572	7.584138	8.359818	n =	51
	within		.0887541	7.77725	8.302313	T =	17
mortgage	overall	2.58337	2.447669	.3	20.74	N =	867
	between		1.178545	.8902821	7.452707	n =	51
	within		2.151227	-4.179337	15.87066	T =	17
lmortgaged	overall	10.26642	.367968	9.13777	11.15768	N =	867
	between		.3451705	9.53263	10.92321	n =	51
	within		.135864	9.725079	10.65377	T =	17
student	overall	9.269856	2.992764	3.13	18.36	N =	867
	between		1.869008	6.278513	13.30294	n =	51
	within		2.351167	1.629996	14.85455	T =	17
lstudentd	overall	8.055473	.5295075	6.507277	9.504501	N =	867
	between		.2101765	7.661606	9.031851	n =	51
	within		.4868472	6.627456	8.77645	T =	17
lmhousehold	overall	11.01164	.1611934	10.47864	11.46764	N =	867
	between		.1487089	10.67662	11.29064	n =	51
	within		.065403	10.81366	11.30329	T =	17
sunem	overall	-.0037484	.0127784	-.0552506	.0393766	N =	867
	between		.010418	-.0285217	.0132137	n =	51
	within		.0075337	-.0304773	.0245378	T =	17
lunem	overall	.0549994	.0195434	.0219246	.1289061	N =	867
	between		.010418	.0302261	.0719614	n =	51
	within		.0165956	.0147125	.1140673	T =	17
lgdppc	overall	3.92553	.2587867	3.426277	5.21533	N =	867
	between		.2545848	3.43844	5.167798	n =	51
	within		.0579188	3.627743	4.185541	T =	17
longt	overall	.0102109	.0098427	-.0037101	.0361221	N =	867
	between		0	.0102109	.0102109	n =	51
	within		.0098427	-.0037101	.0361221	T =	17
linflation	overall	.020681	.010588	-.0035618	.0376724	N =	867
	between		0	.020681	.020681	n =	51
	within		.010588	-.0035618	.0376724	T =	17
lcsent	overall	4.422533	.1373364	4.154184	4.589041	N =	867
	between		0	4.422533	4.422533	n =	51
	within		.1373364	4.154184	4.589041	T =	17
lsp500	overall	2.805111	.270761	2.34658	3.29963	N =	867
	between		0	2.805111	2.805111	n =	51
	within		.270761	2.34658	3.29963	T =	17
finstress	overall	-.053596	.8950571	-.8890423	2.893713	N =	867
	between		0	-.053596	-.053596	n =	51
	within		.8950571	-.8890423	2.893713	T =	17
lunemusa	overall	.0587478	.0172905	.0361712	.0917432	N =	867
	between		0	.0587478	.0587478	n =	51
	within		.0172905	.0361712	.0917432	T =	17
lvix	overall	2.867389	.2965467	2.406065	3.487149	N =	867
	between		0	2.867389	2.867389	n =	51
	within		.2965467	2.406065	3.487149	T =	17

The Stata command *xtsum* was used to obtain the results.

3.2. Method

The empirical research was performed using a least-squares dummy variable estimator (panel with fixed effects). The panel specification is represented in equation (1).

$$Y_{it} = \alpha_i + X'_{it}\beta + \mu_t, \quad 1)$$

where α_i, i = 1, ..., N, are fixed unknown constants (fixed effects) that are estimated along with β; X_{it}, i = 1, ..., N, and t = 1, ..., T, is a k-dimensional vector of explanatory variables; and μ_{it} are the error term assumed to be i.i.d. over individuals and time. The fixed effects, α_i, seize all unobservable time-invariant divergences across individuals.

The characteristics of data and the nature of relationships among variables were assessed through previous analyses. Thus, the empirical work analyzed variables' (i) time-variability, (ii) patterns, (iii) outliers, (iv) structural breaks, (v) cross-sectional dependence, (vi) order of integrations, (vii) normality distribution, (viii) multicollinearity, and (ix) panel effects (see Chart 3, Pre-estimation testing). In addition, a battery of post-estimation tests was performed to grant the appropriateness of estimations. These tests assess the residuals' homoscedasticity, serial correlation, and cross-sectional independence (see Chart 3, Post-estimation analysis). The econometric software Stata 16.1 was used to carry out the empirical analysis.

Chart 3. Pre-estimation and post-estimation analysis

Pre-estimation testing	
Analisys/testing	**Objective**
Descriptive statistics	To summarize variables.
Graphical analysis	Visualize patterns, identify structural breaks, and detect outliers.
Cross-sectional dependence (CSD) test (Pesaran, 2004)	To detect cross-sectional dependence) in the panel's data, the test has a null hypothesis, cross-section independence; CD ~ N (0,1).
Panel Unit Root test (CIPS) test (Pesaran, 2007)	To assess variables' order of integration; the CIPS test has a null hypothesis that the series has a unit root.
Pairwise correlations	To assess the correlation between the variables in the panel data; signal collinearity.
Variance Inflation Factor (VIF) test (Belsley et al., 1980)	To test multicollinearity among independent variables.
Hausman (1978) test	To test panel heterogeneity and supports the decision between a panel with random effects (RE) or a panel with fixed effects (FE).
Bias-corrected LM-based test (Born & Breitung, 2015)	To test serial correlation in fixed-effects panel models; the test has as a null hypothesis the presence of serial correlation up to the second order.
Post-estimation analysis	
Analysis/testing	**Objective**
Wald test (Agresti, 1990)	To test the global statistical significance of the estimated model; the test has a null hypothesis that all coefficients are zero.
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity (Breusch & Pagan, 1979; Cook & Weisberg, 1983)	To test the heteroscedasticity; the test has the null hypothesis of homoscedasticity.
Wooldridge test (Wooldridge, 2002)	To test serial correlation in panel-data models; the test has as a null hypothesis no first-order autocorrelation.
Modified Wald test (Greene, 2000)	To test cross-sectional independence in the residuals of the fixed-effect model; the test has a null hypothesis on residuals' cross-sectional independence.

Auto loans, credit cards, mortgages, and student loans was used to study delinquency and default. The share of several determinants also puts the question of how much delinquency and default behave differently. This situation is not the case in our research. The variables reveal some correlation but not enough to be considered linked (see Table A1 in Appendix). The dependent variables used in this investigation are between 0 and 100 (as they are percentages of the borrowed amount). Individual estimations were performed for each of the four types of credit under research. The model's results compare the spread of unemployment and the unemployment rate instead of the most common literature approaches that only use the unemployment rate. The software Stata 16.0 was used to perform the econometric analyses.

The preliminary analysis revealed that the unemployment rate in percent, the S&P500 index, and the consumer sentiment index were multicollinear. Given that restriction, we opted to use the unemployment rate in this research. Table A2 (in the Appendix) reveals the estimated coefficients if these variables were used instead of unemployment. The econometric approach began with the most general model for each of the four types of credit, including all explanatory variables. The next step consisted of excluding the variables that were not statistically significant to achieve parsimonious models. The models' specifications that follow refer to the parsimonious models.

Eq. 2-5 below describes the panel ARDL model for each type of credit delinquency (and default in student loans). For example, the panel ARDL model to study car loan delinquency is represented by the following equation (2):

$$\begin{aligned} AUTO_{it} = {} & \beta_1 + \beta_{101}DSUNEM_{it} + \beta_{102}DLUNEM_{it} + \beta_{103}DLONGT_{it} + \beta_{104}DLINFLATION_{it} + \beta_{105}DFINSTRESS_{it} \\ & + \beta_{106}DLVIX_{it} + \beta_{107}DLMHOUSEHOLD_{it} + \beta_{108}DLGDPPC_{it} + \beta_{109}DLAUTOD_{it} + \beta_{110}DLCREDITD_{it} \\ & + \beta_{111}DLMORTGAGED_{it} + \beta_{112}DLSTUDENTD_{it} + \gamma_{100}AUTO_{it-1} + \gamma_{101}SUNEM_{it-1} \\ & + \gamma_{102}LUNEM_{it-1} + \gamma_{103}LONGT_{it-1} + \gamma_{104}LINFLATION_{it-1} + \gamma_{105}FINSTRESS_{it-1} + \gamma_{106}LVIX_{it-1} \\ & + \gamma_{107}MHOUSEHOLD_{it-1} + \gamma_{108}LGDPPC_{it-1} + \gamma_{109}LAUTOD_{it-1} + \gamma_{110}LCREDITD_{it-1} \\ & + \gamma_{111}LMORTGAGED_{it-1} + \gamma_{112}LSTUDENTD_{it-1} + \varepsilon_{1it} \end{aligned} \quad 2)$$

The panel ARDL model to study credit card delinquency is represented by the following equation (3):

$$\begin{aligned} CREDIT_{it} = {} & \beta_2 + \beta_{201}DSUNEM_{it} + \beta_{202}DLUNEM_{it} + \beta_{203}DLONGT_{it} + \beta_{204}DLINFLATION_{it} + \beta_{205}DFINSTRESS_{it} \\ & + \beta_{206}DLVIX_{it} + \beta_{207}DLMHOUSEHOLD_{it} + \beta_{208}DLGDPPC_{it} + \beta_{209}DLAUTOD_{it} + \beta_{110}DLCREDITD_{it} \\ & + \beta_{211}DLMORTGAGED_{it} + \beta_{212}DLSTUDENTD_{it} + \gamma_{200}CREDIT_{it-1} + \gamma_{201}SUNEM_{it-1} \\ & + \gamma_{202}LUNEM_{it-1} + \gamma_{203}LONGT_{it-1} + \gamma_{204}LINFLATION_{it-1} + \gamma_{205}FINSTRESS_{it-1} + \gamma_{206}LVIX_{it-1} \\ & + \gamma_{207}MHOUSEHOLD_{it-1} + \gamma_{208}LGDPPC_{it-1} + \gamma_{209}LAUTOD_{it-1} + \gamma_{210}LCREDITD_{it-1} \\ & + \gamma_{211}LMORTGAGED_{it-1} + \gamma_{212}LSTUDENTD_{it-1} + \varepsilon_{2it} \end{aligned} \quad 3)$$

The panel ARDL model to study mortgage delinquency is represented by the following equation (4):

$$\begin{aligned} MORTGAGE_{it} = {} & \beta_3 + \beta_{301}DSUNEM_{it} + \beta_{302}DLUNEM_{it} + \beta_{303}DLONGT_{it} + \beta_{304}DLINFLATION_{it} + \beta_{305}DFINSTRESS_{it} \\ & + \beta_{306}DLVIX_{it} + \beta_{307}DLMHOUSEHOLD_{it} + \beta_{308}DLGDPPC_{it} + \beta_{309}DLAUTOD_{it} + \beta_{310}DLCREDITD_{it} \\ & + \beta_{311}DLMORTGAGED_{it} + \beta_{312}DLSTUDENTD_{it} + \gamma_{300}MORTGAGE_{it-1} + \gamma_{301}SUNEM_{it-1} \\ & + \gamma_{302}LUNEM_{it-1} + \gamma_{303}LONGT_{it-1} + \gamma_{304}LINFLATION_{it-1} + \gamma_{305}FINSTRESS_{it-1} + \gamma_{306}LVIX_{it-1} \\ & + \gamma_{307}MHOUSEHOLD_{it-1} + \gamma_{308}LGDPPC_{it-1} + \gamma_{309}LAUTOD_{it-1} + \gamma_{310}LCREDITD_{it-1} \\ & + \gamma_{311}LMORTGAGED_{it-1} + \gamma_{312}LSTUDENTD_{it-1} + \varepsilon_{3it} \end{aligned} \quad 4)$$

The panel ARDL model to study student loan delinquency and default is represented by the following equation (5):

$$\begin{aligned} STUDENT_{it} = {} & \beta_4 + \beta_{401}DSUNEM_{it} + \beta_{402}DLUNEM_{it} + \beta_{403}DLONGT_{it} + \beta_{404}DLINFLATION_{it} + \beta_{405}DFINSTRESS_{it} \\ & + \beta_{406}DLVIX_{it} + \beta_{407}DLMHOUSEHOLD_{it} + \beta_{408}DLGDPPC_{it} + \beta_{409}DLAUTOD_{it} + \beta_{410}DLCREDITD_{it} \\ & + \beta_{411}DLMORTGAGED_{it} + \beta_{412}DLSTUDENTD_{it} + \gamma_{400}STUDENT_{it-1} + \gamma_{401}SUNEM_{it-1} \\ & + \gamma_{402}LUNEM_{it-1} + \gamma_{403}LONGT_{it-1} + \gamma_{404}LINFLATION_{it-1} + \gamma_{405}FINSTRESS_{it-1} + \gamma_{406}LVIX_{it-1} \\ & + \gamma_{407}MHOUSEHOLD_{it-1} + \gamma_{408}LGDPPC_{it-1} + \gamma_{409}LAUTOD_{it-1} + \gamma_{410}LCREDITD_{it-1} \\ & + \gamma_{411}LMORTGAGED_{it-1} + \gamma_{412}LSTUDENTD_{it-1} + \varepsilon_{4it} \end{aligned} \quad 5)$$

3.3. Diagnostic Tests

Table 2 presents the Wooldridge test (2010), the Pesaran test (2004), and the Breusch-Pagan test (1979) for the four types of credit. The Wooldridge test to check the presence of the first-order autocorrelation of residuals. The Breusch-Pagan test checks the presence of heteroscedasticity of residuals, and the Pesaran test was performed to check the presence of cross-sectional dependence of residuals. The tests show that heteroscedasticity, first-order autocorrelation, and cross-sectional dependence are present for all types of credits analyzed. They also show that there is no multivariate normality in the residuals (see Table 2).

Table 2. Wooldridge, Pesaran, and Modified Wald tests

Model	Wooldridge test	Pesaran test	Modified Wald test
Auto Loans	36.562***	-0.27	1241.15***
Credit Cards	84.749***	32.08***	998.23***
Mortgages	43.907***	7.53***	2222.53***
Student Loans	87.745***	-1.19	1249.65***

Notes: *** denotes statistical significance at the 1% level; H_O of Pesaran test: cross-sectional independence; H_O of Wooldridge test: no first-order autocorrelation; H_O of Modified Wald test: Constant variance for all crosses; the Stata commands *xtserial*, *xtcsd,* and *xttest3*, respectively, were used to compute these tests.

Table 3 reveals the VIF and mean VIF statistics. The VIF statistics were used to test for the presence of multicollinearity. The lower VIF and mean VIF values prove that multicollinearity is not a problem in these estimations (all values are below the benchmark of 10 for individual VIFs and below the benchmark of 6 for mean VIF).

Table 3. VIF and Mean VIF statistics

	VIF			
Variables	**Auto Loans**	**Credit Cards**	**Mortgages**	**Student Loans**
dsunem	1.18		1.01	1.10
dlunem	1.65	1.67		1.40
dlongt	1.58			1.43
dlinflation		1.31		
dfinstress	4.86			1.26
dlvix	3.98	1.03		
dlmhousehold			1.04	
dlgdppc		1.39		
dlautod				
dlcreditd	1.62		1.04	
dlmortgaged				1.29
dlstudentd				1.25
Mean VIF	2.48	1.35	1.03	1.29
sunem	2.30	2.03		2.11
lunem	3.94	2.93	1.68	3.20
lgdppc	1.73			1.83
lmhousehold			3.38	
longt	3.00		1.50	3.14
linflation	3.39		1.63	3.49
finstress	5.46	5.09	1.08	5.48
lvix	8.01	7.44		7.94
lautod	1.49			
lcreditd	4.85	1.12		
lmortgaged	3.20		3.14	1.61
lstudentd				2.83
Mean VIF	3.74	3.72	2.07	3.51

Note: The Stata command *vif* was used.

Table 4 shows the Hausman and the Breusch and Pagan (1980) Lagrangian multiplier (LM) tests. The Hausman test was used to test fixed effects against random effects. The LM test was performed to decide between a random-effects regression and a Pooled Ordinary Least Squares (OLS) regression.

Table 4. Fixed effect vs. random effects and random effects vs. pooled OLS

	Fixed effects vs. random effects	Random effects vs. pooled OLS
Auto Loans	190.65***	0.00
Credit Cards	5087.22***	0.00
Mortgages	269.34***	0.00
Student Loans	223.24***	0.00

Notes: *** denotes statistical significance at the 1% level; the Hausman test was used to test fixed effects against random effects, H_0 of the Hausman test: difference in coefficients not systematic; the Stata command *xttest0* was used to test random effects against pooled OLS, H_0 of Breusch-Pagan Lagrangian multiplier test: variances across entities are zero.

The LM and Hausman tests signal that fixed effects regressions should be used to estimate the four models.

4. Results

Table 5 reveals the estimations of panel ARDL with fixed effects, using the Driscoll and Kray (1998) estimator to control for the presence of undesired properties in residuals.

Table 5. Models' estimations

Variables	Auto Loans		Credit Card		Mortgage		Student Loans	
id2007	0.0284	***					-0.0125	***
id2008	0.1955	***					-0.0643	***
id2009	0.0775	***	-0.0629	***	0.0097	***	-0.0204	***
id2010			0.0177	***				
id2011	0.0543	***	0.0212	***			-0.0348	***
id2012	0.0685	***	0.0048	***				
dsunem$_t$	-2.7569	***			0.3097	**	0.6460	*
dlunem$_t$	2.9057	***	0.3649	***			-0.6065	*
dlongt$_t$	1.3801	***					-0.4472	***
dlinflation$_t$			-0.7661	***				
dfinstress$_t$	-0.0622	***					0.0176	***
dlvix$_t$	0.0296	***	-0.0112	***				
dlmhousehold$_t$					-0.0096	**		
dlgdppc$_t$			-0.0417	***				
dlcreditd$_t$	0.0240	**			0.0548	***		
dlmortgaged$_t$							0.0541	**
dlstudentd$_t$							0.0266	*
auto$_{t-1}$	-0.1767	**						
credit$_{t-1}$			-0.3236	***				
mortgage$_{t-1}$					-0.1433	**		
student$_{t-1}$							-0.4801	***
sunem$_{t-1}$	0.5751	***	0.3360	***			-0.2080	**
lunem$_{t-1}$	-0.5944	***	-0.1674	***	-0.1047	*	0.2746	**
lgdppc$_{t-1}$	-0.0164	***					-0.0153	*
lmhousehold$_{t-1}$					-0.0118	*		
longt$_{t-1}$	0.2659	***			0.2917	***	-0.5617	***
linflation$_{t-1}$	-2.9965	***			0.3340	***	0.4115	**
finstress$_{t-1}$	-0.0942	***	0.0188	**	0.0039	***	0.0236	***
lvix$_{t-1}$	0.0629	***	-0.0335	**			-0.0136	***
lautod$_{t-1}$	0.0130	***						
lcreditd$_{t-1}$	0.0129	**	0.0374	***				
lmortgaged$_{t-1}$	0.0058	**			0.0412	***	0.0175	**
lstudentd$_{t-1}$							0.0210	***
Constant	-0.1640	***	0.0066		-0.1069		-0.0407	

Notes: ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

Table 6 reveals the computed values of the long-run parameters for the four models.

Table 6. Models' long-run parameters estimation

Variables	**Auto Loans**		**Credit Card**		**Mortgage**		**Student Loans**	
sunem	3.2542	***	1.0382	***			-0.4331	**
lunem	-3.3633	***	-0.5171	**	-0.7311		0.5719	**
lgdppc	-0.0927	**					-0.0318	**
lmhousehold					-0.0821			
longt	1.5043	**			2.0360	**	-1.1698	***
linflation	-16.9544	***			2.3312	**	0.8571	**
finstress	-0.5332	***	0.0582	**	0.0271	**	0.0492	***
lvix	0.3559	***	-0.1034	**			-0.0282	***
lautod	0.0736	**						
lcreditd	0.0731	*	0.1157	***				
lmortgaged	0.0329	**			0.2874	***	0.0364	**
lstudentd							0.0437	***

Notes: ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

5. Discussion

In a sophisticated financial economy like the USA, economic agents have access to credit on a scale and variety that allows them to go further in exploring their preferences between present consumption and saving. This financial sophistication also allows borrowers to have more than one debt, opening the hypothesis of rational behavior to default. The macroeconomic factors influencing delinquency are vast but not identical to all kinds of debts. To preserve the analysis as simple as possible, only the statistically significant variables were shown in Tables 5 and 6. The results of these parsimonious models support that delinquencies and default do not follow a similar behavior suggesting that debtors manage (arbitrate) where they go into default.

At first glance, one can conclude that auto and students loans delinquency and default are influenced by many macroeconomic determinants. On the other hand, mortgage loan delinquency is less complex, with a limited number of determinants. This big picture is also reflected in both temporal dimensions of our analysis, i.e., the short- and the long-run.

The literature shows that if borrowers lose their job, they will probably not be able to pay off their credit (Heitfield and Sabarwal, 2004; Bellotti and Crook, 2013; Gerardi et al., 2013). Nevertheless, our research reveals that the scenario can be more difficult to untangle from a macroeconomic perspective. The analysis of unemployment and the spread of unemployment reveals that the adjustment tends to behave symmetrically.

Indeed, the responses of loan delinquency and default to unemployment reveal a similar behavior for auto loans, credit cards, and mortgages, but not for student loans. This behavior reinforces that student loans are singular among loans delinquency and default. In fact, the ones prone to debt, revealing a preference to present consumption, manage the primary sources of credit in the same way. In other words, in general, they have multiple debts, i.e., auto loans, credit cards, and mortgages. However, in some ways, student loans are similar to investments in human capital.

Consequently, it has a particular place in people's decisions and those that qualify to pursue studies. In the case of the deviation of employment, a possible explanation for the positive signal in the short run and negative in the long run may be that when a State is above the national unemployment rate, borrowers in trouble enter default. However, the persistence of unemployment above the national level encourages borrowers to migrate to other States with better labor markets, reducing the defaults in their home States.

The ARDL model allows the decomposition of explanatory variables in short- and long-run influence in the explained one. This decomposition reveals that unemployment first (in the short run) increases the loan's delinquency and default, but in the long run, as creditors and debtors adjust to a new level of unemployment, it decreases it. This outcome is consistent with economic theory, as economic agents' forecast of the economic situation is involved in uncertainty, and shocks are not fully anticipatable. Indeed, unemployment has a dimension of surprise more often than not.

Student loans behave oppositely. Once again reinforces the particular nature of this kind of loan. Macroeconomically, unemployment was caused, at last in some proportion, by structural changes linked to how the economy evolves. This result was compatible with the way human capital is formed. Those who study (or have just finished their studies) are the most flexible workers in the short run. Therefore, they can exploit the situation at the moment.

In periods of rising unemployment, most people who lose their jobs are less qualified, which means that more qualified people occupy their jobs, albeit with a lower salary. The most qualified people disproportionately have student loans. So, if they preserve a job, they can continue to pay their loan installments, reducing delinquency and default (Mincer, 1991). The opposite occurs in the long run. Those who have student loans have more often than not used their studies to specialize, and the specialized people tend to be prepared to cope well with structural changes.

The deviation of the unemployment rate gives us a different picture of how delinquency and default behave, depending on the relative unemployment of states to the U.S. unemployment. Here the results are less common, revealing some idiosyncrasies among the kind of delinquencies and defaults under study. The opposite behavior of deviation of the unemployment concerning the unemployment is compatible with strong debtors' mobility interstates.

The deviation of the unemployment rate impacts auto loan delinquency and default negatively in the short run and positively in the long run. It should be noted that except for student loan debt balance per capita, all other debt balances per capita have explanatory power on auto loan delinquency and default.

This situation reveals that debtors arbitrate between their debts, opting not to become delinquent and default on auto loans. This behavior is compatible with mobile and becomes essential in situations where state unemployment is above the national level. When available jobs become scarce, workers accept the possibility of working in more distant places or even migrating to another state, where the labor market is better for getting a job.

Nonetheless, in the long run, the deviation of the unemployment rate impacts auto loan delinquency and default positively, which is expected, given that situations, where unemployment remains above the national values mean fragility for economic agents that manifest in a lower capacity to honor debts.

The deviation of the unemployment rate impacts credit card delinquency and default only in the long run. This finding is not unexpected at all. Indeed, credit cards also are used as a buffer to smooth consumption in the short run, but that function cannot be extended indefinitely in time.

The unemployment rate deviation impacts mortgage delinquency and defaults positively, but only in the short run. Mortgages are, as a rule, the biggest debt of households. Property is also the most difficult to sell quickly without incurring a loss. Consequently, as the relative unemployment situation worsens more than the national one, households have additional difficulties servicing the debt.

The difference of the unemployment rate impacts student loan delinquency and default positively in the short run and negatively in the long run. This situation is compatible with the loss of jobs, turn it difficult for some debtors to service the debt and promptly default. On the other hand, as people who have studied are more employable, they are more successful in remaining employed or getting jobs in other states in the second round.

The key macroeconomic variables related to the cost of debt and the capacity to service the debt reveal mixed influences on the kinds of debt. The long-term government bond yields (10 years) for the U.S. increase the delinquency and default of auto loans in the short- and the long run, increase it in the long-run for mortgages, and decrease it for student loans in both short- and long-run. In credit cards, an increase in the interest rate does not influence the delinquency and default rate refuting the stipulated by Wadud et al. (2020) that it increases credit charges and, consequently, the delinquency and default rate.

The GDP per capita decreases the delinquency and default of auto and student loans in the long-run and credit cards in the short run. It can represent that a time of economic growth, or recovery, provokes lesser credit delinquency (Ghosh, 2015). The state's real median household income in U.S. dollars decreases the delinquency and default of mortgages in the short run. If borrowers have income, they will be able to pay back loans more quickly, corroborating the results found in the literature (Böheim and Taylor, 2000; Schemeiser et al., 2016; Kim et al., 2018).

Inflation only influences delinquency and default in the short run. Credit cards have this negative effect. In the long run, inflation decreases the delinquency and default of auto loans but aggravates it in mortgages and student loans. A note should be advanced in the case of credit cards. Inflation captures the cost of using a credit card due to increases in interest rates and the cost of a rollover of the debt. Capture a dimension that goes beyond short-run interest rates. Inflation influences the real amount that a debtor can afford. As in interest rates, the same effect occurs with inflation, which usually increases during periods of economic growth, causing a reduction in delinquency and default (Rizvi and Khan, 2015) in auto loans in the long run. Nevertheless, the opposite effect occurs in the other delinquency end default we analyze.

The St. Louis Fed Financial Stress Index decreases the delinquency and default of auto loans in the short- and long run. This result is compatible with Wu et al.'s (2018) findings that the more expensive the car and the longer the loan, the higher the likelihood of delinquency. However, increase it in the short- and the long-run in the case of student loans and increase the delinquency and default in the long run of credit cards and mortgages. Financial stress gauges the worries of economic agents to the occurrence of economic or financial shocks that materializes in anxiety and trigger a negative influence on people.

This period has seen one of the major economic and financial crises. Financial stress tends to increase during periods of economic growth when wages are higher, unemployment is low, and so delinquency and default decrease (Aydin et al., 2016). In addition, borrowers are more pessimistic about the future, making them more careful when requesting loans, thus decreasing the delinquency rate (Boef and Kellstedt, 2004). When borrowers have high expectations, this could lead them to borrow more than they can pay in the future (Wadud et al., 2020).

The CBOE Volatility Index (VIX) increases the delinquency and default of auto loans in the short- and long run. Nevertheless, it also decreases the delinquency and default of credit cards in the short- and long run. In addition, VIX decreases the delinquency and default of student loans in the long run. The VIX is a gauge of expectations about the volatility in the stock market. Many Americans invest in the stock markets, so the VIX influences the in-debt decisions. However, it also reflects the difficulty in using the investment made in the capital markets to deal with unforeseen events and in being able to use it to service the debt.

As expected, the debt balance per capita increases the delinquency and default of all kinds of debts in the long run. Indeed, increased debt makes it more difficult for borrowers to repay their loans, increasing the likelihood of delinquency and default (Kelly and McCann, 2016). In the short run, the debt balance of credit cards increases the delinquency and default of auto loans and mortgages.

The debt balance of mortgages increases the delinquency and default of student loans in the short- and long run. The debt balance of credit cards and mortgages increases the delinquency and default of auto loans in the long run. As can be seen in Fig.1, the debt balance per capita of mortgages reveals a relationship between student and auto loans. It can also be seen that credit card debt balances are related to delinquency and default on auto loans and mortgages.

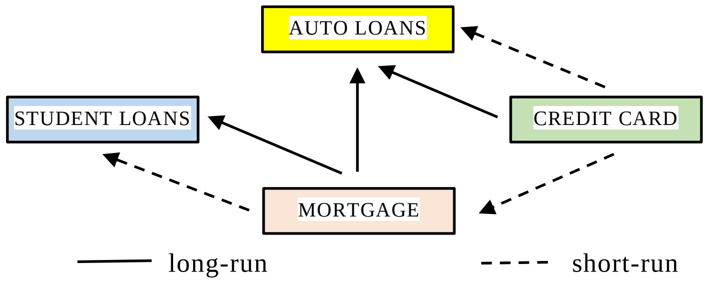

Figure 1. Relationships between debt balances

The error correction is negative and statistically significant for all models. The student loans model is the one with the greatest speed of convergence to equilibrium (48.0%), followed by credit cards (32.4%), auto loans (17.6%), and mortgages (14.3%). Long-term relationships are a sign that the phenomenon of delinquency and default has a stable link over time. Auto loans are the most complex, followed closely by student loans in the long run. In contrast, mortgages and credit cards are the simplest.

6. Conclusion and policy implications

This research focuses on the impacts of the spread of unemployment, unemployment, and income on the USA's debt delinquency rate and credit default. For this purpose, an analysis of delinquency in auto loans, credit cards, mortgages, and student loans was performed. Data from 2003 to 2019 from the 50 states of the USA and the federal state of Columbia were used. In addition, unemployment and the spread of unemployment were used. The unemployment spread is the deviation of each state's unemployment concerning the USA's unemployment. The long-term government bond yields (10-year) were also used for the US GDP per capita, the state's real median household income in U.S. dollars, inflation, the St. Louis Fed Financial Stress Index, and the CBOE Volatility Index, VIX.

The four delinquencies and defaults are different, respond differently to macroeconomic conditions changes, and do not share entirely the same determinants. The findings also support that the debtors have more than one credit, so they decide which credits to default on some extension. Most of the identified determinants of delinquency and default identified in the literature are microeconomic. Nevertheless, some macroeconomic factors were expected to impact the volume of credit delinquency and default.

Further research should be carried out to disentangle the behavior of debtors concerning their multiple kinds of debt. Indeed, debtors are likely to have more than one type of credit and arbitrate between different credit sources, deciding where it is most likely to default. The empirical results point out that the purpose of credit is also essential, as well as the amount and maturity of credit operations play a role in debtors' behavior. Indeed, the differences in the spread of unemployment and unemployment suggest that debtors have interstate mobility.

In particular, the USA's federal structure allows mobility and specific measures at the state level that look to mitigate the influence of unemployment, as revealed by the spread of unemployment and the state's unemployment. This empirical analysis indicates that to understand the macroeconomic mechanisms of adjustment in federations, states' availability of disaggregated information may facilitate understanding economic agents' financial adjustment phenomena.

Most determinants have contrary impacts on the delinquency and default of borrowers. This finding means that policymakers must use a mix of instruments to minimize the global delinquency and default. Policymakers also have to be aware that there are temporal inconsistencies, with short- and long-run opposite signs. Hence, it is essential to assess the impact of macroeconomics and U.S. delinquency and default rate determinants to prevent the contagion phenomenon.

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Appendix

Table A1. Matrix of correlations - debt delinquency rate and credit default

	auto	credit	mortgage	student		dauto	dcredit	dmortgage	dstudent
auto	1				**dauto**	1			
credit	0.4952	1			**dcredit**	0.5486	1		
mortgage	0.4434	0.7180	1		**dmortgage**	0.5998	0.6298	1	
student	0.5286	0.1011	0.1393	1	**dstudent**	-0.1304	0.1185	0.0805	1

Table A2. Models' estimations – replacing unemployment by standard & poor index or consumer sentiment

Variables	Auto Loans		Credit Card		Mortgage	Student Loans	
			(…)				
dlsp5000	-0.1183	***	-0.0384	**		0.0498	*
lsp5000	0.0786	***	0.0238	***	0.0264	-0.0479	***
			(…)				
dlcsent	0.2337	***	-0.0137			0.0140	
lcsent	-0.9793	***	0.0981	**	0.0310	-0.0813	***