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Delinquency and Default in USA Student Debt as a Proportional Response to Unemployment and Average Debt per Borrower

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Abstract: We research the response of the proportion of student borrowers with ninety or more days of delinquency or in default to variables such as unemployment and the average debt per borrower after the financial crisis of 2007–2008, in the United States, using panel data of 50 states from 2008 to 2015. The proportion of borrowers with delinquency or default was modelled as a function of unemployment, the average debt per borrower, consumer sentiment, and financial stress, using a logit and probit binomial model. The specification tests support that no relevant variable was omitted. Unemployment and the average debt per borrower are statistically significant and contribute to increasing delinquency or default in the 50 states of the panel sample. The results also reveal a differential impact of unemployment among the four regions considered by the US Census Bureau.

Keywords: student loan default; unemployment; average debt per borrower; consumer sentiment; financial stress; fractional probit; panel data

JEL Classification: I23; G21; C23

1. Introduction

Student debt and default have been a hot topic of research in recent decades, and the majority of these studies centre on the United States of America. Indeed, student loan debt is becoming a huge concern for the US economy. It is the second-highest consumer debt, after mortgages and higher than credit card and auto loans debt. Student debt was around $1.3 trillion at the end of 2016, an increase of 170% since 2006. Reasons for this increase are more students taking loans with more substantial amounts and slowed repayment rates. This paper aims to study the response of the proportion of USA student borrowers with ninety or more days delinquency or in default to variables such as unemployment and average debt per borrower at a state level. For that purpose, a probit and logit binomial model for panel data for student borrower delinquency or default data analysis were used. Our primary hypothesis in this paper is that higher unemployment and average debt per borrower will lead to a higher proportion of student borrower delinquency or default.

Around 5% of borrowers have more than $100,000 in debt, but represent 30% of total debt. Recent graduates leave educational institutions with about $34,000 in student debt, on average. Default rates increased until 2012 and stabilised after that. The payment progress is slower for more recent graduates because of higher borrowing amounts and higher default rates (Chakrabarti et al. 2017). The risk of student loan default could be a potential trigger for the next financial crisis, since the 30+ day delinquency rate increased from 11% to 17% between 2004 and 2014, which is much higher than any other kind of debt (Sánchez and Zhu 2015). College enrolment grew by 20% between 2005 and 2010, faster than any period since the 1970s, and has been declining since (Haughwout et al. 2015), with an increase in the student loan borrowing during the Great Recession (2007–2012), doubling in real terms between 2005 and 2012. Higher tuition and college costs have probably driven this increase.

Constrained family finances and weak labour markets after the recession could also be a reason for students to attend graduate and professional schools. High loan debt might not be a problem if investment leads to high returns in the future and the repayments are made (Monge-Naranjo 2014). Some institutions have price discrimination, which benefits students from low-income families, making education a more significant burden for students of wealthier families (Wolla 2014). Most students in repayment say that the benefits of education made possible through borrowing were worth more than any problem associated with paying off the loans. However, there is also an indication of increasingly negative attitudes against education debt. Borrowers from low-income families have a more significant probability of having a problem with repayments (Baum and O'Malley 2003).

College is, on average, a better investment today than a generation ago, but there is a probability of having large, small, or even negative returns. Students from community colleges have low completion rates and are unlikely to have substantial earnings associated with degree completion. For-profit institution students, with weak levels of income are usually connected with elevated levels of borrowing, making it more usual for them to default on loans (Avery and Turner 2012). Completion of a degree increases the amount of debt as the borrowing increases, meaning that borrowers with high debt completed either an associate or bachelor's degree, compared to those with low debt. The default may have originated from different causes; for example, in recent years, individuals with less than a bachelor's degree and with low debt may have difficulties repaying their loan because of the slow labour market conditions. Those with a bachelor's degree were better able to enter labour markets, but still sometimes not well enough to repay their high debt. The most severe cases are the ones with high debt and no advanced degree (Monge-Naranjo 2014).

Previous literature reveals that borrowers who experienced unemployment showed an increase in their probability of default over their initial probability. Likewise, borrowers whose loans are held by more than one provider were more likely to default. Moreover, the number of loans, but not the amount borrowed, is related to default, with more loans signalling a higher risk (Woo 2002). Furthermore, students from for-profit institutions also end up with higher unemployment rates (Deming et al. 2012).

The primary purpose of this paper is to verify the response of student borrowers towards unemployment and the average debt per borrower. The remainder of the paper is organised as follows: the next section provides a literature review on the proportion of students with loan defaults. Section 3 presents the methodology, followed by Section 4 with the data. Section 5 presents the tests and diagnostics for the panel data and Section 6 reports the empirical results and presents the discussion. Finally, Section 7 has concluding remarks.

2. Literature Review

This paper contributes to expanding the literature on student debt and default in the USA. We researched the response of the proportion of student borrowers with ninety or more days of delinquency or in default to variables such as unemployment and the average debt per borrower after the financial crisis of 2007–2008 in the United States, using panel data from 50 states, from 2008 to 2015. Nearly all the existing literature on student loan default is focused on the United States, where student loans are a prominent issue for higher education and are the most substantial consumer debt in the country. One of the studies outside the US by Han et al. (2015), carried out in South Korea, analyses factors affecting defaults on student loans, concluding that defaults are a function of gender and loan amount, while also documenting new variables that affect defaults, such as the grace period and the repayment period.

2.1. Student Characteristics and Default

The literature on the US reveals that programme completion, persistence, and success were strong predictors of student loan default, as were race or ethnicity, gender, and the type of course in which students enrolled. The roles of student success and graduation indicate that they are substantial in eventual loan repayment (Herr and Burt 2005). Debt makes graduates choose higher-salary jobs and reduce the choice on low-paid, public-interest jobs; college students are not life cycle agents, because they are credit-constrained and averse to holding debt, which can eventually reduce student donations to the former institutions (Rothstein and Rouse 2011). Poor academic performance is the main reason for student departure (Brown et al. 2015), and departure before completing the degree is one of the reasons for loan default (Volkwein and Cabrera 1998); the number of hours missed in university by student borrowers also increases the chance of default (Steiner and Teszler 2003; Christman 2000). Families of students whose parents had higher levels of education were less likely to default than first-generation university students (Choy et al. 2006; Volkwein et al. 1998; Volkwein and Szelest 1995), and other studies found that male and older students increase the borrower's chance of defaulting (Woo 2002; Podgursky et al. 2002; Flint 1997).

Researchers have been remarkably consistent on the conclusion that students of colour are more likely to default than Caucasian students (Harrast 2004; Woo 2002; Christman 2000; Volkwein and Cabrera 1998; Volkwein and Szelest 1995). When it comes to comparing non-financially at-risk students with financially at-risk students, the latter have much higher student loan balances and usually prioritize their credit card bills before repaying their student loans (Pinto and Mansfield 2006). A study by Woo (2002) reveals that borrowers who were in delinquency more than once are more likely to end up defaulting. Students who obtain information indicating that they might not be able to repay their loans are more likely to change to higher-earning majors, with students obtaining higher academic results showing a preference for choosing the science, technology, engineering, and mathematics (STEM) fields (Schmeiser et al. 2016).

2.2. Institutional Characteristics and Default

When examining the relationship between institutional characteristics and student loan default, significant differences can be found such as admission yield, geographic region, the percentage of minority students, a private or public institution, endowment, and expenditures for student services (Webber and Rogers 2014). The most increments in default are associated with borrowers from for-profit schools, two-year institutions, and non-selective institutions. These students only represent a small share in all student borrowers. The majority come from low-income families, attended institutions with poor educational outcomes and faced weak labour market outcomes after leaving the educational institutions. When it comes to borrowers who attended most four-year public and non-profit private institutions, default rates remained low, which represent the substantial part of the federal loan portfolio. Higher earnings, low unemployment rates and better family resources appear to have helped this category of borrowers during tough times (Looney and Yannelis 2015).

2.3. Enrolment and Default

Continuous enrolment can also be associated with student loan default. Borrowers that withdraw from the university for whatever reason have higher default rates, with the rates rising at the same time as the number of those withdrawing rises; default rates are higher for students who withdraw for administrative or academic reasons than students who withdraw for work-related reasons (Steiner and Teszler 2003). In a time range from four to eight semesters, students who are continuously enrolled or complete their programme are less likely to default than are students who drop out during the same period (Podgursky et al. 2002). Learning ability and the initial stock of human capital combined have an influence on the decision to enrol in college, and parental wealth has minimal effects and increases enrolment with repayment flexibility (Ionescu 2009).

2.4. Income Level and Default

Ionescu and Simpson (2016) observed borrowing default behaviour across family income and student preparation and found that more government borrowing limits the increase in college investment and leads to more default in private market student loans, and that tuition subsidies increase college investment and reduce default rates. Knapp and Seaks (1992) found that the chances of default decrease when the borrower has two parents and a high income. However, when it comes to family assets, net worth from households without an outstanding student loan is almost three times higher than households with outstanding student debt. Households with outstanding student loan debt incurred a loss around 54% of the net worth compared with households with similar net worth levels but without student loans in the same period (Elliott and Nam 2013).

Credit constraints may play an essential role in the dropout decision for some students. Nevertheless, reasons besides credit constraints should be attributed to the majority of students from low income families (Stinebrickner and Stinebrickner 2008). It is no surprise that borrowers with high earnings after they leave school are less likely to default than those with low earnings. This fact highlights the risk that students assume when taking out massive loans and then entering a labour market with low-paying careers. Moreover, borrowers who have gone into delinquency more than once are more likely to default (Woo 2002). Student debt is also negatively related to the predisposition to start a firm, in particular with more extensive and successful ventures (Krishnan and Wang 2018).

2.5. Unemployment, Debt and Default

The prior literature on student debt and default suggests that borrowers that had undergone unemployment tended to exhibit an increase in their probabilities of default relative to their initial probabilities of default, i.e., before being unemployed. There are three more phenomena stressed by the researchers. First, borrowers whose loans are held by more than one provider were more likely to default, with each additional provider increasing the odds of default by 18%. Second, the number of loans, but not the amount borrowed, is related to default, with more loans signalling a higher risk (Woo 2002). Finally, students from for-profit institutions also end up with higher unemployment rates (Deming et al. 2012).

The literature about the amount of debt suggests that as the debt burden increases, so do the odds of default. The average debt burden may differ by the type of institution, but whatever the type of institution, the more a student borrows, the higher are the odds of default (Choy et al. 2006; Lochner and Monge-Naranjo 2004; Dynarski 1994). If the monthly debt burden exceeds 8% of income, the loan debt is considered unmanageable. Choy and Li (2006) remarked that 11% of borrowers proclaimed unmanageable debt levels by 2003, with more than 20% of these students ending up defaulting. However, an exception can be found with respect to high debt and odds of default, in that the students who incurred high levels of debt by attending a graduate school were less likely on average to default (Woo 2002; Volkwein et al. 1998).

High and rising tuition, but relatively low student financial resources in the for-profit sector are likely the key factors contributing to increased borrowing in the for-profit sector (Cellini and Darolia 2015). For-profit institutions systematically encourage ill-advised loans. The results are economically significant, with default rates generally 5 to 6 percentage points higher in for-profit institutions (Goodell 2016). An increase in credit limits and expansions in credit availability resulted in an increase in the amount borrowed by students (Looney and Yannelis 2018). This literature helps to complement this investigation when it comes to determining why unemployment and the average debt per borrower affect the proportion of student borrowers with ninety or more days delinquency or in default. Figure 1 represents default and its causes according to the previous literature.

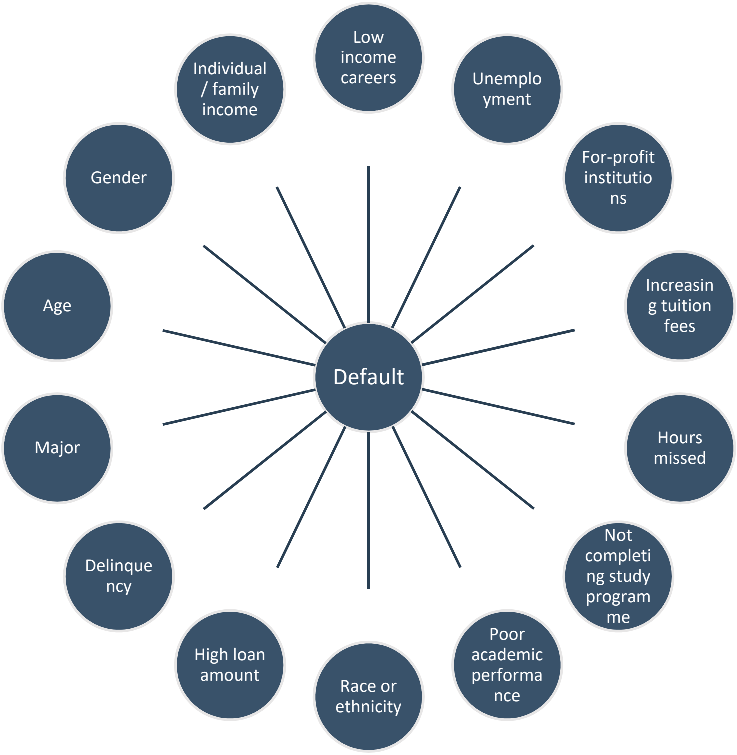

Figure 1. Representation of default and its causes according to previous literature.

This figure shows the leading causes of default by different authors in the previous literature over recent decades from different universities and regions in the USA. It includes unemployment and loan amounts, critical factors for this study, and others like for-profit institutions and increased tuition fees over the years. As the figure demonstrates, there are various causes for the increase in default among student borrowers, with some having more impact than others.

3. Methodology

In this study, we estimate our model using a generalised estimating equation (GEE). The GEE incorporates many models such as logistic and probit regression, ordinary least squares, ordinal outcome regression, regression models for the analysis of survival data, and other models (Liang and Zeger 1986). The GEE is a generalisation of the generalised linear models (GLM), but which considers the within-group correlation, as the GLM is inadequate when data are longitudinal or are otherwise grouped, so that observations within the same group are expected to be correlated (Hardin and Hilbe 2013). Using a generalized estimating equation on Stata 14, the model was estimated specifying a probit and logit link function, a Bernoulli distribution and an exchangeable correlation matrix, using robust standard errors and 500-bootstrap iteration to calculate standard errors. Such a model allows the presence of serial correlation and heteroskedasticity to be accounted for.

For comparison purposes, we will also use a linear model and present results together with the probit and logit GEE model. That allows us to compare the gain obtained from a proper treatment of the proportion of delinquents and defaulters as fractional responses. We also included the fractional regression models (FRM), which avoids the problems associated with the application of those above linear and Tobit models. The FRM, developed by Papke and Wooldridge (1996, 2008), requires the assumption of a functional form, the dependent variables of which are limited to the interval [0, 1]. This functional form for y, which enforces the desired constraints on the conditional mean of the dependent variable (Ramalho et al. 2010), $E(y|x) = G(x\theta)$, is therefore bonded to that same interval, where $G(.)$ represents a non-linear function satisfying the condition: $0 \leq G(.) \leq 1$, which Papke and Wooldridge (1996) suggested as possible specifications for the $G(.)$ function of any cumulative distribution function, such as that already applied to model binary data. The most widely used are logit and probit functional forms, although there are other alternatives, such as logit, probit, loglog and cloglog fractional regression standard models (e.g., Raheli et al. 2017; Ramalho et al. 2010).

4. Data

In this study, we use panel data for the 50 states of the USA, from 2008 to 2015. According to the US Census Bureau, we selected four regions. Region 1 includes the states of Maine, New Hampshire, Vermont, Massachusetts, Rhode Island, Connecticut, New York, Pennsylvania, and New Jersey. Region 2 includes Wisconsin, Michigan, Illinois, Indiana, Ohio, Missouri, Dakota Soul, Dakota North, Nebraska, Kansas, Minnesota, and Iowa. Region 3 includes Delaware, Maryland, Columbia, Virginia, North Carolina, South Carolina, Georgia, Florida Kentucky, Tennessee, Mississippi, Alabama, Oklahoma, Texas, Arkansas, and Louisiana. Finally, region 4 includes the states Idaho, Montana, Wyoming, Nevada, Utah, Colorado, Arizona, New Mexico, California, Oregon, Washington, Alaska, and Hawaii.

In both the two proposed models, we considered the proportion of student loan borrowers with ninety or more days past due accounts, including defaults by state, the dependent variable, data for which was retrieved from the Federal Reserve Bank of New York and Equifax. The data was created from a 1% sample of the US population with credit information and included both federal student loans and private student loans. Some independent variables were included, more specifically the following: (i) Natural log of the average student debt per borrower, data retrieved from the Federal Reserve of New York and Equifax; (ii) natural log of the unemployment rate by state, which represents the proportion of the active population which is unemployed in the 50 states from the period analysed and which has the US Bureau of Labor Statistics as a source; (iii) natural log of consumer confidence, which represents a consumer sentiment index from the (University of Michigan 2018) and indicates consumer attitudes towards personal finance and country's economy on a federal level, data retrieved from Federal Reserve Economic Data; and (iv) natural log of financial stress, an index from the Federal Reserve Bank of St. Louis, which measures financial stress in the markets constructed with 18 data series on a federal level, including seven interest rate series, six yield spreads and other five indicators with each capturing some aspect of financial stress. The data were retrieved from Federal Reserve Economic Data. In this last financial index, zero is viewed as representing normal financial market conditions, with values below zero proposing below-average financial market stress and values above zero proposing above-average financial market stress.

5. Tests and Diagnostics for Panel Data

For a good estimation in a heterogeneous panel, we tested for violations on assumptions like normality or homoskedasticity on residuals (see Table 1). Given the sensitivity of the panel estimator, if some assumptions are violated, some treatment will be required.

Table 1. Diagnostic tests.

	Breusch–Pagan and Doornik–Hansen Tests	
	Homoskedasticity	Normality
Statistics	F(1,398) = 29.64 ***	$\chi^2_{(2)}$ = 3.082
	Pesaran and Wooldridge Tests	
	Cross-section Independence	No Serial Correlation
Statistics	N(0,1) = 50.18 ***	F(1,49) = 85.975 ***

Table 1. Diagnostic tests.

Ramsey Test		
Omitted Variables		
Statistics		F(3,38) = 1.28
Variable	VIF	
ln(fstress)	1.83	
ln(adb)	3.84	
ln(unem)	2.29	
ln(cs)	3.08	
ln(unem) × reg2	2.03	
ln(unem) × reg3	2.40	
ln(unem) × reg4	2.76	
Mean VIF	2.60	
Breusch–Pagan test for random effects		
Random effects vs. OLS		
Statistics	Chibar2(01) = 385.48 ***	

Note: *** $p < 0.01$. H_0 of Breusch–Pagan Test: Constant variance. H_0 of Doornik–Hansen Test: Normality of Residuals. H_0 of Pesaran Test: Cross-sectional independence. H_0 of Wooldridge Test: no AR(1). H_0 of Ramsey RESET test: model has no omitted variables. The H_0 of the Breusch–Pagan test for random effects: random-effects model is the most appropriate. The Stata commands used: *hottest*, *mvtest normality*, *xtcd*, *xtserial*, *ovtest*, and *xttest0*.

To check for the presence of heteroskedasticity the Breusch–Pagan (1979) test was used, complemented by Wooldridge (2013) F-statistic version that drops the normality assumption. Heteroskedasticity demands a robust errors estimation. The Doornik–Hansen test (Doornik and Hansen 2008) checks the violation of normality of residuals. Non-normality alters the *p*-values and confidence intervals. The Breusch—Pagan test indicates the presence of heteroskedasticity; however, the Doornik–Hansen test does not reveal normality in the residuals. Pesaran (2004) cross-dependence test was performed for cross-sectional dependence. The Woolridge (2002) test was performed to check for the presence of autocorrelation. The Pesaran CD test reveals cross-sectional dependence causing some complications from omitted variables bias when the regressors are correlated with unobserved common factors (Pesaran 2006). The test for the existence of AR(1) confirmed that there is no first-order autocorrelation in the panel. Ramsey (1969) reset test analyses whether some relevant variable was omitted in the specification process. The test reveals that no relevant variables were omitted. To check for multicollinearity, we used the VIF test. Multicollinearity can be a problem when the VIF exceeds 10, meaning that some regressors are closely correlated to another distorting the standard errors, confidence intervals and providing less reliable probability values. The nonexistence of multicollinearity is sustained with the low value of VIF for all variables considered. The Breusch–Pagan (Breusch and Pagan 1980) Lagrange multiplier test for random effects was performed to ascertain if random effects are more appropriate than the linear model (OLS) to compare with the fractional model. The test suggests that a random-effects model should be adopted.

The models and econometric techniques proposed will answer our investigation question which is to ascertain the response of the proportion of student loan borrowers towards unemployment and the average loan debt per student borrower and can have the following hypotheses:

Hypothesis 1 (H1). *Higher unemployment and average debt per borrower will lead to a higher or lower proportion of student borrower delinquency or default.*

Hypothesis 2 (H2). *Higher unemployment will lead to a lower or higher proportion of delinquency or default and higher average debt per borrower will lead to a higher OR lower proportion.*

Hypothesis 3 (H3). *Higher student loans in different regional state groups and average debt per borrower will lead to a lower or higher proportion of student borrower delinquency or default.*

6. Empirical Results and Discussion

A logit and probit binomial model with a generalised estimating equation, which specifies conditional means of state and year unobserved effects as linear functions of the covariates was used to model the proportion of borrowers with delinquency or default as a function of unemployment, the average debt per borrower, consumer sentiment and financial stress. The specification tests indicate normality, the absence of autocorrelation and homoscedasticity, and supports that no relevant variable was omitted.

6.1. Empirical Results—Econometric First Approach

Table 2 reports the random-effects linear model and the fractional probit model estimates of the proportion of borrowers with ninety or more days' delinquency or default with robust standard errors for the presence of heteroskedasticity. Bootstrapping is a nonparametric approach used for the precise estimation of coefficients, standard errors and confidence intervals, revealing robust *p*-values (Guan 2003; Mooney et al. 1993). Using the same models with bootstrapped standard errors, according Table 2, for all models, i.e., linear random effects, probit and logit, we obtain the same coefficients and margins for the three variables ln(unemp), ln(adb) and ln(cs), but different standard errors from the models with robust standard errors (compare the results of Table 3 with Table 2).

Table 2. Estimated results with bootstrapped standard errors.

Dependent Variable is Def	**Linear Random Effects-GLS Model**	**Probit Binomial Model**		**Logit Binomial Model**	
	Estimate	Estimate	Average Marginal	Estimate	Average Marginal
	(Standard Error)	(Standard Error)	(Standard Error)	(Standard Error)	(Standard Error)
ln(unem)	0.00455 *** (0.0012)	0.020162 *** (0.0074)	0.003507 *** (0.0012)	0.03679 *** (0.0014)	0.003287 *** (0.0013)
ln(adb)	0.038937 *** (0.0100)	0.19870 *** (0.0568)	034562 *** (0.0097)	0.382477 *** (0.1102)	0.034177 *** (0.0097)
ln(cs)	0.094105 *** (0.0134)	0.540503 *** (0.0704)	0.094014 *** (0.0126)	1.0407 *** (10.360)	0.092995 *** (0.0126)
ln(fstress)	0.01703 *** (0.0045)	-	-	-	-
reg1 * ln(unem)	0.009813 *** (0.0020)	0.147453 *** (0.02633)	0.025647 *** (0.0047)	0.286813 *** (0.0518)	0.025628 *** (0.0048)
reg2 * ln(unem)	0.006361 *** (0.0019)	0.122116 *** (0.0255)	0.021240 *** (0.0045)	0.233516 *** (0.0495)	0.020866 *** (0.0045)
reg3 * ln(unem)	−0.004389 ** (0.0023)	0.071810 *** (0.0269)	0.012490 *** (0.0047)	0.146015 *** (0.0523)	0.013047 *** (0.0047)
reg4 * ln(unem)	Omitted	0.094510 *** (0.0263)	0.016439 *** (0.0046)	0.187621 *** (0.0513)	0.016765 *** (0.0046)
Constant	−0.54521 *** (0.0450)	−4.84710 *** (0.257)		−9.0525 *** (0.509)	
# Observations	400	400	400	400	400
# States	50	50	50	50	50
R^2	0.4896				
Wald χ^2	531.48 ***	603.16 ***		553.73 ***	

Note: Dependent variable is defined in the first row of the Table. Values in parentheses below coefficients are the robust standard errors. Level of significance: *** for *p*-value > 0.01, ** for *p*-value > 0.05, * for *p*-value > 0.1. The Stata commands *xtreg, revce(robust)* and *xtgee, family(bionomial) link(probit) corr(exchangeable) vce(robust)* were used.

Moreover, the results of the average differential change on the average proportion of borrowers who are ninety or more days delinquent or in default (dependent variable) shows a positive increase of 0.0529 and 0.0992 of a percentage point, when the proportion of the active population unemployed increases one percent in the states included in region 1 compared to the states included in region 4. The average differential change in the dependent variable (def) shows a positive increase of 0.0276 and 0.0458 of a percentage point when the proportion of the active population in unemployment increases one percent in the states included in region 2 compared to the states included in region 4. However, the average differential change in the average proportion of borrowers who are ninety or more days delinquent or in default shows a negative decrease of 0.0226 and 0.0416 of a percentage point, when the proportion of the active population in unemployment increases one per cent in the states included in region 3 compared to the states included in region 4.

This thus establishes that linear, probit and logit binomial models are coherent with prior studies and show us that unemployment has a positive and statistically significant effect on the proportion of student borrowers with ninety days or more of delinquency or in default (Looney and Yannelis 2015; Woo 2002) and the average debt per borrower (Lochner and Monge-Naranjo 2004; Choy et al. 2006; Dynarski 1994). This result implies that when unemployment and average debt increases, so do the number delinquencies or defaults.

6.2. Empirical Results—Econometric Second Approach: FRM Models

Table 3 summarises the results obtained for the one-part and two-part models. Moreover, Table 3 shows that all tests fail to reject any of the four models estimated for the second component of the two-part models. This result suggests that the central issue in the regression analysis of the proportion of student loan borrowers with ninety or more days delinquency or in default is not so much their bounded nature as the existence of a mass-point at unity in their distribution of this dependent variable. On the one hand, the GOFF tests do not reject any of the simpler functional forms; we proceed by considering four alternative two-part models, which use logit and cloglog specification in the first part and a logit, probit, loglog or cloglog model in the second part. On the other hand, we applied versions of the P test that enable testing of the selected one-part model against the full specification of the four selected two-part models, and vice-versa, and testing of the selected full specification of the two-part models, with each being tested against the others. In no case were we able to reject any of the tested specifications. These results indicate that only a few specifications are admissible according to the results of the RESET test. Indeed, only the cloglog model and its type II generalisation are never rejected at the 1% level. Moreover, almost all the other specifications are rejected when the P test uses one of the acceptable models as the alternative hypothesis.

Given that the GOFF-I test does not reject the correct specification of the standard cloglog model and given that the size of our sample is relatively small, we select the cloglog model as the most suitable one-part model. In fact, given that the distribution of the proportion of student loan borrowers with ninety or more days delinquency or in default in our example is asymmetric, according to the results estimation, logit and cloglog functional forms would be our preferred choice of one-part model. For each explanatory variable, we report the value of the associated estimated coefficient and its p-value and, thus, it is comparable across models and overestimation methods. The values of R2 are similar in specification 1 and specification 2, and they provide further evidence that the selected cloglog model fits the data at least as well as the preferred models in one-part and two-part models.

Table 3. Specification tests for one-part and two-part models.

Specification Test	One-Part Model				Two-Part Model-GFRM II			
	Logit		Probit		Logit		Probit	
	Model 1	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**
RESET test	6.509 ***	4.916 **	8.014 ***	3.877 **	5.709 **	5.733 **	7.143 ***	4.577 **
GOFF-I test	7.788 ***	4.521 **	5.930 **	4.552 **	6.906 ***	5.34 **	5.171 **	5.301 **
GOFF-II test	3.227 *	6.040 **	9.726 ***-	3.372 *	2.648 *	6.941 ***	8.775 ***	4.035 **
P Test								
H1: FRM II–Logit			37.147 ***	0.432			35.66 ***	0.226
H1: FRM II–Probit	34.30 ***	0.003			32.82 ***	0.056		
H1: FRM II–Loglog	10.90 ***	8.330 ***	8.605 ***	7.571 ***	9.965 ***	9.230 ***	7.762 ***	8.395 ***
H1: FRM II–Cloglog	1.997	3.656 **	7.022 ***	1.460	1.518	4.453 **	6.141 **	1.974
	One-Part Model				**Two-Part Model-GFRM II**			
	Loglog		**Cloglog**		**Loglog**		**Cloglog**	
	Model 1	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**
RESET test	18.478 ***	1.306	1.352	8.116 ***	17.26 ***	1.681	0.995	9.201 ***
GOFF-I test			0.547	8.756 ***	19.28 ***		0.329	9.877 ***
GOFF-II test	20.536 ***	0.926				1.252		
P Test								
H1: FRM II–Logit	23.910 ***	0.091	0.053	13.01 ***	22.53 ***	0.015	0.006	14.15 ***
H1: FRM II–Probit	18.346 ***	0.084	1.361	12.91 ***	17.07 ***	0.218	1.030	14.06 ***
H1: FRM II–Loglog			1.723	18.45 ***			1.376	19.60 ***
H1:FRM II–Cloglog	17.136 ***	0.241			15.82 ***	0.087		
			1.352					

Note: ***, ** and * denote test statistics which are significant at 1%, 5% or 10%, respectively; FRM fractional regression model.

The first striking point to emerge from the analysis of the regression coefficients displayed in Table 4 is that all estimators produce the same conclusions in terms of their sign and significance in the one- and two-part models.

According to Table 4, 19 results of FRM–complementary loglog–one-part model, specification 1, shows that a one percentage point increase in the natural log of unemployment (ln Unemp) is associated with a 0.0564 percentage point rise in the proportion of borrowers who are ninety or more days delinquent or in default (dependent variable). The coefficient is significant at the 1 per cent level. The natural log of student loan (StudLoan) has a coefficient of 0.0321 and is statistically significant at the 1 per cent level. A one percentage point increase in the natural log of the consumer sentiment (ln Consent) is associated with a 3.355 percentage point rise in the dependent variable at the 1 per cent level. The natural log of financial stress (Fef Fund) has a coefficient of 0.0162, indicating that a percentage point raises the dependent variable by this amount and is statistically significant at the 1 per cent level. On the other hand, the natural log of financial stress (Fef Fund 12) has a negative coefficient of 0.0388, indicating that a percentage point raises the dependent variable by this amount and is statistically significant at the 1 per cent level. In the same FRM, complementary coglog–second part specification 1, all signals of coefficients, and their statistical significance accomplish all results analysed in the one-part model.

So, according to the results shown for the cloglog model, and for new proposed specification 2, the highest average differential on the average proportion of borrowers who are ninety or more days delinquent or in default is a positive increase of 1.10 percentage points when the proportion of the active population in unemployment increases by one per cent in the states in region 1. The average differential change in the average proportion of borrowers who are ninety or more days delinquent or in default shows a positive increase of 0.0666 of a percentage point when the proportion of the active population in unemployment increases by one per cent in the states included in region 2.

Table 4. Estimation results for the selected fractional regression models.

Variables	One-Part Models				Two-Part Models–Second Part							
	Logit		Cloglog		Logit		Probit		Loglog		Cloglog	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Ln Unemp	0.72498 (0.00) ***		0.56442 (0.00) ***		0.714818 (0.00) ***		0.430817 (0.00) ***		0.430377 (0.00) ***		0.555790 (0.00) ***	
Ln Consent	4.1849 (0.00) ***	3.47629 (0.00) ***	3.3550 (0.00) ***	2.69794 (0.00) ***	4.11833 (0.00) ***	3.41889 (0.00) ***	2.48705 (0.00) ***	2.07142 (0.00) ***	2.44960 (0.00) ***	2.13408 (0.00) ***	3.29949 (0.00) ***	2.64841 (0.00) ***
Ln StudLoan	0.45470 (0.00) ***		0.32198 (0.00) ***		0.456299 (0.00) ***		0.282758 (0.00) ***		0.315330 (0.00) ***		0.324207 (0.00) ***	
Ln FedFund	0.21001 (0.00) ***	0.140725 (0.00) ***	0.16276 (0.00) ***	0.098352 (0.017) **	0.206927 (0.00) ***	0.1382437 (0.00) ***	0.124222 (0.00) ***	0.083950 (0.00) ***	0.123363 (0.00) ***	0.096257 (0.00) ***	0.160409 (0.00) ***	0.096487 (0.019) **
Ln FedFund12	−0.47782 (0.00) ***	−0.386794 (0.00) ***	−0.38829 (0.00) ***	−309652 (0.00) ***	−0.471323 (0.00) ***	−0.381190 (0.00) ***	−0.28751 (0.00) ***	−0.228414 (0.00) ***	−0.272293 (0.00) ***	−0.224709 (0.00) ***	−0.382974 (0.00) ***	−0.304826 (0.00) ***
Region1 × Ln Unemp		1.10069 (0.00) ***		0.904759 (0.00) ***		1.09451 (0.00) ***		0.651306 (0.00) ***		0.628539 (0.00) ***		0.899260 (0.00) ***
Region2 × Ln Unemp		0.66666 (0.00) ***		0.527119 (0.00) ***		0.661803 (0.00) ***		0.401305 (0.00) ***		0.4058867 (0.00) ***		0.522815 (0.00) ***
Region3 × Ln Unemp		0.090182 (0.584)		0.005711 (0.964)		0.077027 (0.639)		0.052234 (0.600)		0.1287208 (0.230)		0.0054921 (0.964)
Region4 × Ln Unemp		0.38483 (0.00) ***		0.310101 (0.00) ***		0.380502 (0.00) ***		0.231298 (0.00) ***		0.241940 (0.00) ***		0.305699 (0.00) ***
Region1 × Ln StudLoan		0.7788 (0.00) ***		0.570535 (0.00) ***		0.781294 (0.00) ***		0.478170 (0.00) ***		0.522313 (0.00) ***		0.574361 (0.00) ***
Region2 × Ln StudLoan		0.648943 (0.00) ***		0.457115 (0.00) ***		0.651841 (0.00) ***		0.403390 (0.00) ***		0.455813 (0.00) ***		0.4613107 (0.00) ***
Region3 × Ln StudLoan		0.533799 (0.00) ***		0.339007 (0.00) ***		0.533100 (0.00) ***		0.333980 (0.00) ***		0.416123 (0.00) ***		0.340367 (0.00) ***
Region4 × Ln StudLoan		0.614946 (0.00) ***		0.429088 (0.00) ***		0.618155 (0.00) ***		0.383997 (0.00) ***		0.441950 (0.00) ***		0.433428 (0.00) ***
Constant	−21.910 (0.00) ***	−20.7485 (0.00) ***	−17.694 (0.00) ***	−16.1810 (0.00) ***	−21.6425 (0.00) ***	−20.5164 (0.00) ***	−13.1288 (0.00) ***	−12.4903 (0.00) ***	−12.8187 (0.00) ***	−12.7431 (0.00) ***	−17.4776 (0.00) ***	−15.9932 (0.00) ***
Observations	765	765	765	765	764	764	764	764	764	764	764	764
R^2	0.3898	0.52767	0.38579	0.521970	0.382689	0.52576	0.380290	0.525543	0.374636	0.52880	0.383142	0.51968

Note: Below the coefficients we report *p*-values in parenthesis, ***, and ** denote coefficients which are significant at 1% and 5%, respectively.

Other significantly statistical evidence reports that the highest average differential on the average proportion of borrowers who are ninety or more days delinquent or in default shows a positive increase of 0.57 of a percentage point when the proportion of the student loan increases by one per cent in the states in region 1. The average differential change on the average proportion of borrowers who are ninety or more days delinquent or in default shows a positive increase of 0.0457 of a percentage point when the proportion of the student loan increases by one per cent in the states included in region 2.

6.3. Discussion

Our empirical study on the response of the proportion of student borrowers with ninety days or more delinquency or in default generates the following results. First, there is a significant and positive relationship between unemployment, the average debt per borrower and consumer sentiment with the proportion of delinquent or in default student borrowers. Second, the estimated coefficients on the financial stress variable are not statistically significant. Third, we can see a difference in the estimated coefficients between the probit and logit binomial models and the linear model. Fourth, this is the first attempt to use the probit and logit for panel data on a student loan delinquency or default data analysis.

The positive relationship between unemployment and the proportion of delinquent or in default student borrowers suggests that, in this period, higher unemployment leads to a higher proportion of delinquent or in default borrowers, which is in keeping with previous literature (Looney and Yannelis 2015; Woo 2002). This may occur more often among borrowers with degrees that have high unemployment rates, borrowers with high debt burden that just became unemployed without a considerable amount of savings to repay their loans monthly, and, according to Deming et al. (2012), borrowers from for-profit institutions, who have higher unemployment rates than other types of institutions.

Private and public lenders should require more collateral when making these loans, higher interest payments to students who choose degrees with low unemployment rates, from for-profit institutions and students that borrow a higher amount of loans. When compared to students who choose lower unemployment degrees from public or non-profit institutions and low amounts of debt, these represent less risk of default when borrowing a loan.

The positive response of the average debt per borrower and the proportion of delinquency or default indicates that, between these years, students incurring higher debt tend towards more delinquency or default. This increase in the average debt burden is possibly driven by the rise in the cost of university tuition over the years (Haughwout et al. 2015).

The type of institution might also affect the average debt per borrower (Looney and Yannelis 2015), but whatever the nature the nature of the institutions, higher debt means higher odds of default (Choy et al. 2006; Lochner and Monge-Naranjo 2004; Dynarski 1994).

Student borrowers with low-income careers have more problems with unmanageable loan debt than student borrowers who have higher income careers and higher chances of repaying their debt (Choy et al. 2006). The choice for degrees for higher income is also a crucial factor for some student borrowers who incur high levels of student debt, the exception being students with high debt level (Woo 2002; Volkwein et al. 1998).

In other words, degrees that typically have higher wages cost less to the borrower than degrees that lead to low income. Given that low-income borrowers have a higher risk of default than higher-income borrowers, the solution for this problem could also be higher interest payments to cover the risk of default by the low-income borrowers. This conclusion can also be applied to students from for-profit institutes, who have a higher level of debt average when compared to other types of institution, representing a more significant risk of default.

In this study, we also find a positive relationship between consumer sentiment and the proportion of student borrowers in delinquency or default. This finding supports that, in this period, when the consumer is feeling positive about his or her financial health in the short term, growth of the economy in the long term causes a rise in the proportion of student borrowers in delinquency or default. The possible cause for this could be, in specific periods, the following psychological mechanism: when the consumer is feeling confident about the positive trend of the economy and his or her financial situation, the consumer might start to think about investment in education for better job opportunities and will probably use loans to pay their study costs. That might lead to more defaults, in cases where the degrees chosen have a high unemployment rate or low income in a future job, making it financially unviable for the borrower to continue the repayments to the lenders.

Other ways to decrease the proportion of delinquency or default can be using the endowment income received by universities from former students to provide to newly qualified students who are otherwise unable to possess the financial resources without having to take a loan and having unmanageable debt.

There can also be a reduction in the number of vacancies or even removing the existence of some degrees in the case where these have high unemployment rates, and the labour market cannot absorb all these students and degrees that give only access to low-income careers, with the risk of not making the repayments on time being higher.

The government can also adopt the same higher education system as some countries in Europe, which consists of the government partially paying the cost of tuition, and the student paying the rest. Alternatively, like some other European countries, students do not have to pay the cost of their education. That could probably lower the proportion of student borrowers in delinquency or default, but it would also mean an increase in the fiscal burden for the taxpayer.

7. Conclusions

In this paper we investigate the response of the proportion of student borrowers with ninety or more days of delinquency or in default to variables such as unemployment and the average debt per borrower, in the United States, using panel data of 50 states from 2008 to 2015.

This study is the first experiment with the use of a probit and logit binomial model for panel data for student borrower delinquency or default data analysis. The existing studies about US student debt default use data from a specific university or region; in this study, we use data of the 50 states.

The empirical evidence found that unemployment, the average debt per borrower and consumer sentiment are significant in their contribution to ninety days or more delinquency or default, and financial stress is not statistically significant in this study.

Since this paper shows that unemployment and average debt per borrower have a positive impact and represent a significant risk for delinquency or default, lenders must consider giving higher interest payments to borrowers who have a higher risk of default, or universities could also limit the number vacancies to degrees for states with high unemployment rates. Another alternative is for the government to change its higher education system to one similar to some European countries in which the state partially or fully pays tuition. That could have a significant effect on the proportion of student borrowers in delinquency or default.

This study has a limitation of excluding data on the cost of attendance in different types of institutions and the number of student borrowers by state. That could be an area to examine in upcoming studies. Future studies should also include countries like England and Australia to compare with the situation in the USA.

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