The Determinants of Demand for Financial Inclusion in Digital Finance and Consumer Credit Market: Evidence from China

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Abstract

This paper analyzes the determinants of demand for financial inclusion in aspects of digital finance and consumer credit in China, using World Bank's Global Financial Inclusion database 2017. Our findings address the problem of information asymmetry between policy makers and inclusion-resistant individuals that leads to the inactive user problem: low uptake of government inclusion initiatives that lowers economic returns. This paper takes an unconventional approach by characterizing financial inclusion as a choice with many alternatives, while focusing on the aspects of digital finance and loan services. We specify an additive random utility model (ARUM) using a mixed logit approach, and estimate the probability of an individual choosing some pre-specified financial inclusion alternative given their individual characteristics (choice-invariant) and cost of financial alternatives (choice-variant). We find that individual characteristics and costs to using financial services statistically significant factors in determining financial inclusion, and provide evidence for future policy-making against possible issues of inactive user problem and financial detachment.

1 Introduction

Financial inclusion is the uptake and usage of a range of appropriate financial products and services by individuals to realize the benefits of inclusive economic growth such as reduced poverty, increases in income, productive investment, and employment (Toward Universal Financial Inclusion in China, 2018). Government efforts to improve financial inclusion may be faced with individuals who are resistant to being included or become inactive after inclusion (Ozili, 2020). For example, a bank branch established in a rural district to create accessibility to loan service may face a lack of clients due to aversion to new forms of financial practices arising from financial illiteracy. A general lack of demand for such services may also be associated with a lack of savings, lack of digital devices or literacy, or distrust in the system, all of which are commonly associated with the low-income group in rural districts (Ozili, 2018). 11 percent of account holders in China did not make any deposits or withdrawals from their account in 2017 and those with primary education (or less) who are in the lowest income quin-tile are more likely to have inactive accounts (Toward Universal Financial Inclusion in China, 2018).

For this reason, explicating the relationship between characteristics of an individual and her demand for financial integration would allow village and township banks and microcredit companies to provide levels of services that match the demands of a region. Resistant users' lack of access to finance would adversely effect the economic growth, increase poverty since the poor will have difficult time accumulating savings in order to invest in income-generating projects (Cumming et al. 2013). This inactive user problem, by reducing the volume of financial transactions, decreases the tax revenue to the government which in turn affects the economic output negatively (Ozili, 2020). Underlying the potential factors that determines one's choice of financial inclusion may have a dynamic effect on the economy and will serve as a benchmark for policy makers in their financial inclusion initiatives. The dynamic effect comes from the "two-way causality" of digital finance and financial inclusion (Ozili, 2018). Essentially, greater digital finance may lead to greater financial inclusion if the inactive user problem and other risks associated with financial inclusion such as moral hazard problem (Ozili, 2020) is negligible. Moreover, greater financial inclusion will increase individuals' awareness of the financial system, makes them realize the use financial services for their own convenience which in turn results in greater digital finance.

This research analyzes how demand in China for different extents of financial inclusion into digital finance and the credit market depends on the socioeconomic and personal characteristics of individuals and the associated costs of inclusion. China has higher rural population than an average G-20 country which makes it harder to achieve urban-rural financial inclusion parity compared to other countries (Toward Universal Financial Inclusion in China, 2018). Financial Inclusion is a key developmental priority in China (Toward Universal Financial Inclusion in China, 2018). Given the country's vast population and highly diverse population characteristics, it is crucial to deepen the understanding of the factors underlying the country's demand for Financial Inclusion to enable optimal policy design.

Contrary to popular research focus on the basic level of financial inclusion, which pertains to bank account ownership for example, we focus on the higher levels of financial inclusion, such as digital finance and consumer credit market inclusion. This focus is motivated by the following reasons: On the one hand, China has already made considerable progress in increasing depth of basic financial inclusion. Bank account ownership at state-owned commercial banks has increased from 1,635 million in 2006 to 5,937 million in 2016 (Toward Universal Financial Inclusion in China, 2018, p.33), which has shifted the government's future goals towards digital finance by "improving the level of application by financial institutions of science and technology" as stated in the "Plan for Advancing Inclusive Finance Development (2016-2020)" (State Council of the People's Republic of China, 2015, p.8). Digital finance, even on the simplest level such as making purchasing and paying bills through the internet, has "profound impacts on financial products, operations, organizations and services" (Toward Universal Financial Inclusion in China, 2018, p.2). On the other hand, researching the higher levels of financial inclusion in this digital age is more than relevant. Lastly, any insights found using China's data may benefit countries who are following China's footsteps towards higher level financial inclusion in the future.

2 Literature Review

There is an abundance of literature on the determinants of Financial Inclusion. Fungáčová and Weill (2015) found that Financial Inclusion in China as indicated by the use of formal accounts is increasing in income, education, gender, and age. In other countries such as Zimbabwe, the same factors were found to have significant effects on financial inclusion (Abel et al, 2018). Fungáčová and Weill (2015) have also found country-specific effects on financial inclusion in China: higher frequency of borrowing from relatives and friends instead of using formal credit as compared to other BRICS countries. Investigating the determinants of financial inclusion country-specific matters and merging different countries data in one single data without differentiating countries may give biased estimates. For example, Rashdan & Eissa (2019) concludes no significant relationship between gender and the level of financial inclusion in Egypt on the other hand Fungáčová and Weill (2015) says otherwise for China.

On the global level, Allen et al (2016) examined data across 123 countries and confirmed that the effectiveness of policies that encourage account usage is dependent on characteristics such as gender and age, after controlling for country-specific effects. They also showed that account ownership is associated with factors that enable accessibility, including costs and geographical distances. As an example, in China, 19 percent of adults with no financial accounts do not have an account because of the transportation cost caused by the long distance between their home and financial institutions.

This paper aims to investigate exogenous impacts on a more comprehensive form of financial inclusion, one that is not merely represented by the adoption of one financial product or service (e.g. account ownership). Financial inclusion is more than owning basic accounts but a range of financial products and services designed to meet the needs of undeserved (Toward Universal Financial Inclusion in China, 2018, p.6). Characterizing financial inclusion with one financial product not only restricts our understanding of individuals' decision making towards financial inclusion but also ignores the inherited differences in financial services such as borrowing and saving. Alexandra Zins, Laurent Weill (2016) find that use of the alternative sources of borrowing does not vary with age and education but age increases likelihood of each saving motivation (for farm or business, for old age, for education.

In "Toward Universal Financial Inclusion in China" (2018), People's Bank of China and the World Bank Group recognizes the inactive user problem in their report, arguing that low levels of financial capability of individuals will stagnate the effort to reach the financial inclusion regardless of the safety and convenience of the financial services, thus emphasizing the factors that constitute demand for financial inclusion. Moreover, as supported by Ozili (2018), they expect distrust to financial providers and financial capability to be negatively correlated.

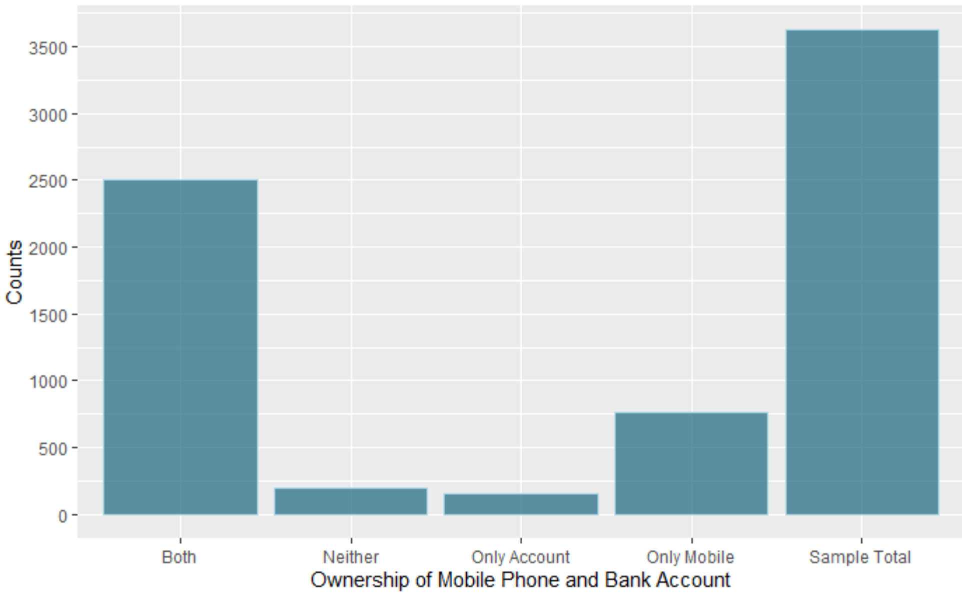
We want to bypass the need of calculating a sophisticated index for financial inclusion, as done by Mandira Sarma (2012), so that our results can enable a more practical interpretation: the dependent variable is the adoption of a range of financial products and services and not an index that does not separately identify unique financial inclusion choices. Thus, we chose to model financial inclusion choice as a demand system defined on a characteristics space.

3 Data

We have obtained data from the 2017 Global Financial Inclusion Database report on China, provided by The World Bank (The Global Findex Database, 2017). The data contains mostly binary responses to yes or no questions regarding an individual's activities in relation to financial integration. We use information on individual characteristics, such as age, sex, level of education and their economic status in the national income quintile. There are three levels of education: level 1 if respondent's highest education is primary or less, 2 if secondary, and 3 if tertiary or higher. The quintile levels are replaced by mean quintile monthly incomes (in Yuan) of 2017, which are obtained from the National Bureau of Statistics China.

In total, there are 3627 individual-level sample points, with 102 variables for each observation. In order to study the higher levels of financial inclusion as mentioned in the introduction, we focus on the 2,510 individuals who owns both a mobile phone and a bank account. This allows for a greater variety of choices that reflect higher level financial inclusion to be studied i.e. having a mobile phone is a prerequisite to many digital financial inclusion choices. [1] Choosing this subset of the sample does not lead to under-representation of the population, as this subgroup comprises of the majority in our sample.

Figure 1: Counts of Sample Points by Mobile and Account Ownership



For the purpose of this study, we create a vector of binary variables, where each entry of the vector represents a financial inclusion component. We have selected choice components that face the greatest inactive user problem, and choices that perhaps represent the inclusion goals set by the Chinese government. These components are: Internet Purchasing (NetBuy), Borrowing from a Financial Institution (BorrowFI), Having a Credit Card (Credit), and Using mobile phone to

[1] In the actual data processing and model estimation, this sample number decreases due to *NA* or *Refused* responses.

pay Utility Bills (MobBill). NetBuy and MobBill aligns with the Chinese government's efforts to promote digital finance, while Credit and BorrowFI are susceptible to the inactive user problem in terms of credit risk.

These choices are embedded in the vector X_j, denoting j^{th} financial inclusion alternative. For example, if an individual answered "yes" to "Having a Credit Card", then it is assigned a value of 1, and 0 otherwise. Figure (2) shows the differing levels of characteristics given the number of components in the financial inclusion choice.[2]

Figure 2: Mean characteristics by the number of components in the choices they made

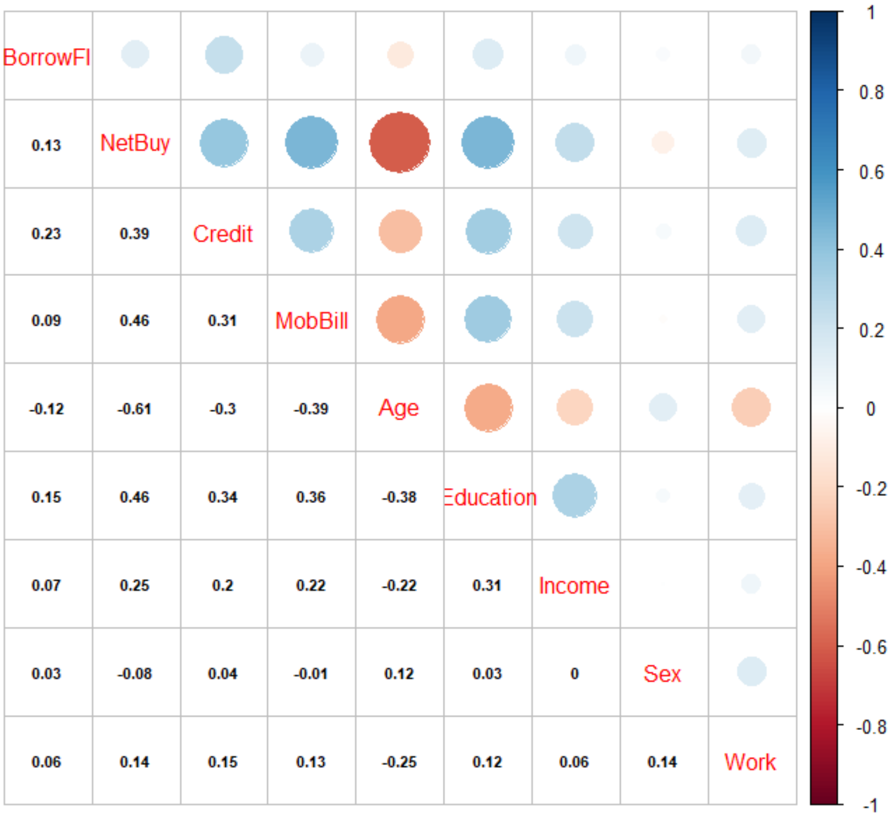
Counts of Components in the FI Choice	Freq.	mean(age)	mean(educ~n)	mean(income)	mean(sex)
0	892	55.4484	1.17937	37622.86547	.53139
1	400	42.71	1.41	44045.5125	.4325
2	314	36.0382	1.73248	51043.14331	.509554
3	167	34.7365	1.95808	57212.53293	.491018
4	39	33.7692	2.17949	62044.97436	.564103
Total	1,812	46.8974	1.41943	43697.34823	.502759

Of the 1,812 people with complete information in the sample, there are about 39 individuals (about 2%) who have chosen full inclusion ($j = 4$) and 892 (approximately 49%) of the sample population have chosen zero inclusion as defined by the four components. It is also clear that people who chose financial inclusion choices that contain more components are younger, more educated, and have higher income on average. Sex is an indicator for a male individual (equals to one if respondent is a male). Any explanation for the proportion of males observed for each level of inclusion is not yet clear, but we can further analyze and infer potential relationships between some of the variables from the correlation plot below in Figure (3).

The first four variables from the left − *BorrowFI, NetBuy, Credit* and *MBill* − are binary components that constitute the financial inclusion choice vector, X. For example, the variable *NetBuy* is derived from the survey question asking whether an individual has ever used the internet to purchase goods. Variable $MBill$ asks a similar question of whether an individual has ever used mobile to pay bills. The remaining variables − *Age, Educ, Income, Sex* and *Work* − describe individual characteristics, and may be continuous or binary. The correlations do comply with the outputs in Figure (2). We can see that age is negatively correlated with all of the financial inclusion components, and the (negative) relationship is especially strong with internet-related components.

[2] *NA* and *Refused* answers were ignored for this study.

Figure 3: Correlation Plot of Relevant Variables



This may not be surprising, as it has been shown that older generations are less likely to use the internet (van Deursen and Helsper, 2015).

On the other hand, education has positive correlation with all of the inclusion components. Furthermore, education, unlike age, has a positive and moderate relationship with NetBuy. In addition to this, we see that there exists a negative correlation between age and education. Thus, we may hypothesize that educated younger generations in China are more financially included, on average. Notable relationships among financial inclusion components can be observed from the moderate positive correlation between purchasing online (NetBuy) and paying bills from mobile device (MobBill). As part of our model, we will also be integrating a vector of prices of financial inclusion choice p_j. The technicalities of the model will be soon discussed, but as a short introduction, the price contributes negatively to utility, which arises from having to pay for a specific combination of financial inclusion choices, indexed by j.

Table 1: Prices of FI Choice Components.

FI Component	Price/Rate	Description
Borrow	4.3 (percent)	2017 policy lending interest rate
Credit	14.5 (percent)	2019 Credit Card Interest Rate

The price vector contains the cost of Borrowing, which is the 2017 policy interest rate (World Bank, 2018). The costs have been proxied using the national average. Mortgage rate, or more generally loan rate, in 2017 China would have probably differed among different financial institutions; therefore we would use the central bank interest rate as a proxy for the average mortgage/loan rate. The effective credit card interest of 14.5 percent (Ren, 2019). The cost of getting a debit card is ignored in this study as the one-time service fee of getting the card is negligible and is non-recurring. Costs of NetBuy and MBill are also omitted, because we are unable to separately identify if internet used for mobile bill payments are broadband Wi-fi or 4G data plan (and thus the costs cannot be separately identified).

4 Theory and Model

The preexisting literature have different approaches when it comes to estimating the demand for financial inclusion. One of these approaches is to have one dependent variable such as "have a formal saving account" as a proxy for demand for financial inclusion and run regression with several covariates (Rashdan and Eissa, 2019). Another approach is to develop an index for the perception of barriers to the use of financial services (Hoyo, Pena and Tuesta, 2013) and run regressions by having that index as a dependent variable. However, these approaches restricts one's choice of financial inclusion to only one variable. By using a multinomial mixed logit model with utility interpretation, we allow more flexibility in the observed financial inclusion choice and estimate one's decision to participate into the opportunities provided by financial technology more accurately.

In our model, every individual i makes a “Financial Inclusion Choice” X_j, from a total of J unordered alternatives. We need alternatives to be unordered so that probability of choosing one alternative should not be in any deterministic relation with another alternative. For example, having a credit card and made an online bill payment using credit card would violate this assumption and would give us biased estimates.

We defined X_j in the data section as:

$$\mathbf{X_j} = [\text{NetBuy}_j \;\; \text{BorrowFI}_j \;\; \text{Credit}_j \;\; \text{NetBill}_j]$$

The components of a financial inclusion choice are dummy variables. We also denote the components by l, where $l \in \{1, 2, 3, 4\}$. For example:

$$X_{j3} = \text{Credit}_j = \begin{cases} 1 & \text{if the individual's choice j involves using a credit card} \\ 0 & \text{otherwise} \end{cases}$$

Thus, given that a "financial inclusion choice" is made of 4 components, the individual faces a total of $J = 2^4 = 16$ alternatives. Generally, an individual face $J = 2^f$ choices, where f is the number of components constituting a financial inclusion choice. Notice that the cost of financial products and services constitutes an important factor in one's decision making to join the financial system. Assuming that people are rational and have close to perfect information on prices, by relying on microeconomic theory, we expect that if the prices of financial products increases, there will be lower demand due to lower utility obtained from that financial product. Therefore, the prices of the products will come with a negative sign into our functional form of utility.
Let P_l be the price of the l-th component of financial inclusion choice $\mathbf{X_j}$. Then, with reference to the data section, the prices for our 4-component choice vector are:

$$p_1 = p_{NetBuy} = 0$$
$$p_2 = p_{BorrowFI} = 4.3$$
$$p_3 = p_{Credit} = 14.5$$
$$p_4 = p_{NetBill} = 0$$

Zero prices are kept for formal representation, or as a place holder if prices become separately identifiable in the future. Moreover, as discussed more in detail in the literature review, personal characteristics have found to play a significant role in determining the demand for financial inclusion. Therefore, we control for the individual characteristics in our model with the inclusion of the row vector $\mathbf{Z_i}$. With reference to the data section, we use information on the individual's Age, Income, Education, Sex, and Work status to describe individual characteristics:

$$\mathbf{Z_i} = [\text{Age}_i \;\; \text{Income}_i \;\; \text{Education}_i \;\; \text{Sex}_i \;\; \text{Work}_i]$$

Then we assume that the ordinal utility obtained by individual with characteristics $\mathbf{Z_i}$ from choosing a financial inclusion choice with components X_{jl} with prices P_{jl} is defined by a utility function of the form:

$$U_{Z_i}(\mathbf{X_j}) = -\sum_{l=1}^{L} \alpha_l p_l X_{jl} + \sum_{l=1}^{L} \beta_l X_{jl} + \sum_{k=1}^{K} \gamma_{jk} Z_{ik} + \epsilon_{ij} \tag{1}$$

That is, the utility individual i gets from choosing choice j is dependent on the costs of that choice, his individual chacteristics, and also the financial components the choice contains. Continuing from our previous examples,

$$
\begin{aligned}
U_{Z_i}(\mathbf{X_j}) = & -\alpha_1 p_{NetBuy} \cdot NetBuy_j - \alpha_2 p_{BorrowFI} \cdot BorrowFI_j - \alpha_3 p_{Credit} \cdot Credit_j - \alpha_4 p_{NetBill} \cdot NetBill_j \\
& + \beta_1 NetBuy_j + \beta_2 BorrowFI_j + \beta_3 Credit_j + \beta_4 NetBuy_j \\
& + \gamma_{1j} Age_i + \gamma_{2j} Income_i + \gamma_{3j} Education_i + \gamma_{4j} Sex_i + \gamma_{5j} Work_i \\
& + \epsilon_{ij}
\end{aligned}
$$

Since individual characteristics are invariant across Financial Inclusion alternatives, we let their coefficients vary with alternatives for model identification (gammas, the coefficients of individual characteristics Z, are indexed by choice j). By the same reasoning, since choice components and prices vary by alternatives, we fix their coefficients. This leads to a mixed logit model explain in the next sub section.

4.1 Empirical Model

The utility function, by construction, varies with different financial inclusion choices. We assume that the individuals are rational in their decision making and their goal is to maximize their utility. Therefore, the individual i will choose financial inclusion Choice X_j in favor of any other choice X_q if and only if:

$$U_{ij} > U_{iq} \qquad \forall q \neq j$$

Thus, the probability of a financial inclusion choice X_j being chosen by an individual i (P_{ij}) is:

$$
\begin{aligned}
P_{ij} &= P[\text{i's Choice} = j] && (2) \\
&= P(U_{Z_i}(\mathbf{X_j}) > U_{Z_i}(\mathbf{X_q})) && (3) \\
&= P(-\sum_{l=1}^{L} \alpha_l p_l X_{jl} + \sum_{l=1}^{L} \beta_l X_{jl} + \sum_{k=1}^{K} \gamma_{jk} Z_{ik} + \epsilon_{ij} > && (4) \\
& -\sum_{l=1}^{L} \alpha_l p_l X_{ql} + \sum_{l=1}^{L} \beta_l X_{ql} + \sum_{k=1}^{K} \gamma_{qk} Z_{ik} + \epsilon_{iq}) \qquad \forall q \neq j && (5)
\end{aligned}
$$

Further, assume that ϵ_{ij} and ϵ_{iq} are i.i.d extreme value distribution, then

$$P_{ij} = \frac{exp(-\sum_{l=1}^{L} \alpha_l p_l X_{jl} + \sum_{l=1}^{L} \beta_l X_{jl} + \sum_{k=1}^{K} \gamma_{jk} Z_{ik})}{\sum_q exp(-\sum_{l=1}^{L} \alpha_l p_l X_{ql} + \sum_{l=1}^{L} \beta_l X_{ql} + \sum_{k=1}^{K} \gamma_{jk} Z_i + \epsilon_{iq})} \qquad 0 \leq P_{ij} \leq 1 \qquad (6)$$

Also, the sum of all probabilities of choosing the available financial inclusion choices must equal to one:

$$\sum_{j=1}^{J} P_{ij} = \frac{exp(-\sum_{l=1}^{L} \alpha_l p_l X_{jl} + \sum_{l=1}^{L} \beta_l X_{jl} + \sum_{k=1}^{K} \gamma_{jk} Z_{ik})}{\sum_q exp(-\sum_{l=1}^{L} \alpha_l p_l X_{ql} + \sum_{l=1}^{L} \beta_l X_{ql} + \sum_{k=1}^{K} \gamma_{jk} Z_{ik} + \epsilon_{iq})} = 1$$

To find the log-odds of individual i choosing financial choice j against choosing Alternative 1 (i.e. to find the odds of him choosing to be financially included to some extent against him choosing to be not included), the model gives the log relative risk ratio as:

$$ln\left(\frac{P_{ij}}{P_{i1}}\right) = -\sum_{l=1}^{L} \alpha_l p_l X_{jl} + \sum_{l=1}^{L} \beta_l X_{jl} + \sum_{k=1}^{K} \gamma_{jk} Z_{ik}$$

This is the form for the log-odds or log relative risk ratio of financial inclusion Alternative j to Alternative 1. Thus, if a covariate has a positive estimated coefficient, then the odds of the individual choosing Alternative j against no inclusion is increasing in that covariate. The opposite holds for covariates with negative coefficients.

To find the marginal effect of a change in a covariate, such as price, on the probability of individual i choosing Alternative j: The proofs of the derivations are given in the appendix.

4.2 Estimation

STATA uses maximum simulation likelihood to estimate the parameters of the mixed logit through the function **asmixlogit**.[3] The simulated probability and likelihood for individual i are define as following:

$$\hat{P}_{ij} = \frac{1}{M} \sum_{m=1}^{M} P_{ij}(\beta^m), \quad \beta^m \sim f(\beta) \tag{7}$$

$$L_i = \sum_{j=1}^{J} d_{ij} \hat{P}_{ij}, \quad d_{ij} \in \{0, 1\} \tag{8}$$

where M is the number of random draws from the distribution $f(\beta)$.

5 Empirical Results

5.1 Estimates

In Figure (4) below, we present the estimated coefficients for the mixed logit model, for prices and financial inclusion components that are not changing across each financial inclusion alternative (Fixed Coefficients), and for the coefficients of individual characteristics that are choice-variant, specifically for the 16^{th} alternative. This is the alternative that represents full financial inclusion

[3]To be specific, STATA 15 was used in fitting the model.

as defined by the set of alternatives. For the fixed coefficients, only estimates for price of using credit card Price(Credit) and price for borrowing from a financial institution Price(BorrowFI) are significant, with p-values less than 0.001. The alternative-varying coefficients that are significant at the 1% level are for the covariates Age, Income, and Education. The signs of the covariates are mostly consistent with theory. Prices contribute negatively to log-odds of choosing some extent of financial inclusion against no inclusion, while choice components contributes positively. Log-odds are also increasing in income and education, while decreasing in age.

Figure 4: Selected Estimated Coefficients of Mixed Logit Model

Mixed Logit			
	Fixed Coefficients		Alternative-varying Coefficients
Price (Credit) "credit card interest rate %"	-0.1611645*** (0.0269727)	Age (Alternative 16)	-.1394364*** (0 .0167607)
Price (BorrowFI) "loan interest rate %"	-0.5868568*** (0.1192149)	Income (Alternative 16)	0.0000201** (6.86e-06)
MobBill	-0.723414 (0.379707)	Education (Alternative 16)	2.591759*** (0.2928024)
NetBuy	2.683538*** (0.3877085)	Sex (Alternative 16)	0.2938336 (0.3696862)
Credit	1.65e-10 (.)	Work (Alternative 16)	0.7065537 (0.6075443)
BorrowFI	4.00e-10 (.)		

Standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.2 Implications and Interpretations

As previous literature reviews have already demonstrated the positive effects of financial inclusion, we expect rational policy makers to aim for the highest level of inclusion, Alternative 16. As we have hypothesized beforehand, older generations exhibit a lower probability of full inclusion, while more educated individuals are more likely to participate in all four of the financial inclusion components. Role of government in education is a classical issue with numerous proposed theories and empirical evidences. Policy makers may wish to actively support and encourage higher level of educational attainment through previously demonstrated policies, such as call for minimum-level of education and for its funding.

In lieu of this context of education, financial literacy, which can be proxied by education to some degree, may also prove to be a crucial factor in achieving full financial inclusion. Consequently, it is especially necessary to educate the older citizens who may suffer from both lack of education and unfamiliarity with the fast-evolving financial structure. Furthermore, income proves to be a more relevant and significant factor in determining an individuals' full inclusion decision rather than their working status. Specifically, the model estimates that individuals with higher income are more likely to choose Alternative 16.

In regards price components, credit card interest rate, while significant, fails to offer any meaningful policy implications other than that overdue payment rates do impact one's financial inclusion decision. Interest on lending and borrowing, which was proxied by the Chinese central bank rate in 2017, has some interesting behavioural implications. We assume that those who are primarily borrowers would be discouraged from engaging in further inclusion if rates were to go up. On the other hand, there maybe those that take advantage of the high rates through active lending, thus undertaking in higher level of financial inclusion.

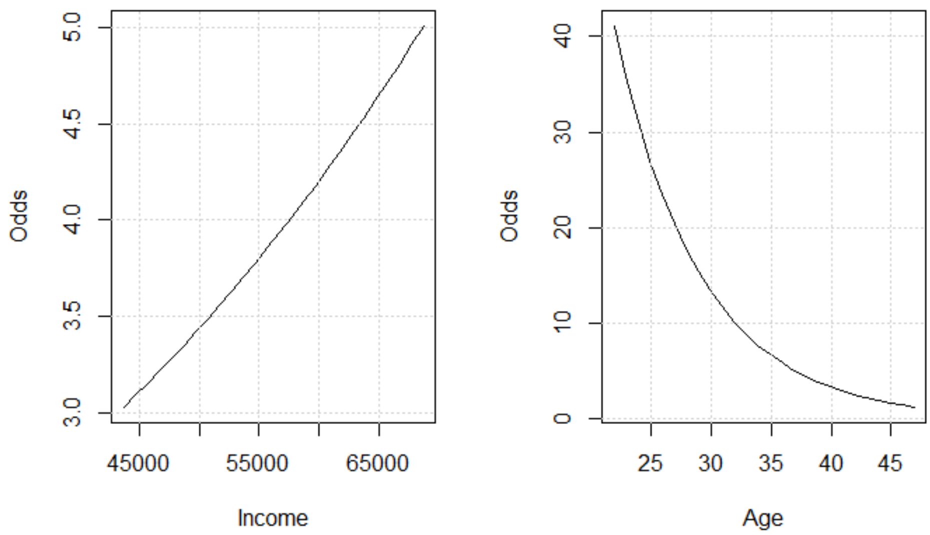
We now shift our analysis in defining and deriving the relative risk. The relative-risk or the odds of an individual choosing full financial inclusion as defined by choice 16 against no financial inclusion as defined by choice 1 is

$$\frac{P_{ij}}{P_{i1}} = exp\left(-\sum_{l=1}^{L}\alpha_l p_l X_{jl} + \sum_{l=1}^{L}\beta_l X_{jl} + \sum_{k=1}^{K}\gamma_{jk} Z_{ik}\right)$$

The expression on the right hand side of the equation gives the proportionate change in the relative risk of choosing alternative j rather than 1 when X_{jl} or Z_{ik} changes by 1 unit, holding all else constant. To demonstrate this, we use a male who is in the workforce with average age, income, and education of the sample (refer to data section Figure 2). We increase income incrementally by 1000 from the average income ($Z_{\text{i=average},k=Income}$), holding all else constant at the sample averages. We do the same with age, increasing age incrementally by 1. We see that the odds of full financial inclusion against none decreases dramatically with age, holding all else constant, from about 40 times likelier to choose full inclusion than no inclusion at age 20, to equally likely (odds of 1) at age 45 (See figure 5 below). The changes in odds are less drastic for income, with odds of full inclusion against none increasing by by 2 if income increases by 20,000 yuan.

Since the estimates for age and income are significant at the 1% level, this is evidence that the inactive user problem lies with the older generation and the less wealthy population. With information on population characteristics, governments can use this measure to determine whether an initiative to spread financial inclusion in a new region is feasible.

Figure 5: Ceteris Paribus Change in Odds of Choosing Full Financial Inclusion Against No Financial Inclusion, for changes in Income and Age



The alternative-specific regressors in our model are prices and financial inclusion components. We can compute the marginal effect on probability of individual i choosing financial inclusion choice j for a change in prices for alternative k, holding the prices/costs of all other alternatives constant:

$$\frac{\partial P_{ij}}{\partial x_{jil}} = \begin{cases} P_{ij}\left(1 - P_{ij}\right)\beta_l & j = k \\ -P_{ij}P_{ik}\beta_l & j \neq k \end{cases}$$

If β_l is positive, then the own-price-effect is positive whereas the cross-price-effect is negative. Our estimates show that the fixed coefficients for borrowing rate and credit card rates are significantly negative at the 1% level, meaning that cross-price effects are positive. In other words, the marginal change in probability of choosing no inclusion (with no costs) is negative with a decrease in costs associated to borrowing and using credit card. This says that a subsidy on full inclusion will be effective in reducing the probability of choosing no inclusion. This can either be done through direct cash incentives or reductions in costs of borrowing.

6 Evaluation/Discussion

A disadvantage using a mixed logit model over conditional logit model is that, although it is richer than the CL model, if an additional alternative is added to the choice set then one can not predict its probability of selection, since the parameters of our mixed logit model do vary across alternatives. On the other hand, one advantage of the mixed logit over a pure conditional or multinomial logit is that it allows us to relax the assumption of independent of irrelevant alternatives (IIA) by including random coefficients to allow for correlation between alternatives. This is a potential future extension of this research.

We did not specify interaction terms that could potentially effect utility in a positive (complementaries) or negative (substitutes) direction depending on the nature of independent variables. Moreover, there are potential biases in certain variables such as BorrowFI. If an individual did not borrow from a financial inclusion in past 12 months, it could be that their expectation on the state of economy such as high or low inflation affected his decision. Similarly if we an individual did not purchase anything online, the reason for that may be dependent on the expectation of lower prices in future due to the state of economy. We also try to control for the effect of financial literacy and knowledge on utility as much as possible with education and income but we are aware that special financial knowledge may persist in the error term and create bias for coefficients.

There could also be regional fixed effects that were unaccounted for. China consists of 34 provincial level divisions, and different policies and regulations are present in each of the regions. For example, minimum wage differs throughout some provinces, and this will have a direct impact on an individual's income level. Additionally, provinces are also unique in their geo-political characteristics, such as the relative size of the labour market.

One of the main challenges for the study was in determining the right econometric model. Assuming IIA holds, we fit a separate purely multinomial logit, with individual characteristics being the sole set of predictors. The coefficient estimates for Alternative 16 are summarized in the table below.[4] All of the individual characteristic components are significant, and the estimated values very closely correspond to the mixed logit estimates. This finding may serve as a signal that prices do not constitute a crucial part in determining an individual to choose the full inclusion alternative. It could also mean that prices are better modelled with random coefficients.

[4]Estimates were calculated using *multinom()* from *nnet* package.

Table 1: Estimated Coefficients of Multinomial Logit Model for Alternative 16

Variables	Estimates	Standard Errors	P-values
Age	-0.177505	0.009497	0.000000
Education	2.130610	0.000353	0.000000
Income	0.000017	0.000005	0.001207
Sex	0.293268	0.000110	0.000000
Work	0.195724	0.000183	0.000000

7 Conclusion

In this paper, we discuss the reasons behind the call for higher levels of financial inclusion, as well as some of the challenges faced by policy makers in attempt to achieve the inclusion goals set by governments. Many previous researches and models on this topic were limited to constructing indices to measure individual or sub-population's degree of financial inclusion. Instead, we propose a different methodology that adopts the additive random utility model to estimate the demand for financial inclusion, using three different set of predictors: X_j, P_j and Z_i. Then, probability of individual i choosing some alternative j, P_{ij}, was estimated using the multinomial mixed logit framework.

The results of our estimation are not surprising, and comply with many previous theories and texts of financial inclusion. Older citizens are predicted to have a lower probability of financial inclusion across all alternatives, while more educated individuals are more likely to engage in higher levels of inclusion. We further extend our empirical findings to the context of relative risk and marginal effects to help address the underlying issues of the inactive user problem.

There are still plenty of areas to be explored. The addition of time dimension into the model is another consideration for future work. Another analysis can be done on the significance of regional differences as factors in determining one's level of financial inclusion. For example, China consists of 34 provincial level divisions, and different policies and regulations are present in each of the regions. Thus, we hypothesize that many more individual-related factors should be considered for for future research. Furthermore, while our model specifies inclusion choices using just $J = 4$ components, in reality, far more components may need to be accounted for. In conclusion, we wish that the evidences and results from this paper provides meaningful insight for policy makers and contribution to the topic of financial inclusion.

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9 Appendix

9.1 Figures and Tables

Table 2: Income Quntile and Education Level

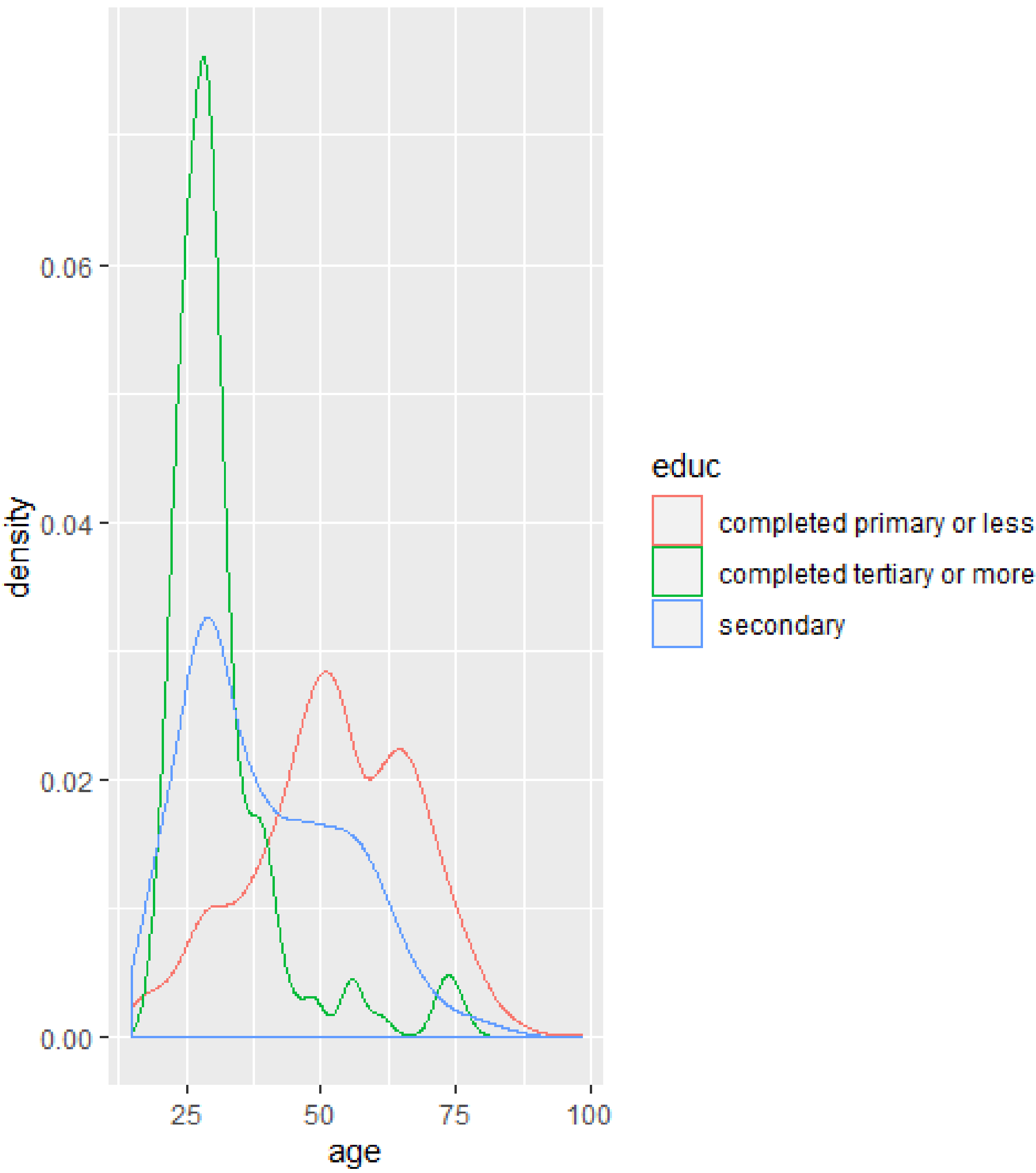
Income[5]

Education Level	Q1	Q2	Q3	Q4	Q5
Primary	269.00	225.00	215.00	250.00	156.00
Secondary	32.00	175.00	102.00	57.00	217.00
Tertiary +	2.00	14.00	6.00	2.00	61.00

Table 3: Education Level and Chosen Alternative

Alt.	Primary	Secondary	Tertiary +
1	737.00	150.00	5.00
2	128.00	102.00	8.00
3	29.00	12.00	0.00
4	12.00	13.00	2.00
5	46.00	18.00	0.00
6	29.00	62.00	11.00
7	14.00	4.00	0.00
8	9.00	8.00	6.00
9	42.00	14.00	1.00
10	51.00	88.00	14.00
11	1.00	3.00	0.00
12	3.00	7.00	0.00
13	5.00	4.00	1.00
14	24.00	82.00	24.00
15	1.00	3.00	0.00
16	6.00	20.00	13.00

Figure 6: Distribution of Education via Age



9.2 Proofs and Derivations

9.2.1 Relative Risk

For any $j \neq 1$,

$$ln\left(\frac{P_{ij}}{P_{i1}}\right) = ln\left(\frac{exp(-\sum_{l=1}^{L}\alpha_l P_l X_{jl} + \sum_{l=1}^{L}\beta_l X_{jl} + \sum_{k=1}^{K}\gamma_{jk}Z_{ik})}{\sum_q exp(-\sum_{l=1}^{L}\alpha_l P_l X_{ql} + \sum_{l=1}^{L}\beta_l X_{ql} + \sum_{k=1}^{K}\gamma_{jk}Z_{ik} + \epsilon_{iq})} \times \frac{\sum_q exp(-\sum_{l=1}^{L}\alpha_l P_l X_{ql} + \sum_{l=1}^{L}\beta_l X_{ql} + \sum_{k=1}^{K}\gamma_{1k}Z_{ik} + \epsilon_{iq})}{exp(-\sum_{l=1}^{L}\alpha_l P_l X_{1l} + \sum_{l=1}^{L}\beta_l X_{1l} + \sum_{k=1}^{K}\gamma_{jk}Z_{ik})}\right.$$

$$= ln\left(\frac{exp(-\sum_{l=1}^{L}\alpha_l P_l X_{jl} + \sum_{l=1}^{L}\beta_l X_{jl} + \sum_{k=1}^{K}\gamma_{jk}Z_{ik})}{exp(-\sum_{l=1}^{L}\alpha_l P_l X_{1l} + \sum_{l=1}^{L}\beta_l X_{1l} + \sum_{k=1}^{K}\gamma_{1k}Z_{ik})}\right)$$

$$= \left(-\sum_{l=1}^{L}\alpha_l P_l X_{jl} + \sum_{l=1}^{L}\beta_l X_{jl} + \sum_{k=1}^{K}\gamma_{jk}Z_{ik}\right) - \left(-\sum_{l=1}^{L}\alpha_l P_l X_{1l} + \sum_{l=1}^{L}\beta_l X_{1l} + \sum_{k=1}^{K}\gamma_{1k}Z_{ik}\right)$$

Since $X_{1l} = 0 \;\forall\; l$

$$= -\sum_{l=1}^{L}\alpha_l P_l X_{jl} + \sum_{l=1}^{L}\beta_l X_{jl} + \sum_{k=1}^{K}\gamma_{jk}Z_{ik} - \sum_{k=1}^{K}\gamma_{1k}Z_{ik}$$

$$= -\sum_{l=1}^{L}\alpha_l P_l X_{jl} + \sum_{l=1}^{L}\beta_l X_{jl} + \sum_{k=1}^{K}(\gamma_{jk} - \gamma_{1k})Z_{ik}$$

Since γ_{1k} is normalized to $0 \;\forall\; k$

$$= -\sum_{l=1}^{L}\alpha_l P_l X_{jl} + \sum_{l=1}^{L}\beta_l X_{jl} + \sum_{k=1}^{K}\gamma_{jk}Z_{ik}$$

This is the equation for the log-odds or relative risk of financial inclusion alternative j to alternative 1.

9.2.2 Derivation of P_{ij}

Recall that an individual chooses financial inclusion choice X_j if and only if $U_{ij} > U_{iq} \;\forall\, q \neq j$. Now, define Y to be an element of all the financial inclusion choices. In other words:

$$Y = \begin{cases} j & \mathrm{U}_{ij} > U_{iq} \\ 0 & \text{otherwise} \end{cases}$$

So,

$$Y = \mathbf{j}[\sum_{l=1}^{L} -\alpha_l P_{jl} X_{jl} + \sum_{l=1}^{L}\beta_l X_{jl} + \sum_{k=1}^{K}\gamma_{jk}Z_{ik} + \epsilon_{ij} > \sum_{l=1}^{L} -\alpha_l P_{ql} X_{ql} + \sum_{l=1}^{L}\beta_l X_{ql} + \sum_{k=1}^{K}\gamma_{qk}Z_{ik} + \epsilon_{iq}]$$

$$= \mathbf{1}[\epsilon_{iq} - \epsilon_{ij} < (\sum_{l=1}^{L} -\alpha_l P_{jl} X_{jl} + \sum_{l=1}^{L}\beta_l X_{jl} + \sum_{k=1}^{K}\gamma_{jk}Z_{ik}) - (\sum_{l=1}^{L} -\alpha_l P_{ql} X_{ql} + \sum_{l=1}^{L}\beta_l X_{ql} + \sum_{k=1}^{K}\gamma_{qk}Z_{ik})]$$

Next, assume that

$$(\epsilon_{iq}, \epsilon_{ij}) \perp\!\!\!\perp ((\sum_{l=1}^{L} -\alpha_l P_{ql} X_{ql} + \sum_{l=1}^{L} \beta_l X_{ql} + \sum_{k=1}^{K} \gamma_{qk} Z_{ik}), (\sum_{l=1}^{L} -\alpha_l P_{jl} X_{jl} + \sum_{l=1}^{L} \beta_l X_{jl} + \sum_{k=1}^{K} \gamma_{jk} Z_{ik}))$$

To simplify the notation in further steps, define:

$$v_0 := \sum_{l=1}^{L} -\alpha_l P_{ql} X_{ql} + \sum_{l=1}^{L} \beta_l X_{ql} + \sum_{k=1}^{K} \gamma_{qk} Z_{ik} \tag{9}$$

$$v_1 := \sum_{l=1}^{L} -\alpha_l P_{jl} X_{jl} + \sum_{l=1}^{L} \beta_l X_{jl} + \sum_{k=1}^{K} \gamma_{jk} Z_{ik} \tag{10}$$

Also, we assume that the error terms follow Type I Extreme Value Distribution with following PDF and CDF:

$$f_\epsilon(\epsilon) = e^{-\epsilon} e^{-e^{-\epsilon}}$$

$$F_\epsilon(\epsilon) = e^{-e^{-\epsilon}}$$

Therefore,

$$Pr(Y = j|v_0, v_1) = Pr(\epsilon_{iq} - \epsilon_{ij} < v_1 - v_0|v_0, v_1)$$

$$= Pr(\epsilon_{iq} < \epsilon_{ij} + v_1 - v_0|v_0, v_1)$$

$$= \int Pr(\epsilon_{iq} < \epsilon_{ij} + v_1 - v_0|\epsilon_{ij}, v_0, v_1) f_\epsilon(\epsilon_{ij}) d\epsilon_{ij}$$

$$= \int_{-\infty}^{+\infty} F_\epsilon(\epsilon_{ij} + v_1 - v_0) f_\epsilon(\epsilon_{ij}) d\epsilon_{ij}$$

$$= \int_{-\infty}^{+\infty} e^{-e^{-(\epsilon_{ij} + v_1 - v_0)}} e^{-\epsilon_{ij}} e^{-e^{-\epsilon_{ij}}} d\epsilon_{ij}$$

Let $u = e^{-\epsilon_{ij}}$ and thus $du = -e^{\epsilon_{ij}} d\epsilon_{ij}$

$$\implies \int_{+\infty}^{0} e^{-ue^{-(v_1 - v_0)}} e^{-u} (-du)$$

$$= \int_{0}^{+\infty} e^{-ue^{-(v_1 - v_0)}} e^{-u} (du)$$

Let $k := e^{-(v_1-v_0)} + 1$

$$\implies \int_0^{+\infty} e^{-uk}(du) = (-\frac{1}{k}e^{-u\cdot\infty}) - (-\frac{1}{k}e^{-u\cdot 0})$$

$$= \frac{1}{k} = \frac{1}{e^{-(v_1-v_0)}+1} = \frac{e^{v_1}}{e^{v_1}+e^{v_0}}$$

Recall that $v_1 := \sum_{l=1}^{L} -\alpha_l P_{jl} X_{jl} + \sum_{l=1}^{L} \beta_l X_{jl} + \sum_{k=1}^{K} \gamma_{jk} Z_{jk}$ and v_0 stands for all the financial inclusion choices $q \neq j$, thus one think of denominator consisting of v_1 and many v_0's. Therefore, we obtain:

$$P_{ij} = \frac{exp(\sum_{l=1}^{L} -\alpha_l P_{jl} X_{jl} + \sum_{l=1}^{L} \beta_l X_{jl} + \sum_{k=1}^{K} \gamma_{jk} Z_{ik})}{\sum_q exp(\sum_{l=1}^{L} -\alpha_l P_{ql} X_{ql} + \sum_{l=1}^{L} \beta_l X_{jl} + \sum_{k=1}^{K} \gamma_{qk} Z_{ik})} \qquad \square$$

9.3 Raw Regression Output

Figure 7: Full Mixed Logit regression output

```
Alternative-specific mixed logit              Number of obs      =     28,992
Case variable: id                             Number of cases    =      1,812

Alternative variable: number                  Alts per case: min =         16
                                                             avg =       16.0
                                                             max =         16

Integration points:            0                 Wald chi2(79)   =    2594.86
Log likelihood =       -2691.602                 Prob > chi2     =     0.0000
```

choiceyes	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
number						
creditrate	-.1611645	.0269727	-5.98	0.000	-.2140299	-.1082991
interestrate	-.5868568	.1192149	-4.92	0.000	-.8205136	-.3531999
1.netbuy	2.683538	.3877085	6.92	0.000	1.923643	3.443432
1.borrowfi	4.00e-10	.	.	.	.	.
1.credit	1.65e-10	.	.	.	.	.
1.mobbill	-.723414	.379707	-1.91	0.057	-1.467626	.0207981

1	(base alternative)					
2						
age	-.1152581	.0072725	-15.85	0.000	-.1295119	-.1010042
income	8.98e-06	3.47e-06	2.59	0.010	2.18e-06	.0000158
education	.9995943	.1630605	6.13	0.000	.6800017	1.319187
sex	-.3448622	.1754861	-1.97	0.049	-.6888087	-.0009156
work	-.2492277	.2005855	-1.24	0.214	-.6423681	.1439128
3						
age	-.0214614	.0097038	-2.21	0.027	-.0404806	-.0024423
income	-6.43e-07	6.94e-06	-0.09	0.926	-.0000142	.000013
education	.7364141	.3125607	2.36	0.018	.1238063	1.349022
sex	-.5419507	.3390388	-1.60	0.110	-1.206455	.1225532
work	-.0969881	.3402627	-0.29	0.776	-.7638906	.5699145
4						
age	-.1151817	.0150464	-7.66	0.000	-.1446721	-.0856912
income	-3.36e-06	8.52e-06	-0.39	0.693	-.0000201	.0000133
education	1.308151	.3238221	4.04	0.000	.6734709	1.94283
sex	.1276683	.4076179	0.31	0.754	-.6712481	.9265847
work	.0350481	.5005334	0.07	0.944	-.9459792	1.016075
5						
age	-.0261992	.0079595	-3.29	0.001	-.0417996	-.0105987
income	3.85e-06	5.46e-06	0.71	0.481	-6.85e-06	.0000145
education	.2909629	.2723715	1.07	0.285	-.2428754	.8248013
sex	.4021477	.2725057	1.48	0.140	-.1319535	.936249
work	.490249	.3141065	1.56	0.119	-.1253884	1.105886
6						
age	-.1304958	.0103065	-12.66	0.000	-.1506962	-.1102954
income	.0000151	4.55e-06	3.33	0.001	6.22e-06	.000024
education	1.750843	.2032033	8.62	0.000	1.352572	2.149114
sex	.1276787	.2426896	0.53	0.599	-.3479841	.6033415
work	.1191373	.3154266	0.38	0.706	-.4990875	.7373621
7						
age	-.0300698	.0160381	-1.87	0.061	-.0615039	.0013643
income	-5.40e-07	.000011	-0.05	0.961	-.000022	.000021
education	.4137689	.503712	0.82	0.411	-.5734885	1.401026
sex	.988745	.5836744	1.69	0.090	-.1552358	2.132726
work	1.584363	.8452028	1.87	0.061	-.0722038	3.24093
8						
age	-.1224788	.0172765	-7.09	0.000	-.1563402	-.0886175
income	.0000252	8.34e-06	3.03	0.002	8.88e-06	.0000416
education	1.784747	.3447408	5.18	0.000	1.109068	2.460427
sex	.1082235	.4519556	0.24	0.811	-.7775933	.9940402
work	.244714	.6156105	0.40	0.691	-.9618604	1.451288
9						
age	-.0537174	.008541	-6.29	0.000	-.0704575	-.0369774
income	.0000107	5.53e-06	1.93	0.054	-1.82e-07	.0000215
education	.3891978	.2757755	1.41	0.158	-.1513122	.9297078
sex	-.0633921	.2860757	-0.22	0.825	-.6240902	.4973061
work	-.2321403	.2989901	-0.78	0.438	-.8181502	.3538695
10						
age	-.1548121	.0101378	-15.27	0.000	-.1746819	-.1349424
income	.0000135	4.09e-06	3.31	0.001	5.52e-06	.0000216
education	1.538393	.187063	8.22	0.000	1.171756	1.90503
sex	.0211448	.2138743	0.10	0.921	-.3980411	.4403306
work	.2914405	.2880443	1.01	0.312	-.273116	.8559969

11						
age	-.0995024	.0305505	-3.26	0.001	-.1593804	-.0396245
income	.0000273	.0000176	1.56	0.120	-7.10e-06	.0000617
education	.8761045	.7682996	1.14	0.254	-.6297351	2.381944
sex	-.2711286	.9694783	-0.28	0.780	-2.171271	1.629014
work	.4630202	1.24857	0.37	0.711	-1.984131	2.910172
12						
age	-.1472781	.026407	-5.58	0.000	-.1990349	-.0955213
income	-5.34e-06	.0000138	-0.39	0.698	-.0000323	.0000216
education	1.526705	.494552	3.09	0.002	.5574004	2.496009
sex	.5381526	.6731035	0.80	0.424	-.781106	1.857411
work	.4695491	.9582075	0.49	0.624	-1.408503	2.347601
13						
age	-.0876367	.0199648	-4.39	0.000	-.126767	-.0485064
income	.0000188	.0000119	1.58	0.114	-4.48e-06	.000042
education	1.027191	.5261963	1.95	0.051	-.0041345	2.058517
sex	.7194037	.6909024	1.04	0.298	-.6347401	2.073547
work	.2694748	.8387887	0.32	0.748	-1.374521	1.91347
14						
age	-.1367869	.0107662	-12.71	0.000	-.1578883	-.1156856
income	.0000179	4.35e-06	4.11	0.000	9.35e-06	.0000264
education	2.182972	.2004561	10.89	0.000	1.790085	2.575859
sex	-.0963257	.2319093	-0.42	0.678	-.5508596	.3582082
work	.4685328	.3285329	1.43	0.154	-.1753798	1.112446
15						
age	-.0952188	.034273	-2.78	0.005	-.1623926	-.028045
income	.0000256	.0000184	1.39	0.164	-.0000104	.0000615
education	1.048365	.8302971	1.26	0.207	-.5789874	2.675717
sex	2.420859	1.685418	1.44	0.151	-.8824991	5.724216
work	.4522445	1.569939	0.29	0.773	-2.62478	3.529269
16						
age	-.1394364	.0167607	-8.32	0.000	-.1722868	-.1065861
income	.0000201	6.86e-06	2.93	0.003	6.68e-06	.0000336
education	2.591759	.2928024	8.85	0.000	2.017877	3.165641
sex	.2938336	.3696862	0.79	0.427	-.430738	1.018405
work	.7065537	.6075443	1.16	0.245	-.4842113	1.897319