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Essays in Labor Economics

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ESSAYS IN LABOR ECONOMICS

by

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ABSTRACT

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This dissertation consists of two chapters on labor economics. Despite differentia between topics, both share a similar property: causal effects analysis in the presence of unobserved variables.

The first chapter examines the effects of China's two-child policy on childbearing, marriage, and female labor force participation. Using data from the China Labor-Force Dynamic Survey (CLDS) for 2012, 2014 and 2016, it generates three broad results. First, the universal two-child policy had a significant positive impact on having a second child during a portion of its phase-in. Second, the two-child policy did not influence the likelihood of marriage for young people. Third, female labor participation increased after the two-child policy, regardless of the number of children. Moreover, one child mothers' work hours and participation did not fall relative to other mothers as might be expected if employers newly saw one child mothers as less likely to persist in employment because of the policy change.

The second chapter studies the effects of lender-borrower interactions on the microfinance market. Based on data from the Wisconsin Women’s Business Initiative Corporation (WWBIC), we analyze the potential influence of training and consulting assistance on the borrowers’ timely repayment. Using pooled data of monthly repayment by clients, initial results suggest that increased consulting services are associated with a decreased rate of missed payments. After a series of robustness tests, including client fixed effects, this relationship remains but only for those with a higher credit rating (620 or above). Attempts to aggregate data by client provide mixed evidence in

both traditional and IV estimates. The results show that more risky clients respond more to the consulting service while consulting services can significantly improve the borrower's repayment regardless of the client's riskiness.

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Chapter 1

Childbearing, Marriage and Labor Participation: The Two-child Policy in China

1 Introduction

Recently China relaxed its one-child policy. Over the course of a handful of years, various groups of parents were successively allowed a second child. The timing of the rollout was based on whether the parents themselves were or were not single-child. Eventually, all parents were allowed to have two children by 2015.

The one-child policy has been of enormous interest to economists, and its relaxation is equally interesting. This paper examines the extent to which the number of second children (and children more generally) increased as a result of the policy, how the marriage behavior of young people changed, and changes in the labor market participation of women.

It uses three waves of the China Labor Force Dynamic Survey to conduct tests. The tests examine three related hypotheses. The first is that parents, indeed, had more children and, specifically, were more likely to have a second child following the policy change. The second is that to accommodate a likely second child, the marriage took place earlier in life as a result of the policy change. The third is that the policy change altered the relative advantage of various women in the labor market. Prior to the policy change, it may be the case that women with one child were in higher demand because they would not be demanding maternity leave or quitting; employers would know they had a more "reliable" employee. After the policy change, women with one child would lose this advantage. Consequently, their relative labor market participation or the intensity

of their participation may be diminished as a result of the policy change.

The results indicate that the universal two-child policy in 2015 significantly increased the probability of a group of parents (those where neither parent was themselves a single-child) giving birth to a child. Moreover, this group was also significantly more likely to have a second child as a result of the policy change when compared to controls for whom the policy did not change their ability to have two children.

In terms of the marriage decision, even though the selective two-child policy in 2013 allowed parents who are an only child in their original family to have two children, they did not significantly increase their higher marriage rate.

From the perspective of labor participation, we divide women into three groups according to whether they have zero, one, or two children. Compared to the year 2012, the possibility of women participating in the labor market has increased significantly, regardless of the number of children they have, while there is no significant difference between 2014 and 2016 for all the three groups. Among those who have a job, compared to the year 2012, only women with two children have a significant decrease in typical working days per month in the year 2016. The typical weekly working hours of all the three groups reduced significantly in 2016, while the women with two children decreased the most hours. Hence, we cannot observe that the work hours and participation of women with one child fell relative to other women after the universal two-child policy.

In what follows, the next section provides a theoretical background and presents the central hypotheses. The third section provides the data of the China Labor Force Dynamic Survey (CLDS). The fourth section presents the methodological approach and is followed by the regression results in the fifth section. The final section concludes and gives policy suggestions.

2 Background and Hypotheses

Three separate policy changes relaxed the one-child policy in China. Starting in 2011, two children were allowed if both the husband and wife were single-child[1] in their original family. Starting in 2013, if either the husband or the wife was single-child in their original family, they became eligible to have two children.[2] Finally, in 2015, two children were permitted for all the parents, including those for whom neither parent was a single-child[3]. Thus, as a consequence of these policy changes, the selective two-child policy evolved into the universal two-child policy. This process is identified in Table 1.1.

<Insert Table 1.1 here>

The change in policy isolated in Table 1.1 may change behavior in at least three ways that we identify as our central hypotheses. 1) Most obviously, the policy may increase the likelihood of having a second child. 2) The policy may increase the likelihood of marriage or earlier marriage. 3) The policy may decrease the likelihood of married women participating in the labor market and change the work pattern among women with differing numbers of children. Specifically, after the universal two-child policy, those women with one child are able to have a second child and so present the employer with a new opportunity for quitting or taking maternity leave as a consequence. The policy causes them to appear to be less "reliable" workers. This may put them

[1] Single child, or only child is a person with no siblings.
[2] There is modest provincial variation in the exact date during that year as some provinces started the new policies few months in advance.
[3] The universal two-child policy was passed in the session of the National People's Congress Standing Committee in September of 2015.

at a labor market disadvantage relative to the period prior to the policy change. We now turn to describe each of these hypotheses in more detail.

China's strict one-child policy has effectively controlled the birth rate in the last several decades (Guo et al., 2018). Under the one-child policy, couples who gave birth to more than one child faced enormous fines and penalties and could lose their formal jobs. However, in the process of China's gradual change from the one-child policy to the two-child policy, the cost of having a second child decreased substantially as these punishments were removed and so families are more likely to have a second child than before (Chen 2019; Liu and Liu 2018; Yu, Cao, and Kang 2018). This policy effect may also appear as an earlier first birth/ shorter first birth interval. Thus, anticipating a second child, couples may move up the birth of their first child. Consequently, the period immediately after the policy change may be associated with increased births of both first and second children.

Marriage timing and birth decisions are often linked. Jones et al. (2009) suggest in a study of East Asian countries that low fertility rates in East Asian countries are associated with delayed marriage. In China, the low fertility rate is related to economic development and the strict fertility policies, including a minimum age for marriage (22 years for men and 20 years for women) and the one-child policy. Ye (1992) confirmed that China's one-child fertility policy effectively delayed the age of first marriage. However, the impact of marriage delay on fertility has been reduced by the accelerated birth or shorter first birth interval after marriage. Huang and Zhou (2015) show that the one-child policy has also significantly increased the unmarried rate[4]. Thus, we anticipate that as the two-child policy replaces the one-child policy, the expected number of children in the

[4] The sample is selected from 25-55 years old.

family may increase. As a consequence, couples may need or wish to give birth to the first child earlier to allow time for the birth of the second child. In turn, this may make the average age of marriage younger and may even increase the probability of marriage.

The two-child policy may affect family fertility decisions, which in turn affects women's labor force participation (Cooke 2017). The increase in the number of children in the family may affect women's labor supply in different ways. On the one hand, as the home production load increases, women with more children need to increase their home hours and shorten their paid work and/or leisure time (He and Zhu 2016). Moreover, studies show that different numbers of children have different effects on female labor participation. Women with more than two children are much more likely to exit from the labor market (Doren 2019). Many studies show that as the number of young children in the family increase, mothers are less likely to participate in the labor market and work fewer hours if they do (Angrist and Evans 1996; Doren 2019). Moreover, women tend to choose more flexible work hours and in order to fulfill childcare duties. Yet, Ngo's (2020) research on Vietnam points out that the impact of the number of children on female labor participation is related to a women's age and education. Only young and highly educated women have a significantly lower probability of participating in work when the number of children increases. Nonetheless, the advent of more second children may decrease labor force participation and work hours of women.[5]

On the other hand, women with more children need to increase market labor time to earn more money due to higher living costs associated with additional children. The housework generated by more children is typically solved in China through the intergenerational transfer of labor. Grandparents help take care of the children (Guo et al., 2018; Posadas and Vidal-Fernandez, 2013;

[5] From the female employee side, the closer the employment interruption, the less worthwhile are investments in increasing human capital. Therefore, even before a child is born, women expecting a career interruption may choose not leave the labor market or change to a job more convenient for taking care of children.

Yu et al., 2018), allowing the mother to return to work with perhaps even greater intensity.

There may, however, be more subtle influences on the demand side. After the universal two-child policy, gender discrimination in the labor market has become more serious. It was observed that after the universal two-child policy, in the job fairs in China, women with one child were not as competitive as those with two children or as competitive as they would have been before the two-child policy. The possible explanation is that under the new universal two-child policy, women who have no children or have one child are more likely to have maternity leave than women who already have two children. From the employer's side, the cost of hiring a woman who will have maternity leave or quit in the future is relatively high[6]. Critically, in China, the cost to the employer of such leaves is not fully compensated for by the government maternity insurance. These payments fall far below the employer's costs. Thus, women who have two children are now thought to be unlikely to generate maternity costs are preferred by position formerly reserved for those with one child.

These observations from the press in China hint at this issue. The Yangzi Evening News (2016) wrote that "[A]fter the two-child policy, SMEs[7] 'upgraded' the unspoken rules that give priority to 'married and childbearing' women to give priority now to 'married, two children' women." Similarly, Bond Times (2015) wrote that employers "not prepared for the two-child policy had intensified gender discrimination against those not yet with two children." Again, such observations hint that women who previously had one child were advantaged in employers' eyes but lost that when a second child was allowed by the policy change.

Based on these thoughts, the policy change may be reflected in reduced labor force

[6] As shown in Table A1.1.

[7] Small and Medium Enterprises.

participation, attachment, or hours for women with one child. They lost their advantage in the eyes of employers relative to women without children. Moreover, women with two children might be anticipated to now appear to be the most "reliable" employees. Thus, our central hypotheses are that the two-child policy should increase the number of second children (and perhaps first children due to timing), lower the age of marriage (or increase its likelihood), and reduce the relative labor market participation and attachment of women who have one child when compared to those with no child or two children.

3 Data

We use three repeated cross-sections in our paper. They are from the nationally representative China Labor Force Dynamic Survey (CLDS) for 2012, 2014, and 2016, sponsored by the Center for Social Survey at Sen Yat-sen University and included in the Chinese social science survey platform. It covered 29 out of 31 province-level administrative areas of mainland China and was sampled by a multi-stage stratified sampling method (Gong, Luo, and Ling, 2016; Liu and Liu, 2018; Wang, Zhou, and Liu, 2017). The three waves include separate family and individual variables, including marital status, age, labor market participation, income, labor mobility. We merge the family and individual questionnaires to pair the female-related individual data with the information of their spouse and family structure.

As we investigate three issues, there are three sets of dependent variables. First, we examine the childbearing behavior of women. To do this, we create the dependent variables to show whether there is a child born after each of the successive two-child policies. Since the survey is conducted in the summertime of 2012, 2014, and 2016, children less than one-year-old are those born after

the relevant policy change.[8] The critical independent variables are policy dummies and their interaction with the treated group associated with each policy change, which is determined by parents' status, as described in Table 1.1. Controls include the presence of senior family members (grandparents), family income, first child gender (depending on specification), whether the family location is rural or urban, and the women's age, education and health self-evaluation.

Second, we investigate marriage behavior. Here the dependent variable we use is simply married or not. The sample is young men and women between 18 and 30 years old in the year 2014 survey. The policy dummy here is the 2013 policy. Other control variables are similar to the above. Critically, we recognize that different potential marriages could be influenced by the policy changes given the status of both the individual and their potential spouse, as identified in Table 1.1. Thus, we examine the 2013 policy for young men and women who are single-child in their original family. This policy change means that regardless of the status of their spouse, they will be able to have a second child. Prior to this, such a person could only have a second child is if they married another person who was also a single child.

Third, we create three labor participation variables from the survey. First, we simply examine whether or not the respondent worked in the last year. If they have worked, we examine two measures of intensity of participation. The first of those measures identifies how many days they usually work in a month. The second measures how many hours they typically work per week. This variety gives us ample opportunity to see whether women's labor force participation changed in response to the universal two-child policy introduction.

Critical controls include the daily wage in Chinese Yuan (*Wage (Yuan/Day)*), which is generated by total annual labor income divided by the total days she worked last year. This variable

[8] The calculation method of age is the year of survey minus the year of birth. Age less than one year old is a newborn..

has a history of use in Chinese labor market studies. The average daily income is 151 Yuan, which is about $21. We also imputed the missing wages for women not working by using the personal characters, including education, work experience, age, health status and region. The education years variable is calculated by the highest degree and education history. Generally, China's education system is six years in elementary school, three years in junior high school, three years in high school/vocational high school, four years in undergraduate, two or three years in postgraduate, and more than three years in doctor. Potential work experience is calculated by using age minus education years minus six years old[9]. Other family member income is the difference between the total annual family income and individual yearly total income. The first child gender is 1(one) if the first child in the family is a boy.

Table 1.2 shows the descriptive statistics of childbearing age taken to be 18 to 42.[10] We will also explore a younger age range of 18 to 38. The sample consists of relatively fewer single-child parents. Indeed, the share of families with one or both single-child parents is 13%, 15% and 17% over the three years. One single-child parents accounted for 9%, 11%, and 12% of the three-year sample, respectively. Both single-child parents have the smallest percentages, at 4% in the year 2012 and 2014, and 5% in 2016. These relatively small numbers may reflect both the timing of the one-child policy and the success of its enforcement. Thus, parents where neither were single-child in their original family are older.

<Insert Table 1.2 about here>

[9] Minimum age for employment is 16 years old.
[10] Other sources use 15-49 years old as the childbearing age range. The combination of Chinese law on underage birth and the data provided in CLDS forced our choice. Minor ethnic group parents are not included.

The data also shows that families where one or both parents were single-child in their original family, have higher household income, a greater proportion live in an urban area, and fewer children in the household. Finally, comparing the number of children in families in different years, we can find that the average number of children in the family follows the same trend for all parents. The number of children increased from 2012 to 2014 and then decreased in 2016.

4 Methodology

As we have three related hypotheses, we will briefly explain our approach to testing each separately.

4.1 Two-child policy and childbearing

We use a difference-in-difference (DID) method to estimate the coefficients of the fertility policy on whether there is a newborn child in the family after the policies. Since CLDS does not have the data before the first selective two-child policy in 2011 (which allowed families where both parents were single children to have a second child), we can only use a DID method to analyze the two subsequent policies in the year 2013 and 2015.

To evaluate the impact of the 2013 policy (which allowed families in which one parent was a single child to have a second child), we use the data of all three years, 2012, 2014, and 2016. The treated group is the families newly allowed a second child in 2013. The policy period is 2014 and 2016. The control group is the families where both parents were single children who had been allowed a second child throughout our observation period.

When estimating the universal two-child policy in 2015, we again use the data for all three years, 2012, 2014, and 2016. The treated group is the families where neither parent was a single child. Again the control group is families where both parents were single-child, and the policy

period now is only 2016.

4.2 Two-child policy and marriage

In the analysis above, our research object is the childbearing of married women. Nevertheless, the two-child policy may influence marriage decisions at the same time. Young people who can now have two children may decide to marry earlier. Indeed, if this influence is large enough, the pool of married people in the earlier analysis could substantially grow. If the newly married people are relatively less likely to have children immediately, this could even bias down the share of married people having children following the policy changes.

To examine whether the two-child policy influenced marriage decisions, we estimate whether or not the marriage rate increased after the policies were implemented. Finding appropriate treatment and control is complicated because of the variety of potential marriage partners. In short, the single-child status of a potential spouse influences whether or not one would anticipate an earlier marriage. The cleanest test we could think of uses data in the years 2012 and 2014. The sample consists of young people between 18 and 30 years old. Within this sample, the treated group are individuals who are themselves single-child. As a single child, the policy change in 2013 newly allows him/her to have a second child regardless of whom he/she marries. This was not true prior to that policy change. The control group is those in the sample who have siblings. This group is limited to finding a spouse who is a single child if they wish to have a second child once married. They hypothesize is that those for whom any spouse will allow a second child are more likely to move up a marriage than those who are more limited in spousal choices that allow a second child.

4.3 Two-child policy and female labor participation

To explore how the married childbearing age women's labor market participation varies by the number of children, we estimate the following model separately by the number of children that the women have, zero, one or two.

$$Y_{it} = X_{it}\beta + 1\{t = 2014\}\gamma_1 + 1\{t = 2016\}\gamma_2 + \varepsilon_{it}$$

In the equation, Y_{it} is the employment status of specific women in one of our three years. It is proxied with the dummy variable indicating whether or not she has worked for money in the last year.[11] If the answer is yes, we then estimate variants of the equation that measure the typical working days per month and the typical working hours per week. These measure the intensity of participation. Individual and household socioeconomic characteristics are in X_{it}. Individual variables are age, education, health status, and wage. Household variables are the number of preschool-age children in the family, other family member income, and family locates in a rural area or not. The wage rate of women who are not involved in the labor market cannot be observed. So we impute the missing values of daily wages. The regressors of imputed wages are experience, education, living in an urban or rural area, health self-evaluation, marital status, number of children, communist or democratic party member. Possible experience is age minus education years.[12]

If hypothesis 3 holds, the pattern of coefficients on the period dummies should look different for women with one child. They should lose their favored status of being more "reliable" in the employer's eyes relative to those with no children, who might always be viewed as less reliable and relative to those with two children who will now be viewed as the more reliable. Thus, there should be declines over time in the participation and intensity of participation for one child mothers

[11] The timing of the survey and the dates of the policy announcement make it possible that in some cases a women may have worked prior to the announcement but within the year. This obviously introduces measurement error if she withdrew in response to the announcement and yet would still be included as working.

[12] Minimum age to work is 16

relative to other women.

5 Results

We now turn to the results of testing each of the three related hypotheses.

5.1 Two-child policy and childbearing

Table 1.3 shows the results when the dependent variable is whether or not the family had a second child after the policy. The OLS models with control variables in columns 3 and 4 have better r-squared than the models in columns 1 and 2 without control variables.[13] According to the coefficients on the control variables, younger people and those with higher education are more likely to give birth to a child after the 2013 selective two-child policy. In terms of the 2015 universal two-child policy, women with more education and those living with seniors (grandparents) are more likely to have a newborn after the policy. Other control variables do not typically have significant effects.

Column 3 shows examine the influence of the 2013 policy that allowed those with one single parent in their original families to have a second child. The control is families with two single parents in their original families as these families were allowed a second child throughout the sample period. The probability of newborns in all the families decreased by 16.5% in the years after the policy. The coefficient on the difference-in-difference term *Policy2013* one single-child* is not statistically different from zero. This shows that the treatment group (families with one single-child parent) did not significantly increase their births relative to the control group (both single-child parents) after the policy change.

[13] None of the critical results shown in this subsection vary in general size or statistical significance if they are estimated using probit (available upon request).

Column 4 examines the universal two-child policy in 2015 that allowed those with no single children in their original families to have a second child. Again, this treatment group is compared to two single-child parents who were allowed a second child through the sample period. The results show a decreasing tendency to have children with time. The treated group also has significantly fewer newborns, as would be anticipated as families in the control group who have been allowed to have two children for some time. The difference-in-difference term shows a significant and positive effect on the probability of having a child. This shows that families in which neither parent was a single-child (the group influenced by the 2015 change) were more likely to have a second child within the months after the policy change relative to the control, families eligible to have two children throughout our sample period. The average increase in the probability of having a second child within one year after the 2015 policy change is 13.6% in this treated group relative to the control. This is a substantial as well as a statistically significant increase.

<Insert Table 1.3 about here>

We also tried to pool all the data to measure the impact of the two-child policy as a whole on having a second child. This model includes parental type fixed effects and year fixed effects in order to focus on the policy. The policy variable takes the value of 1 (one) for all three years for families with two single-child parents. It takes a 0 (zero) in the first year and 1 (one) in the next two years for families with one single-child parent. It takes a zero for the first two years and one for the last year for those without a single-child parent. The result in Table A2 shows insignificant policy variables. This suggests that the policy influence is limited to the result isolated in Table 3. Those families without a single-child parent are more likely to have a second child in response to

the policy. The substantial increase in the second child for the both single-child parents group might hide an influence on hurrying to have a first child. To reflect this influence, we now turn to examine the influence of the policy on both first and second children.

Table 1.4 estimates the policy impact on a new birth in the family after the policy. This child can be either a first or second child. The sample was expanded to families with one child or no children before the two-child policy. Again, we anticipate both a direct influence on having a second child and also that the two-child policies may also impact first birth patterns for families without any children. When families expect to have two children instead of one, the plan to have the first child may be advanced to allow time for the second.

It follows from an expanded estimation from Table 1.3. The added independent variables are the interaction of the difference-in-difference variable with whether or not the family has one child not born in the last year. Adding this variable means that the original coefficient on the difference-in-difference variable influences having a first child, and the sum of the coefficient on that original interaction and the new interaction is the influence on having a second child.

<Insert Table 1.4 about here>

Table 1.4 shows that both the two-child policies in 2013 and 2015 significantly impacted the new births. Both regressions without and with control variables have the same signs of coefficients, but the latter regressions have the better adjusted R^2.

According to the third regression in Table 1.4, one single-child parent families are 40.9% more likely to have their first child right after the 2013 policy change than both single-child parent families. However, the policy effect on giving birth to the second child right after the policy is not

significant. Again, this may reflect a moving up of the first birth to accommodate an eventual second birth.

In the fourth column, the treated group of families where neither parent is a single-child can be contrasted with the control of families where both parents were single children. The treated group is 30.7% more likely to have their first child. However, the policy effect on giving birth to the second child right after the policy is not significant.

Based on these results, we believe that the two-child policies have significantly impacted family birth decisions. In both policy experiments, we found an increased probability of first childbirth for the treated group. This suggests that the policies pushed up the timing of the first child likely in anticipation of a second child. The 2015 policy change had an independent influence that increased the probability of having a second child. This is the direct result anticipated given the policy, and its magnitude is large. We recognize these are relatively short term results given the nature of the data, and additional testing is warranted to find longer-term responses. Nonetheless, just as implementing the one-child policy was found to reduce childbirths, the early indications are that relaxing the one-child policy with a two-child policy has increased childbirths.

5.2 Two-child policy and marriage

Table 1.5 shows the estimation results of whether the selective two-child policy that began in 2013 has an impact on whether young people get married or not. Since 2013, only if one of the couples is single-child they can have two children. So we treat young people[14] who are single-child as the treatment group and those with siblings as the control group. If the policy impacts marriage decisions, then the single-child people in 2014 are more likely to be married than in 2012.

[14] Age 18 to 30, both men and women.

The sample includes young people in the year 2012 and 2014 between the ages of 18 and 30, which is the first marriage age range for most people. The dependent variable is a dummy variable, so we use probit regression and also use OLS regression as a reference. All regression coefficients are marginal effects.

The regression results in the first two columns include only the key independent variables, policy year, whether the respondent is single-child, and the interaction term of the policy year and single-child (*Policy2013* Single-Child*). On average, the sample population had a 2% lower marriage rate in 2014 than in 2012, while the single-child young people's marriage rate was 1.1% lower than that of non-single-child. However, the coefficient of *Policy2013* Single-Child* is not significant, i.e., the effect of the two-child policy in 2013 on the single-child marriage possibility is not significant.

The third and fourth regressions include not only policy-related variables but also other control variables that affect marital status: gender, age, education, and whether or not living in rural areas. After adding control variables, pseudo R^2 has been improved. According to the regression results, younger people, people with higher education and are urban areas citizens are less likely to be married. Without *Single-Child* and *Policy2013*Single-Child* variables, the policy year variable coefficient is significantly negative; specifically, the probability of getting married in 2014 is 5% lower than that in 2012. However, when we add treatment group and policy variables into the model, the coefficients of policy-related variables are no longer significant. Therefore, it cannot be verified that the two-child policy has an impact on fertility decisions. [15]

[15] This conclusion prevents a potential bias in estimating the impact of the two-child policy on fertility. If we assume that newly married people are less likely to have children immediately, then when the two-child policy leads to an increase in newly married women, the impact of the policy on fertility will be underestimated. However, in this article, because policy changes did not increased the short-term marriage rate, there is no need to worry about this bias.

<Insert Table 1.5 about here>

5.3 Two-child policy and female labor participation

Table 1.6 and Table 1.7 show statistical descriptions of the variables of female labor market participation. The sample is 18 to 42 years old married women. Women who worked since last year account for 82% of the sample. Among those who had a job, they worked on average 24 days per month and 38 hours per week. There are the fewest observations for married women without children (*zero-child women*) in our sample. Generally, women without children have higher labor participation and longer work hours. Women with one child have the highest daily wage, 169 *yuan/day*. The average education years for women with two children is 7.8 years, which is much lower than the other two groups, which exceeds ten years.

<Insert Table 1.6 about here>

<Insert Table 1.7 about here>

Table 1.8 estimates the labor participation of women with different numbers of children in different years. This estimation is a linear probability model. For all the groups, women with a college degree are more likely to have been working in the previous year. From the regression results, the higher the wage/imputed wage, the more likely women are not to work. Moreover, compared with 2012, the likelihood of employment in 2014 and 2016 increased significantly.

An imperfect sense of the universal two-child policy in 2015 on female labor participation can be seen by comparing the coefficients of time dummies for 2014 and 2016. These two values are virtually identical for women with zero, one or two children. None of these differences is

near statistical significance.

The significant patterns in labor force participation come from comparing 2012 with either 2014 or 2016. For all groups of women, labor force participation increased. It increased most for the women with two children, 0.25, perhaps because they became to be viewed as the most reliable. The next largest increase was, however, for those with one child, 0.22. This does not seem consistent with the idea that they suddenly became markedly less reliable. One would anticipate their labor force participation decrease or at least increase the least. The smallest increase is for women without children, 0.15. These women would have always been viewed as unreliable. However, it seems that a young woman with zero child has perhaps resulted in them viewed as relatively even less reliable.

While late in life, births may be unlikely, they could represent influential observations. Perhaps employers feel the younger group may be particularly responsive to policy changes. As a robustness check, a sample of women 18 to 38 was examined. As Appendix Table A1.4 and Table A1.5 show, there remains no support for the hypothesis that women with one child have become disadvantaged as a result of the policies.

<Insert Table 1.8 about here>

In addition to the extensive margin, we estimate the intensive participation margin. The sample in Table 1.9 consists of women 18 to 42 years old who have worked in the past year, and the dependent variables are typical working days per month and the usual working hours per week in a recent job.

As we can see from the first result, the workdays per month of married women without

children did not have significant change across the three years. The workdays for women with one child increased by 0.71 in 2014, but this increase vanished in 2016. Women with two children worked fewer days in both 2014 and 2016 than 2012 with the entire declining being about 1.34 day per month. This presents a complicated picture of women with two children having both the largest increase in simple participation but a decline in days per month.

<Insert Table 1.9 here>

The working hours per week shows a general downward trend. The overall declines from 2012 to 2016 are 6.4 hours for women with no children, 4.7 hours for women with one-child and 7.4 hours for women with two children. All of these declines are statistically significant. This pattern is particularly hard to reconcile with employers being reluctant to hire and give full-time hours to women with one child. In a period of declining hours of work for women, the decline for women with one child appears the smallest.

In a robustness check, median regression was estimated. The concern is that the typical point of means associated with regression might not be representative. Yet, the estimates in Table A3 remain consistent with the original regressions in Table 1.9. The first three columns show that the timing of the universal two-child policy did not significantly decrease the usual monthly workdays of women with one child. The second three columns also mimic the original regressions by showing that the working hours per week generally decline for all women over the time window. Moreover, the decline for women with one child is smaller than that for women with two children. On balance, there continues to be no evidence of the employer behavior hinted at in the press about the job fairs. One child women do not seem to have lower

employment workdays or hours.

In short, neither the participation decision nor the extent of participation provides support for their hypothesis that employers will change their beliefs about the reliability of women with one child. Again, it is particularly hard to tie the estimation to the exact policy year changes as the employers know how many children a female applicant or employee has but do not know the single child status of the applicant and her spouse. Thus, the test is simply one of the evolution patterns as it becomes the case that more women, and eventually, all women, can have a second child.

6 Conclusion

This paper focused on the behavioral responses of women to the relaxing of China's one-child policy and its replacement with an eventually universal two-child policy. It examined married women's childbearing decisions, young people's marriage decisions and women's labor participation under the policy change. In each, the object was to see if a behavioral response could be tied to the timing of the role out of the two-child policy.

Perhaps the most dramatic results were on fertility. Both the two-child policies in 2013 and 2015 increased the probability of having children in the short term immediately after the policy. In 2013 it seemed to be an influence on only first children. Nevertheless, the 2015 policy was also associated with a significantly increased probability that families, where neither parent was a single-child, had a second child. This was compared to the control of families where both parents were single-child. The control group was allowed to have a second child throughout the sample period.

The efforts to examine the marriage market returned no significant patterns of interest. The

policy that allowed families with one single-child parent to have two children happened in 2013, but it did not significantly increase the probability of marriage for young people who were a single child. This group we suspected would be most influenced as following 2013, and they were allowed to have a second child regardless of the status of their spouse. No influence on marriage age or likelihood was found.

Finally, in the process of gradually changing from the one-child policy to the two-child policy, women with one child may have been perceived as increasingly unreliable. They became eligible for maternity leave and long absences that would not have been associated with women with a single child before the policy. While employers typically know the number of children of their applicants, they do not know whether the employees are eligible for the "selective two-child policy". Thus, it was anticipated that over the course of the three waves, employers would reduce the hiring hours of women with one child, relative to either no children mothers (always less reliable) or two children mothers (who would be anticipated to have no more children). We could not find that the labor participation nor the labor attachment influenced in a fashion consistent with this hypothesis.

Future work could be improved by access to fully longitudinal data that followed women year by year rather than this paper's use of a repeated cross-section. Also, knowing the exact working dates of women within each year and the exact dates of the birth of their children would allow a better match between the policy dates and the critical dependent variables. Nonetheless, the finding that the two-child policy appears to have significantly increased childbirth stands as a notable finding upon which future studies can build.

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Chapter 1 Figures and Tables

Table 1. 1 When a second child was allowed based on the parent's status

	Both parents single-child	One parent a single-child	Neither parent a single-child
2011	Two children	One child	One child
2013	Two children	Two children	One child
2015	Two children	Two children	Two children

Table 1. 2 Descriptive statistics for married women of childbearing age (18-42)

Neither single-child parents						
	2012		2014		2016	
	Mean	Sd	Mean	Sd	Mean	Sd
Age	34.34	5.73	34.65	5.70	34.55	5.67
Edu years	9.49	3.70	9.07	3.97	9.18	3.93
52 to 69 years old family member (dummy)	0.18	0.38	0.33	0.47	0.32	0.47
Family income (yuan)	48636	47874	63134	73175	69965	82044
Location (rural=1, urban=0)	0.55	0.50	0.58	0.49	0.57	0.50
Number of children	1.37	0.57	1.46	0.53	1.42	0.60
N	1288		1612		1344	
One single-child parents						
	2012		2014		2016	
	Mean	Sd	Mean	Sd	Mean	Sd
Age	31.15	5.13	34.01	5.22	32.81	5.45
Edu years	11.56	3.84	11.18	4.24	11.90	3.97
52 to 69 years old family member (dummy)	0.19	0.40	0.33	0.47	0.31	0.46
Family income (yuan)	64687	68073	89587	152693	105560	122373
Location (rural=1, urban=0)	0.39	0.49	0.38	0.49	0.31	0.46
Number of children	1.01	0.59	1.20	0.44	1.13	0.61
N	134		214		186	
Both single-child parents						
	2012		2014		2016	
	Mean	Sd	Mean	Sd	Mean	Sd
Age	30.48	4.91	32.62	4.40	31.80	4.77
Edu years	13.13	3.63	12.69	3.27	13.22	3.77
52 to 69 years old family member (dummy)	0.21	0.41	0.27	0.45	0.21	0.41
Family income (yuan)	85553	70241	92639	88441	150049	208779
Location (rural=1, urban=0)	0.19	0.40	0.25	0.44	0.16	0.37
Number of children	0.73	0.60	1.13	0.44	0.91	0.66
N	52		71		81	

Table 1. 3 Difference-in-differences (DID) estimates of the effect of policies on the second child (married women, 18 to 42 years old)

Policy	**2013**	**2015**	**2013**	**2015**
Treatment group	**1 single-child**	**0 single-child**	**1 single-child**	**0 single-child**
Control group	**2 single-child**	**2 single-child**	**2 single-child**	**2 single-child**
Policy2013	-0.141**		-0.165**	
	(0.0673)		(0.0771)	
Policy2015		-0.154***		-0.146**
		(0.0505)		(0.0606)
One single-child parents	-0.117*		-0.118	
	(0.0680)		(0.0790)	
Neither single-child parents		-0.156***		-0.151***
		(0.0391)		(0.0432)
Policy2013* one single-child parents	0.0895		0.0937	
	(0.0759)		(0.0873)	
Policy2016* neither single-child parents		0.145***		0.136**
		(0.0514)		(0.0611)
Control variables				
Age			-0.963***	-0.0647
			(0.0651)	(0.308)
Age groups (3 years)				
Age*age groups (3 years)				
Edu years			0.00146	0.00453***
			(0.00650)	(0.00147)
Edu years*collegesome			0.00748**	0.0000272
			(0.00320)	(0.00110)
52 to 69 years old family member (dummy)			-0.0136	0.0232**
			(0.0299)	(0.0113)
Family income (yuan)			-7.99e-08	-0.000000119
			(8.49e-08)	(7.38e-08)
Location_rural			-0.0237	0.00807
			(0.0331)	(0.0103)
First child gender (1=boy, 0=girl)			0.00601	-0.0138
			(0.0280)	(0.00902)
Cons	0.286***	0.244***	19.44***	2.015
	(0.0605)	(0.0387)	(1.293)	(6.085)
N	715	4192	592	3761
Adj. R^2	0.012	0.008	0.239	0.164

Notes: The dependent variable is the presence of a newborn, identified by a child less than one year old in the household. We use the data of all three years, 2012, 2014 and 2016.
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1. 4 Difference-in-differences (DID) estimates of the effect of policies on childbirth (married women, 18 to 42 years old)

Dependent variable	**Any child age <1**			
Policy	**2013**	**2015**	**2013**	**2015**
Treatment group	**1 single-child**	**0 single-child**	**1 single-child**	**0 single-child**
Control group	**2 single-child**	**2 single-child**	**2 single-child**	**2 single-child**
Policy2013	-0.138*		-0.161*	
	(0.0713)		(0.0856)	
Policy2015		-0.159***		-0.119*
		(0.0557)		(0.0694)
One single-child parents	-0.103		-0.122	
	(0.0727)		(0.0877)	
Neither single-child parents		-0.123***		-0.130***
		(0.0421)		(0.0471)
Policy2013* one single-child parents	0.293***		0.409***	
	(0.0995)		(0.117)	
Policy2015* neither single-child parents		0.263***		0.303***
		(0.0659)		(0.0810)
Policy2013*one single-child *child before 2013	-0.268***		-0.371***	
	(0.0623)		(0.0633)	
Policy2015*neither single-child * child before 2015		-0.146***		-0.222***
		(0.0365)		(0.0427)
Linear combinations of parameters				
Policy2013; one single-child; second child	0.025		0.038	
	(0.082)		(0.098)	
Policy2015; neither single-child; second child		0.117*		0.081
		(0.058)		(0.071)
Control variables				
Age			-0.0369	0.238
			(0.0247)	(0.311)
Age groups (3 years)			Yes	Yes
Age*age groups (3 years)			Yes	Yes
Edu years			-0.00121	0.00298
			(0.0102)	(0.00315)
Edu years*collegesome			0.00612	-0.000902
			(0.00418)	(0.00156)
52 to 69 years old family member (dummy)			-0.0190	0.0278*
			(0.0351)	(0.0169)
Family income (yuan)			-4.48e-08	-0.000000132
			(0.000000104)	(0.000000119)
Location_rural			-0.00334	0.0376**
			(0.0405)	(0.0164)
First child gender (1=boy, 0=girl)			0.00356	-0.0540***
			(0.0318)	(0.0151)
Cons	0.302***	0.263***	1.849***	-3.865
	(0.0633)	(0.0413)	(0.464)	(6.172)
N	606	2568	492	2258
Adj. R^2	0.050	0.013	0.290	0.206

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1. 5 Probit regressions of the effect of the selective two-child policy in 2013 on married or not (men and women, 18 to 30 years old)

Policy			2013	
Data			2012, 2014	
Treatment group			Single-child	
Control group			Not single-child	
Policy2013	-0.0208*	0.00446	-0.0510***	-0.0142
	(0.0112)	(0.0377)	(0.00803)	(0.0320)
Single-child		-0.108*		-0.0349
		(0.0576)		(0.0493)
Policy2013* single-child		0.00285		0.0157
		(0.0708)		(0.0587)
Control variables				
Gender			-0.159***	0.0618**
			(0.00707)	(0.0264)
Age			0.0587***	0.0688***
			(0.00476)	(0.0166)
Age groups (3 years)			Yes	Yes
Age*age groups (3 years)			Yes	Yes
Edu years			-0.0159***	-0.0229**
			(0.00200)	(0.00904)
Edu years*collegesome			-0.00732***	-0.00122
			(0.000893)	(0.00365)
Location_rural			0.0610***	0.145***
			(0.00790)	(0.0303)
Cons				
N	9366	1034	9352	1033
Pseudo R^2	0.000	0.007	0.425	0.263

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1. 6 Summary statistics of female labor participation variables of married women, 18 to 42 years old

Variable	Obs	Mean	Std. Dev.
Worked since last year	4,933	0.82	0.39
Usual Work days/month	4,005	24	7
Usual hours/week	4,918	38	26
Wage (yuan/day)	3,980	122	234
Imputed wage (yuan/day)	4,415	151	634
Edu years	5,345	9.67	3.93
Collegesome	5,345	0.2	0.4
Age	5,521	34.19	5.67
Health	5,520	3.27	1.18
Family member income	4,381	41621	71992
Preschool children at home	5,521	0.4	0.58
Location_rural (rural=1, urban=0)	5,517	0.55	0.5
Year 2014	5,521	0.36	0.48
Year 2016	5,521	0.31	0.46
One child	5,521	0.53	0.5
Two child	5,521	0.41	0.49
Senior age 52 to 69 (dummy)	5,521	0.49	0.78
First child gender (1=boy, 0=girl)	5,190	0.55	0.5
Farming	5,521	0.35	0.48
Party member	5,521	0.06	0.24

Table 1. 7 Statistical comparisons of married women between 18 and 42 years old with different numbers of children

	Zero child			One child			Two children		
Variable	**Obs**	**Mean**	**Std. Dev.**	**Obs**	**Mean**	**Std. Dev.**	**Obs**	**Mean**	**Std. Dev.**
Worked since last year	270	0.86	0.35	2,658	0.83	0.38	2,005	0.79	0.41
Usual Work days/month	231	24	5	2,195	24	6	1,579	24	7
Usual hours/week	270	39	21	2,649	38	25	1,999	38	29
Wage (yuan/day)	229	157	171	2,180	139	230	1,571	93	244
Imputed wage (yuan/day)	232	141	265	2,419	169	649	1,764	127	647
Edu years	296	12.31	3.85	2,888	10.78	3.74	2,161	7.83	3.39
Collegesome	296	0.47	0.5	2,888	0.28	0.45	2,161	0.05	0.21
Age	302	29.77	5.55	2,946	33.99	5.61	2,273	35.05	5.46
Health	302	3.04	1.29	2,946	3.34	1.16	2,272	3.21	1.18
Family member income	248	51998	77215	2,365	46482	78254	1,768	33663	60916
Preschool children at home	302	0.04	0.25	2,946	0.33	0.5	2,273	0.52	0.68
Location_rural (rural=1, urban=0)	302	0.3	0.46	2,942	0.43	0.49	2,273	0.74	0.44
Year 2014	302	0.11	0.31	2,946	0.38	0.48	2,273	0.37	0.48
Year 2016	302	0.5	0.5	2,946	0.29	0.45	2,273	0.32	0.47
One child	302	0	0	2,946	1	0	2,273	0	0
Two child	302	0	0	2,946	0	0	2,273	1	0
Senior age 52 to 69 (dummy)	302	0.4	0.74	2,946	0.5	0.79	2,273	0.5	0.77
First child gender (1=boy, 0=girl)				2,936	1	0	2,254	0	1
Farming	302	0	0	2,946	0	0	2,273	1	1
Party member	302	0.11	0.31	2,946	0.09	0.29	2,273	0.02	0.14

Table 1. 8 Linear probability estimation of female labor participation of married women, 18 to 42 years old

	Zero child	One child	Two children
Wage (1000 yuan/day)	0.00543	0.0106	0.0215
	(0.0625)	(0.0188)	(0.0241)
Wage square	-0.00924	-0.0604***	-0.0583***
	(0.0219)	(0.00819)	(0.0105)
Edu years	-0.0133	-0.000197	0.00116
	(0.0114)	(0.00208)	(0.00178)
Collegesome	0.179**	0.0542***	0.0455**
	(0.0747)	(0.0150)	(0.0206)
Age	0.0674	0.0290**	0.000718
	(0.0441)	(0.0137)	(0.0140)
Age_sq	-0.00102	-0.000423**	0.0000138
	(0.000691)	(0.000198)	(0.000203)
Health	0.0107	0.00424	-0.00685
	(0.0174)	(0.00608)	(0.00669)
Family member income	-0.0193	-0.00997*	-0.0218***
	(0.0181)	(0.00536)	(0.00606)
Preschool children at home	0.0105	-0.0458***	-0.0359***
	(0.0318)	(0.0140)	(0.0134)
Location_rural (rural=1, urban=0)	-0.0244	0.0116	-0.0154
	(0.0401)	(0.0116)	(0.0147)
Year2014	0.153***	0.172***	0.219***
	(0.0417)	(0.0134)	(0.0208)
Year2016	0.151***	0.173***	0.201***
	(0.0539)	(0.0174)	(0.0221)
Year2016-year2014	-0.002	0.014	-0.018
	(0.043)	(0.011)	(0.012)
_cons	0.0275	0.432*	1.012***
	(0.706)	(0.234)	(0.252)
N	202	1964	1310
Adj. R2	0.119	0.395	0.350

Notes: These estimates use the imputed wage for women that did not work in the previous year.
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1. 9 OLS estimation of the extent of labor participation of married women, 18 to 42 years old

	Recent Usual Days/Month			Recent Usual Hours/Week		
Variable	**Zero Child**	**One Child**	**Two Children**	**Zero Child**	**One Child**	**Two Children**
Wage (1000 yuan/day)	-4.157	-15.91***	-11.11***	39.75**	-6.810	-4.919
	(5.014)	(2.283)	(2.660)	(17.77)	(5.128)	(6.473)
Wage square	2.304	5.041***	1.245**	-31.65*	3.143	-1.074
	(4.355)	(1.720)	(0.524)	(16.15)	(2.685)	(1.339)
Edu years	-0.441***	-0.0292	-0.0422	-1.467**	-0.626***	0.106
	(0.146)	(0.0645)	(0.0682)	(0.580)	(0.236)	(0.229)
Collegesome	0.716	-1.048**	-0.448	0.788	-4.013***	-5.806*
	(1.091)	(0.435)	(0.796)	(3.589)	(1.416)	(2.990)
age	0.538	0.359	0.246	0.724	-0.251	-1.472
	(0.763)	(0.375)	(0.578)	(2.259)	(1.255)	(1.509)
Age_sq	-0.00755	-0.00590	-0.00529	-0.00800	-0.000607	0.0180
	(0.0126)	(0.00545)	(0.00841)	(0.0367)	(0.0182)	(0.0223)
health	-0.285	-0.0827	-0.168	-0.0753	-1.484***	-1.009
	(0.520)	(0.155)	(0.231)	(1.287)	(0.534)	(0.783)
family member income	0.305	0.185	0.398*	0.143	-0.203	0.594
	(0.293)	(0.165)	(0.222)	(1.169)	(0.522)	(0.755)
Preschool children at home	-0.555	-0.871**	-0.433	-3.417	-1.500	-2.583**
	(2.353)	(0.369)	(0.400)	(4.960)	(1.180)	(1.183)
Location_rural	-0.435	-0.367	-1.521***	0.246	-2.220**	-3.566**
	(0.741)	(0.304)	(0.399)	(2.538)	(1.035)	(1.498)
Year2014	-0.177	0.758***	-0.685	0.217	-1.158	-4.688***
	(0.822)	(0.291)	(0.467)	(3.311)	(1.011)	(1.681)
Year2016	-2.035	-0.109	-1.265**	-6.648*	-4.661***	-7.457***
	(1.408)	(0.447)	(0.619)	(3.715)	(1.491)	(2.168)
Year2016-Year2014	-1.86	-0.86**	-0.58	-6.86	-3.50**	-2.77
	(1.54)	(0.41)	(0.63)	(4.40)	(1.4)	(2.1)
Cons	19.37*	19.43***	21.92**	46.64	74.06***	80.93***
	(11.32)	(6.437)	(9.945)	(35.10)	(21.65)	(26.75)
N	186	1771	1185	186	1771	1184
Adj. R2	0.066	0.137	0.055	0.092	0.063	0.021

Note: Sample is women who worked last year.
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Chapter 2

Ancillary Services and Loan Repayment in Microfinance

1 Introduction

This essay examines a microfinance organization in Milwaukee, Wisconsin, to determine whether ancillary services such as training and consulting can improve repayment behavior[16]. Such services have been thought to be crucial in developed countries because more traditional methods from developing countries to encourage repayment (group and social pressure) are often infeasible.

The organization studied provides such services to varying degrees to various clients, and this variation is the source of identification. This variation originates both from the borrower, who may ask for help, and the lender, who may provide it without being asked. While this raises various selection concerns, the primary results seem interesting. Those clients receiving greater services are less likely to miss payments than those receiving fewer ancillary services. Yet, under greater scrutiny (including within client estimates), this remains true only for those who enter the program with higher credit scores. The implications of this result are discussed.

In what follows, the next section provides relevant background from the literature on microfinance. It is careful to distinguish between lessons from developing and developed countries. This sets the stage for my case study, which is described in the third section. The fourth section provides the data from the case study and presents the methodological approach. This approach will use both disaggregate monthly data and aggregated to the client data. The fifth section presents the results, does robustness checks and addresses issues of selection. The final section concludes

[16] The author is grateful to the Women's Business Initiative Corporation (WWBIC) for providing data for the current research. The data is strictly anonymous. The author is not provided with any information to find out the names or other personal information of the WWBIC clients.

and presents policy suggestions.

2 Background

The rise of microfinance organizations (MFOs) is based on the premise that lack of access to credit and other formal financial services are severe constraints on the growth of micro-enterprises. With the credit from MFOs, microentrepreneurs can start or continue their business activities, thereby raising household income levels, increasing employment opportunities, and promoting local economic development. Clients of MFOs often lack qualified collateral, which means that lenders are less sure that borrowers will repay their loans.[17] This, combined with information asymmetry, locks many small borrowers out of the formal financial market. It also leads to the fear that the risk of default by borrowers in microfinance will be substantially higher. In turn, this fear has resulted in many institutional approaches by MFOs design to increase the chance of long-term success and repayment by their borrowers even without collateral. The success of these approaches helps determine the success of MFOs and, ultimately the growth in small businesses.

Joint liability combined with dynamic incentives is the common approach to increase the success of microfinance. These two institutions are designed to elicit greater information from potential lenders and so reduced information asymmetry (Galariotis, Villa, and Yusupov 2011). Joint liability in the form of group lending was an essential innovation of MFOs in developing countries. For instance, in Bangladesh, community leaders divide potential borrowers into small groups. Group members are required to have regular meetings and have joint liability in microcredit. Thus, if one member cannot meet his or her repayment obligation, other members must bear the repayment of the defaulter if they want to continue borrowing from the lender. Through these institutionalized relationships, MFOs take advantage of local information, peer

[17] The lack of qualified collateral is the most crucial reason for formal commercial banks to reject loan applications.

support, and peer pressure to gain additional information and reduce the risk and cost of default.

Group liability is typically paired with dynamic incentives. MFOs start with very minimal loans and gradually increase the loan size as borrowers demonstrate reliability in repayment. Many of the banks, especially in developing countries, even schedule the first payment just a week after the initial loan disbursal and continue weekly after that; this makes the contract look much closer to a consumer loan than a business loan and changes the nature of the risk that the bank is taking on. It often results in regular communication between the MFO and borrowers that less frequent and more arms-length repayment would not.

Group lending approaches in developed countries have not performed well (Chatterjee et al. 2006). For instance, in the United States, most of the first programs copied group lending as conceived in Bangladesh, but have since switched to focus on individual loans (Schreiner and Morduch 2001; Schreiner and Woller 2003). Less than one-sixth of US microenterprise programs make loans to groups (Schreiner 2001). The possible reasons for the lack of success are that in more anonymous markets, borrowers do not know each other and have fewer shared bonds and care less about group reputations. This problem is made worse as the purpose of loans in the United States is more diversified, making it more difficult to find an appropriate peer group of borrowers undertaking similar enterprises. In short, there has been less learning about particular risks and less peer support and pressure in US implementations of group liability.

A primary concern in developed countries in making use of individual loans is the limited human capital of microfinance borrowers. Thus, besides financial constraints, potential borrowers are likely to lack business skills and business experience, which also makes microcredit borrowers a high-risk group. Because group liability has not helped transfer skills, other approaches have emerged. Thus, MFOs in developed countries spend considerable resources on so-called "ancillary

services" that are designed to improve the human and social capital of borrowers. The thought is that providing these services can play an essential role in improving the borrowers' capacity and willingness to repay loans.

Ancillary services take various forms, including business consulting, training, teaching financial literacy (Sayinzoga, Bulte, and Lensink 2016; Schreiner and Morduch 2001), and even psychological consulting. These services help microentrepreneurs accumulate business knowledge, improve their business profits, and increase a sustainable cash flow increasing the ability to repay the loans. This may be especially important for microenterprises in developed countries, where market competition is more severe than less developed economies, and the gaps in education and social capital may be more substantial. In addition to simply building up human and social capital, the provision of ancillary services has been thought to increase the satisfaction of clients. They recognize they are being given tools and see the MFO as part of their team. This builds a strong feeling of reciprocity. Borrowers are less likely to default if they such a sense of responsibility and good will toward the lender. The hope is that they will also seek assistance if troubles develop.

Despite the theory that ancillary services should increase repayment behavior, the existing evidence on its impact is unsettled. Some empirical research demonstrates that training and consulting have a positive effect on the business performance of participants who got loans from microfinance organizations (Abeysekera 2015; Bjorvatn and Tungodden 2009; Rama 2016), while some others suggest that the effect of training and consulting is less clear – in some circumstances positive but other cases simply no influence (Fairlie, Karlan, and Zinman 2015; Mckenzie and Woodruff 2012). Those who find an absence of an effect may be correct in their cases. However, the literature is often not successful in dealing with the extent of heterogeneity or/and selection problems.

Thus, in some cases, the treated group appears to be those least likely to benefit and most likely to succeed (Aakvik, Heckman, and Vytlacil 2005). This cream-skimming exists when those who would do well, in any event, are provided the ancillary services. For this reason, programs that offer mandatory training to all may provide a more accurate measure of success(Paul 2014). This increases the cost of training borrowers (Bhatt and Tang 2001) and may even cause those costs to exceed the social benefits of training (Friedlander, Greenberg, and Robins 1997; Lalonde 1995).

Recent studies have overcome the selection bias problem in the measurement of ancillary services effect by using econometrics methodologies or randomized control experiments. Instrumental variables and latent variable models are widely used in identifying the treatment effects of training. In developing countries, Karlan et al. (Karlan and Valdivia 2011)used a randomized control experiment to prove that business services have little or no evidence on change of business revenue, profits, or employment. Instead, they observed the improvement of business knowledge and customer retention in the treatment group. Berger et al. (2014) argue that business training combined with financial services improves business outcomes for male microentrepreneurs in Tanzania, but not significantly so for female microentrepreneurs. Fewer random controlled studies exist in developed countries. In one notable study, Fairlie et al. (2015) find no long-lasting effects of business training in the United States for individuals who are potentially subject either to credit or human capital constraints or to discrimination in the labor market.

Similarly, Créponetal did not identify significant positive impacts in terms of business outcomes for participants (Kluve et al. 2017). One explanation of training from microfinance organizations (MFOs) has a small influence on increasing income of the low-income family is that

they already have survival skills and do not need to be trained. However, Heckman, Lalonde, and Smith (1999) propose that training from government or other organizations generates small benefits because per-capita expenditures of training are comparatively small, and in general, these programs target relatively unskilled and less able individuals. Another reason why the ancillary service effect in experiments is not significant may be that the borrowers' interactions are not considered in the experimental design. Beyond business outcomes, few studies have focused on the relationship between ancillary services and loan repayment performance. Karlan and Valdivia (2011) find that training improves perfect repayment[18]. However, Giné and Mansuri find that training has no significant impact on repayment rates for microfinance clients in rural Pakistan (McKenzie and Woodruff 2014).

In empirical studies, researchers use different ways to measure repayment performance. Some of them use the share of the money borrowed that is eventually actually repaid. Others use the number of times a payment is missed. Repayment on time suggests good business performance and cash flow. Frequent failure to meet payments means the borrower faces difficulties in running their business. One regularity from past studies is that a substantial share of borrowers eventually repay loans, although this is often happening after the actual end of the loan. Thus, delays in payments occur much more frequently than "loan loss." Following this previous literature, we use the missed payments to quantify the microentrepreneurs' repayment performance.

It is also the case that most previous studies examining ancillary services evaluate the influence of a scheduled large class or classes in improving loan performance. Sustaining one-to-one consulting services have not previously been examined. However, the hope is that such on-going and personal attention will lead to a deeper and closer relationship between the financial

[18] A client is said to have had a perfect repayment record if her payments over the cycle plus her savings were always enough to cover the amount borrowed plus interest.

organization and its clients (Haim et al. 2007). Again, this assistance by the MFO may help improve borrowers' repayment through two channels. First, training and consulting may deliver the business knowledge and skills the clients need. Flexibly and easily scheduled one-on-one consulting can help those who need assistance get it on time. Second, repeated consulting increases the borrower's satisfaction and generates reciprocity. This makes borrowers more willing to pay back on time (Ibtissem and Bouri, 2013; Tchakoute-Tchuigoua and Soumaré, 2019). In this paper, we will test the influence of consulting services on repayment behavior.

3 Institutional setting and intervention

The Wisconsin Women's Business Initiative Corporation (WWBIC) is a non-profit economic development corporation designed to assist those who are interested in starting or expanding their businesses but face barriers in accessing traditional financing or resources.[19] In addition to providing loans, the corporation has offered ancillary business development assistance services since 2000. These include training and consulting. The content of this training and consulting provides entrepreneurship development, business planning, teaching how to access capital, marketing strategies, accounting support, legal information, personal budgeting, eCommerce, and technology support. Clients can talk with the consultants through a phone call, online chat, email, or in a face-to-face meeting[20]. The group training classes are mainly on weekends. [21] Clients can register for a specific class or directly walk-in. Each year, on average, clients participate in over 20,000 collective consulting hours and 500 scheduled group training sessions, typically averaging about an hour. The training attendance rate is relatively low, with fewer total person-hours of

[19] In particular, women, people of color, veterans and low-income individuals are the organization's target population.
[20] Clients can make an appointment with the consultant and meet in the consultant office.
[21] The are also mainly held in the WWBIC office buildings in Milwaukee, Madison, Kenosha, and Racine.

training provided than consulting. Clients prefer to get the business services through consulting, and it is this consulting that begins early and continues well into the relationship with the client while the training is typically at the beginning of the relationship. WWBIC staff makes clear that they spend a far larger percentage of funds to support consulting services than training.

In the WWBIC business assistance project (providing ancillary services), the client's attendance in a training class is voluntary. Nevertheless, the situations in which clients use consulting services are more diverse. Clients can initiate communication with consultants by phone, online chat, or face-to-face meetings. Also, consultants actively initiate calls to clients. Some of these are "check-ups," but they also may reflect a circumstance in which the consultant thinks a client may need supervision or help for their business. Consequently, there may be self-selection (indeed, two-way selection) in measuring the treatment effect of business assistance. However, in the consulting service records data, we cannot tell who takes the initiative to call the other party.

The training and consulting are not mandatory so that clients initiate participation according to their own perceived needs.[22] Nevertheless, consultants actively keep in touch with the clients by calling, especially those whom they think may need supervision or help with their business. Therefore, the use of consulting services sometimes cannot be avoided by the borrowers. Again, the consulting service might be more likely to be provided if a consultant believes that a client faces a high chance of mismanaging or default. In other words, a consultant is likely to initiate contact with a riskier client. While we will discuss the selection issue in more detail in the later sections, this behavior is the opposite of that implied by cream-skimming. Those anticipated to do well and repay the loan will be less treated.

[22] Anyone who registered as WWBIC member count as a client, not only the clients who applied or received loans.

4 Data and Estimation Methods

In this section, I first summarize the data and identify the critical dependent and independent variables. I then describe the estimation methods used in the paper.

4.1 Data description

Data are provided by WWBIC and they include the size of the loan and the critical repayment data. Also included are the socioeconomic characteristics of the clients, the type of business run by the client, and the consulting and training attendance records of the clients. This information is available between the years 2000 to 2015. The critical unit of measure in the aggregated data is each specific loan. A single client can have more than one loan, and this generates more than one observation for the same client however, the vast majority of clients have only a single loan. I eliminate loans with missing data when using the aggregate data at the loan level. The most common source of missing data is the absence of socioeconomic characteristics of the clients. The data set of completed observations is a sample of 730 loans over 472 clients, and the total payment times are 15810. The average repayment period is 21.7 months.

The data provides transaction information on each loan, which indicates whether or not a given client made their payment. Thus, I know the length of the loan to any point in time and the number of payments over that length that have been missed. The data consists of both completed loans and those not yet run to the termination. As we will see, this difference does not prove crucial to the results as the full data set and the data set of completed loans return very similar results. The data on all loans are used to create three measures of repayment difficulty. The first is whether or not the client made a scheduled payment in a given month (*MissedMonthlyPayment*). This allows us to generate a panel of months by a loan that we use in what we refer to as the disaggregated

approach. The second dependent variable is at the loan level and is the ratio of the total number of payments missed, divided by the total number of anticipated payments (*MissedPaymentRate*). The third measures a period of intense difficulty and simply indicates whether or not the loan had three or more missed payments in a row (*MissedThreePayments*). This measure is again at the loan level and part of what we refer to as the aggregate aggregated approach. If a borrower does not repay for three consecutive months, it usually implies that the client's operation encountered severe problems.

Clients who register with WWBIC can receive ancillary services many times and on multiple occasions. In our paper, when we define the training participants in the monthly payment data if a client ever sat in the training classes. Also, if they ever talked with the consultants before payment day, they are identified as a consulting participant. However, in the aggregated payment performance data, participants are those who ever used the ancillary service before the last payment date. Total hours of training and consulting are available for each type of participant.

<Insert Table 2.1 about here>

Table 2.1 shows that 81.6% of the monthly payments have either consulting or training services before them. Of those, 7.9% is only after training services, a remarkable 49% use is only consulting services, and 24.7% use both. Finally, 18.4% of the sample participates in neither ancillary service.

<Insert Table 2.2 about here>

Table 2.2 is the descriptive analysis of the aggregated payment data; each observation is a loan. It shows that 85.8% of the sample use either consulting or training services. Of those, 6.2% use only training services, a remarkable 51.1% use is only consulting services, and 28.5% use both. Finally, 14.2% of the sample participates in neither ancillary service. Among those who used ancillary service, the average training hours are 3.48, and the average consulting hours are a remarkably high 30.95. Thus, more recipients used consulting than training, and those using consulting used it for more hours than those using training. It is the hours of training and consulting that provide the variation within the loan recipients to measure the influence of ancillary services.

Both Table 2.1 and Table 2.2 show that the payment performance is better for those that participated in neither ancillary service than those who never participated in ancillary services. Also, the repayment statistics look better for those receiving consulting than for those receiving only training. This fits the intuition of those providing the services at WWBIC.

In terms of other characteristics, borrowers who only use consulting services have higher household incomes than other categories. Consulting service participants have more years of education. In general, the consulting category has higher average credit scores and lower business course participation ratios than the training participants[23]. Training participants are younger on average than only-consulting participants and borrowers who never participate in any service.

Membership years is the time between when the client registered in WWBIC and their loan payment ended. In Table 2.1 and Table 2.2, clients who never used ancillary service have the shortest membership years. We measure the distance to WWBIC by the driving hours from the clients' home address to the closest WWBIC campus. According to Table 2.1 and Table 2.2, the

[23] The business courses not offered by WWBIC.

users of the consulting service live farther than the clients use the training service, and the groups that use only consulting services always have the longest distance than other groups of the clients.

<Insert Table 2.3 about here>

Table 2.3 shows divide the descriptive statistics of the high credit score group from that of the low credit score group. This division happens at a credit score of 620. As would be anticipated, the on-time payment performance of the high credit score group exceeds that of the low credit score group. The former is above is 90%, while the latter is 80%. Among those with higher scores, 20% of clients experienced three consecutive missed-payments, and this is 41% for the low credit score group. The high credit score group also has a higher average household income, a lower ending-balance-loan ratio, and more years of education. The high credit score group spends less time participating but actually spends longer participating in the consulting.

4.2 Empirical Strategy

The first set of models use each repayment period as an observation. The second set of models follow the description above and use the individual loan as an observation. I identify the first as a disaggregated or panel strategy and the latter as an aggregated observation strategy.

4.2.a The Disaggregated Observations Strategy

Payment data is available for every loan for every month. Thus, we initially take the underlying dependent variable to simply be whether or not a client made the payment in each month. This provides panel data across individuals and across time.

The initial model of estimation follows a reduced linear model:

$$Y = \alpha + \beta_1 Tr + \beta_2 Cn + \delta X + \varepsilon \qquad (1)$$

where Y is whether or not the client missed a payment in the observed month (*MissedMonthlyPayment)*. The value of Y is one when the payment was missed. *X* are the control variables, including client and loan characteristics. Tr and Cn are the total hours of training and of consulting, respectively, that the client attended before the monthly payment was due.

The structure of the data also allows an estimation based on client variation. As the client received more training and consulting, does their individual before the change. This fixed effect estimate controls for sorting. Unchanging characteristics of the client that might influence repayment are held constant.

4.2.b The Aggregated Data Strategy

Alternative use of the data treats each loan as one observation to measure the impact of ancillary service on overall repayment performance. The initial linear model of estimation has the same structure as model (1). However, dependent variable Y now is loan repayment behavior measured by the fraction of missed payment periods out of total payment periods (*MissedPaymentRate)*. Another repayment behavior variable is a dummy variable, *MissedThreePayments*, which shows whether the client missed three times repayment continuously or not. X are the characteristic variables of the client and macroeconomic variables, including credit score, household income, loan interest rate, ending balance ratio, education years, gender, number of children in the family, and GDP growth rate. Cn and Tr are the total hours of consulting and training that the client attended before the end of the loan payment, respectively. The simple model with aggregate ancillary variables shows a correlation of each of ancillary

service variables (consulting and training) with the missed payment behavior.

Note, however, that this may cause estimation difficulties. At some point during the loan, the borrower may have difficulties and might miss payments. Such a problem may elicit a response by WWBIC. In this case, the causation is reversed, loan problems generate ancillary services. If the services help create future repayments, a beneficial influence may yet emerge. Yet if not, the observed correlation could show that additional services are associated with poor repayment. Thus, the initial approach must be examined with this concern in mind. It will be a problem that we will address. For now, we examine the relationship between the sum of all ancillary services used over the course of the loan as the critical explanatory variable in determining repayment behavior.

There is also concern that the hours of consulting are endogenous. There may exist unobservable characteristics that influence both the use of ancillary services and repayment performance. Those who correctly anticipate having a successful enterprise may both be less likely to participate in ancillary services and have a strong repayment history. Such endogeneity would generate a spurious negative correlation between services and repayment. Alternatively, those who have higher ability may have more success in their enterprise and be more likely to believe ancillary services are valuable. This sorting would be a variation on classic ability bias and could generate a spurious positive association between services and repayment. We are uncertain as to the extent of each of these offsetting possibilities.

In order to account for such endogeneity, an instrumental variable estimator will be used. The first instrumental variable is the length of membership of WWBIC. We expect the membership years to influence a person's probability of participating in ancillary services, but not to independently affect the payment performance given the other explanatory variables. Anyone

interested in WWBIC's services can register as a client and they need not be a borrower. Thus, membership is often longer than the time they have had a loan. The second instrumental variable is the distance between the client's home and the closest WWBIC campus[24]. This distance indicates the ease with which customers use face-to-face training and consulting services. Closer customers can participate in training and consulting at a lower cost and so are more likely to use the ancillary services. While phone consulting can be done with an equal cost from anywhere, in-person consulting allows greater opportunities for interaction with multiple consultants and other borrowers. It also allows role-playing and access to on-site computer resources. Critically, we think the distance between the client's home and WWBIC is exogenous to their repayment behavior. Thus, the instruments appear at least sensible.

5 Results and Robustness Checks

The results are initially presented for the disaggregated data and then for the aggregated data.

5.1 Ancillary services and payment performance: Disaggregated data

The first column of Table 4 shows a simplified version of (1) that ignores other control variables. The results show that training services have a positive relationship with missed-payments while consulting services negatively associate with missed-payments. In the second column, we add the year dummy variables to the first column model. As a result, the coefficients of training and consulting have not changed, but the absolute value of the coefficient of the consulting variable has decreased significantly. This may indicate that consulting services is related to the economic and social background over the years. The third column is to add loan-

[24] WWBIC has four office locations. They are located in Milwaukee, Kenosha, Racine and Madison.

specific variables to the first column model, and the coefficients of training and consulting have not changed much. The fourth column is to add the year dummy variable to the third column, and the coefficient signs for training and consulting remain consistent. The fifth column includes loan-specific and client-specific variables. It can be seen that the impact of training on the monthly payment is no longer significant. In the last column, when we add the year dummy variable to the fifth model, neither the effects of training or consulting is significant.

<Insert Table 2.4 about here>

From those regression results, except for the last two models, regardless of whether there are control variables and year fixed effects, consulting hours have always been negatively related to missed-payment behavior, which aligns with our expectations. However, the positive correlation between training and monthly missed-payment was a result that did not meet expectations. Possible reasons are heterogeneity and self-selection among borrowers. People with lower repayment ability and people at higher risk are more likely to miss the payment, and they are also more likely to face difficulties and use training and consulting services. In the last regression in Table 2.4, we added the client variable, but the results were not significant. Based on this model, we use client fixed-effect models to capture the unobserved personal riskiness in this panel data. The results are in Table 2.5.

<Insert Table 2.5 about here>

Table 2.5 includes client-fixed-effect regressions. The first column is the regression result

using the whole sample, and the next two columns are the high credit score sample and the low credit score sample. The watershed for distinguishing high and low credit scores is 620 points, which is about the average credit score of the whole sample. It shows that when we use the client fixed effect, in the overall sample and the low credit score group, the effects of training and consulting become not significant. However, for the high credit score sample, after using the client fixed effect, the relationship between service participation and monthly missed payment behavior is significantly negatively correlated.

In the sample with high credit scores (>620), the coefficient on training is -0.01, and the coefficient on consulting is -0.0008. Making some simple assumptions gives a sense of the magnitude of these coefficients. For example, assume a client whose credit score is more than 620 moved up in the distribution from having no training or consulting (about 18 percent of the sample) to the mean level of 2.44 and 28.1, respectively.[25] The change in training would decrease the average probability of missed payment by 0.024, which is large given the high credit score group mean missed payment rate of 0.08. The change in consulting would decrease the average probability of missed payment by 0.023 which also remains substantial.

The critical credit score was examined to see if the pattern was robust. While magnitudes change modestly in credit scores from 620 to 680, the basic pattern of the regression results remains the same. Table 2.5 shows the results of choosing different critical scores 620, 640, and 680. In each case, the high credit score subsample benefits from training and consulting, as reflected by a lower probability of missing a payment. This is not true for any of the low credit score groups.

To sum up these regression results, we conclude that when using the client fixed-effect on the

[25] Such a comparison provides a more conservative estimate as the standard deviations often used for such exercises are substantially larger than the means.

panel data to correct the heterogeneity bias of individual clients, both training and consulting services have significant positive effects on the monthly repayment performance of high credit score group. However, in the low credit score group, the impact of training is not significant, and consulting is weakly but negatively related to the timely repayment behavior. Generally speaking, the credit score is highly correlated with better education, higher intelligence, and more patient time preferences (Li et al. 2015). Thus, it seems likely that the high credit score clients probably have higher ability and better learning capabilities. They may be more efficient learners and producers of ancillary services. They learn and implement advice more successfully and so within this sample missed payment decrease with greater services.

The correlation for consulting among those with poor credit ratings may reflect reverse causation. The third column in Table 2.5 shows that an hour consulting increases the probability of missing payment by 0.0016. As suggested, consultants reach out to those in trouble. As a consequence, those likely to miss payments may be sought out by the consultants, but it is clear that this is insufficient to change the pattern of results.

To explore the dynamics of the process between ancillary services and missed-payments, we alter the way we measure those services. One concern is that causation may be reversed. After a missed payment or two, the borrower may seek help, or the lender may attempt to provide help. This help that follows an episode of missed payments may then reduce the probability of a second missed payment episode. This would be hard to isolate in the current specification or the aggregate data. To examine this, the variables of interest are changed to measure the ancillary services participation hours that occurred one month and three months after the scheduled monthly payment date, based on whether the payment is on-time, missed, or missed for two consecutive months. According to the results shown in Table 2.6, there does not appear to be more ancillary services

hours following a missed-payment or after two consecutive missed-payments when compared to on-time payment. If anything, it appears to be the opposite. On average, in the month after payment on time, the consulting time is 0.39 hours, and the training time is 0.03 hours, while in the month after a missed-payment, the consulting time is 0.21 hours and the training time is 0.01 hours. So judging from the number of hours of ancillary service participation, the average participation time after missed-payments is less than the time after regular repayment.

<Insert Table 2.6 about here>

Yet, the fact that training and consulting do not seem to spike after missed payment episodes does not mean that the training following such an episode may not be critical. To investigate this further, we changed the critical intervention variations to measures the cumulative training and consulting participation hours since the last missed-payment. If there has been no missed payment, it remains the sum of hours since the loan started. These new independent variables are used to repeat the models in the last column of Table 2.4 and the first three columns in Table 2.5. The regression results are shown in Table 2.7.

As before, the initial results suggest that consulting and training services significantly improve payment performance. In the OLS regression in the first column of Table 2.7, that is, when we control the client-specific characteristics and the year fixed-effect, the probability of a monthly missed-payment is significantly reduced by 0.32% for one additional hour of either consulting or training after the last missed-payment.

In the client fixed-effect models, the repayment behavior of customers with low credit scores is now also significantly improved by services. On average, an additional hour of consulting

service can significantly reduce the probability of monthly missed payment for high credit score groups by 0.35% while significantly reducing this probability for low credit score groups by 0.28%. Thus, while both of the sums of services as well as services since a missed payment matter for high credit borrowers, it appears to be the services provided after a missed payment helps the low credit score group. The implication is that the accumulated services may not play a role for the low credit score group unless they are after a missed payment. This would be consistent with the services provided after a missed payment being of the sort that successfully solves problems.

<Insert Table 2.7 about here>

The fact that services after a missed payment are more effective for low credit score groups suggests that the continuous availability of services is particularly useful for this group. Thus, frontloading all the training and consulting might pay dividends for the high credit score group but is unlikely to benefit the low credit score group.

5.2 Ancillary services and Payment Performance: Aggregated data

In the aggregated data analysis, we first use OLS and Probit estimators to measure the impact of ancillary services on *MissedPaymentRate and MissThreePayment*, respectively. The regression results will be shown in Tables 2.8 and 2.9. We then use a 2SLS estimator and instrumental variables as a robustness test. The test reflects an effort to control for the self-selection by clients of the amount of ancillary services chosen. These results will be shown in Tables 2.10 and 2.11.

Table 8 shows the regression results of the OLS estimator for the full sample, the high credit score group, and the low credit score group, respectively. We can see that the coefficients on

training are not significant, while the coefficients of consulting are each significantly negative. Focusing on the full sample, an increase in consulting by one hour decreases the *MissedPaymentRate* decreases by 0.103%. For the high and low credit score sample, an additional hour of consulting reduces the *MissedPaymentRate* rate by 0.09% and 0.12%, respectively. However, these two coefficients are not significantly different.

<Insert Table 2.8 about here>

Table 2.9 shows the marginal effects of ancillary services when we use *MissedThreePayments* to measure payment performance. Consulting is significantly associated with a reduced incidence of three consecutive missed payments for the overall sample and both of the credit score groups. By increasing one hour of consulting, the rate of three consecutive missed payments decreases by 0.3%. At the same time, the coefficients on training are not significant.

<Insert Table 2.9 about here>

Table 2.10 includes the 2SLS regression results run on the whole sample and the different credit score groups. It can be seen in the first-stage regressions of the whole sample that when the driving distance between the client's home and WWBIC increased by 1%, the probability of participating in the training decreased by 0.9% on average. When the membership increases by one year, total training hours increased by 0.64, and consulting hours increased by 5.3. Distance does not have a significant effect on consulting hours. This may reflect that the majority consulted by phone, which is less related to distance. The first-stage regression results for the high and low

credit score groups largely mimic these results.[26]

<Insert Table 2.10 about here>

In the second stage regression of overall and high credit score group, the coefficients on the consulting variable are significantly negative. The absolute values of the coefficients are larger than the OLS regression which may reflect measurement error. In these estimates, when consulting services increases by one hour, the whole sample *MissedPaymentRate* decreases by 0.203%, and the high credit score sample *MissedPaymentRate* decreases by 0.198%. However, the low credit score sample's consulting coefficient remains insignificant. These results indicate that after a plausible attempt to control for endogeneity, consulting services retain the role of improving the overall and high credit score borrowers' repayment behavior.[27] This largely chimes in with the disaggregate results that at least confirmed a role among those with higher credit scores.

As mentioned, the size of the coefficient on consulting services increases after the use of instrumental variables. This argues that the unobserved bias in the data has a positive correlation with the *MissedPaymentRate*. Thus, those using consulting services are those who are more at risk of missing payments. This fits intuition in which those at risk either search out services or in which the consultants reach out to those at risk.

Yet, this pattern is absent for borrowers with low credit scores. Compared with borrowers with low credit scores, those with high credit scores likely may pay more attention to their reputation

[26] Tests for weak instruments show that in the regressions of the overall and high credit score samples, the minimum eigenvalue statistic are 8.6 and 7.6, respectively. Both of them are higher than critical value 7.03. Therefore, there is no weak IV problem. But the regressions of the low credit score groups cannot pass the weak IV test. This is because, from the F values of the first stage regressions, the instrumental variables can not explain the training hours well.

[27] Endogeneity tests show training and consulting variables in overall and high credit score group are endogenous, but the low credit score group variables are exogenous.

and long-term business development, so they are also more likely to seek help in a crisis. Also, perhaps because of their higher than average education level and perhaps ability, consulting services has produced better results for high credit score borrowers. In this sense, high credit score borrowers may be more efficient producers. They more successfully turn business advice into business success.

To give a further sense of the magnitude of the coefficient on consulting, we assume a client whose credit score is more than 620 moved up in the distribution from having no consulting (about 20 percent of the aggregated sample) to the mean level of 32.25 hours. This change would decrease the average probability of a missed payment by 0.067, which is substantial, given the high credit score group mean missed payment rate of 0.090.

Table 2.11 shows the IV Probit regression results of *MissedThreePayments*. The instrument variables are as before. The first stage regressions show that *membership years* have a significantly positive relationship with training and consulting participation. The *distance* has a significant negative correlation with the hours of training, that is, the farther the client's home is from WWBIC, the shorter training time. However, consistent with the previous estimates, distance cannot explain consulting participation.[28] The second stage coefficient on consulting for the high credit score group continues to be significantly negative and neither service takes a significant result for the low credit score group. [29]

<Insert Table 2.11 about here>

[28] Weak instrument tests show that the weak IV problem exist in these regressions.
[29] Endogeneity tests show that in the overall and low credit score group regressions, training and consulting are endogenous variables, but in the high credit score group, they are exogenous.

In the high credit score group, without instrumental variables, the overall marginal effect of consulting on the *MissedThreePayments* is -0.003 (Table 2.9). With the instrumental variables, the marginal effect is -0.0032 (calculated from Table 2.11). These results indicate that after attempting to control for endogeneity, among those with high credit scores, consulting services still have a significant effect on reducing continuous payment shortfalls. The correction substantially changes the marginal effect as well, with the instrumental variables, the marginal effect is -0.0034 for the overall sample, -0.0032 for the high credit score group and -0.0037 for the low credit score group. These marginal effects are only modestly larger than those from the original probit without instrumenting. To again give a simple illustration, if a client's hours of consulting services increase by 32.25 (as used before), the probability of three consecutive missed-payment will decrease by 0.11. Compared with the ratio of three consecutive missed payments in the high credit score group is 0.18, this value is considerable.

5.3 Additional Robustness Results

An initial concern is that we take a window of loans that include some which have not been completed. If the uncompleted loans are not representative of the completed loans, they may influence the results we have presented. For example, it may be that uncompleted loans will fail, be written off and simply not be completed. Such loans may provide information about success but may not be indicative of completed loans. Put somewhat differently, the completed loans may, despite missed payments, be a selected set of overwise more successful loans, and their repayment history may be better and more to the point, the relationship between ancillary services and their repayment may differ.

The uncompleted loans represent approximately 1/6 of all loans. These were loans still in

process at the time we were given that data. To examine if their presence biases the overall estimates, we exclude them from our sample. We repeat each of the fundamental estimates in the tables for both the disaggregate and aggregate approaches. These are presented in the Appendix as Appendix Tables 2.2 - 2.10. The removal of the uncompleted loans does not fundamentally change the pattern of results. In the disaggregated approach consulting continues to be routinely associated with a reduced likelihood of missed payments in the estimate until the client fixed effect results. It also continues to be associated with a reduced probability of missed payment in the fixed effect results for those with higher credit scores. Similarly, in the aggregate approach, the role of ancillary services is of the same direction, magnitude, and generally of significance. We conclude that the uncompleted loans do not dramatically bias the tenor of our results.

6 Conclusion and policy implications

In this paper, we estimated the influence of repeated and continuing lender-borrower interactions on borrowers' repayment performance. Using the data from WWBIC, we set up the individual fixed-effect models and instrumental variable models and find that sustaining business assistance is helpful to improve the microentrepreneur's repayment behavior, especially for the high credit score borrowers. Total consulting services hours are endogenous, and the riskier borrowers are more likely to get the consulting service. In this regard, the service provided by the lenders may resolve the potential information asymmetry in the sense that the customer realizes that he/she is facing difficulties and actively seeks help from the consultant.

We provide some interesting empirical patterns to describe the effect of lender-borrower interactions on the quality of repayment: (1) training and consulting services can significantly improve the monthly repayment behavior among the high credit score borrowers; (2) training and

consulting services are more effective on high credit score borrowers than low credit score borrowers; (3) riskier borrowers respond more to the consulting service while consulting services can significantly improve the quality of the borrower's repayment regardless of the borrower's riskiness.

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Chapter 2 Figures and Tables

Table 2. 1 Statistical summary of characteristics for service participants and non-participants (disaggregated performance)

	Whole sample		Only training		Only consulting		Both training and consulting		Training or Consulting		Neither training or consulting	
	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
MissedMonthlyPayment [a]	0.16	0.36	0.15	0.36	0.14	0.35	0.15	0.36	0.14	0.35	0.2	0.4
Training hours [c]	2.87	8.3	8.22	14.02	0	0	8.99	12.14	3.51	9.07	0	0
Consulting hours [d]	21.89	25.98	0	0	25.7	21.31	37.63	32.33	26.84	26.36	0	0
Default ratio [e]	0.21	0.32	0.08	0.23	0.22	0.31	0.27	0.34	0.22	0.32	0.16	0.35
Loan interest rate	0.07	0.03	0.09	0.03	0.07	0.03	0.06	0.03	0.07	0.03	0.1	0.03
Household income [f]	2.14	1.75	1.45	1.04	2.41	2.01	1.76	1.23	2.12	1.76	2.24	1.68
Education year	14.82	2.49	14.38	2.05	14.96	2.44	14.65	2.8	14.81	2.53	14.88	2.3
College degree	0.76	0.43	0.7	0.46	0.81	0.39	0.7	0.46	0.77	0.42	0.75	0.43
Gender	0.35	0.48	0.17	0.37	0.42	0.49	0.31	0.46	0.36	0.48	0.29	0.45
Married	0.58	0.49	0.46	0.5	0.63	0.48	0.59	0.49	0.6	0.49	0.52	0.5
Credit score [g]	633.84	85.27	605.93	74.63	650.31	84.03	629	85.72	639.58	84.94	608.42	82.03
Business courses	0.8	0.4	0.93	0.26	0.81	0.39	0.82	0.38	0.83	0.38	0.68	0.47
Business experience	3.19	5.07	2.07	2.58	3.57	5.31	3.18	4.13	3.31	4.79	2.67	6.12
Age [h]	42.14	10.18	38.24	9.92	41.89	10.33	42.26	9.29	41.65	10.05	44.28	10.46
Distance [i]	0.69	2.3	0.34	0.28	0.86	2.66	0.35	0.35	0.65	2.09	0.86	3.06
Membership years [j]	3.09	2.42	3.05	1.87	2.68	1.91	4.5	3.14	3.26	2.49	2.31	1.93
N	15518		1220		7606		3834		12660		2858	

[a] MissedMonthlyPayment is a dummy variable to show whether missed the payment in one month.

[c] Training hours are the total training hours the clients participated before their loan payment ended.

[d] Consulting hours are the total consulting hours the clients participated in before their loan payment ended.

[e] Default ratio is the ratio of loan ending balance and the loan amount.

[f] Household income is the monthly household income per capita.

[g] Credit score was the borrowers' credit score when they applied for the loan.

[h] Age is when borrowers pay or should pay the loan every month.

[i] Distance is the driving hours between the client's home and the nearest WWBIC office.

[j] Membership years is the time between when the client registered in WWBIC and their loan payment ended.

Table 2. 2 Statistical summary of characteristics for service participants and non-participants (aggregated performance)

	Whole sample		Only training		Only consulting		Both training and consulting		Training or consulting		Neither training or consulting	
	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
MissedPaymentRate (%) [k]	0.14	0.21	0.17	0.24	0.12	0.2	0.14	0.2	0.13	0.2	0.22	0.24
MissedThreePayments [l]	0.28	0.45	0.31	0.47	0.26	0.44	0.29	0.46	0.28	0.45	0.34	0.47
Training hours [c]	2.98	8.39	6.68	12.86	0.00	0.00	9.02	12.36	3.48	8.97	0.00	0.00
Consulting hours [d]	26.54	29.13	0.00	0.00	29.54	23.65	40.17	35.68	30.95	29.20	0.00	0.00
Default ratio [e]	0.25	0.36	0.14	0.33	0.25	0.35	0.29	0.37	0.26	0.36	0.18	0.36
Loan interest rate	0.08	0.03	0.10	0.02	0.07	0.03	0.07	0.03	0.07	0.03	0.10	0.02
Household income [f]	2.22	1.85	1.84	1.22	2.49	2.13	1.82	1.42	2.22	1.89	2.24	1.61
Education year	14.91	2.59	14.71	1.80	15.06	2.60	14.76	2.90	14.93	2.66	14.79	2.13
College degree	0.78	0.42	0.78	0.42	0.80	0.40	0.74	0.44	0.78	0.42	0.78	0.42
Gender	0.34	0.48	0.11	0.32	0.43	0.50	0.29	0.46	0.36	0.48	0.25	0.44
Married	0.60	0.49	0.47	0.50	0.63	0.48	0.61	0.49	0.61	0.49	0.49	0.50
Credit score [g]	638.19	84.98	619.64	77.34	653.61	81.65	627.80	90.45	642.60	85.33	611.64	78.08
Business courses	0.80	0.40	0.93	0.25	0.79	0.41	0.82	0.38	0.81	0.39	0.77	0.42
Business experience	3.15	5.00	1.60	2.22	3.76	5.43	2.81	4.07	3.29	4.88	2.32	5.66
Age [m]	40.13	10.72	36.62	11.56	40.37	10.38	39.42	10.43	39.79	10.51	42.23	11.74
Distance [i]	0.63	2.06	0.28	0.13	0.85	2.83	0.35	0.32	0.64	2.21	0.58	0.69
Membership years [j]	3.34	2.21	3.14	1.62	2.99	1.33	4.70	3.09	3.57	2.25	1.98	1.35
N	730		45		373		208		626		104	

[k] MissedPaymentRate is the ratio of missed-payment times and total scheduled payment times multiply by 100.

[l] MissedThreePayments is a dummy variable for having three times or more consecutive missed payments.

[m] Age is when the borrower started to pay back the loan.

Table 2. 3 Means and standard deviations of characteristics for High (>620) and Low (≤620) credit score

	Monthly				Aggregated			
	High credit score		Low credit score		High credit score		Low credit score	
	mean	sd	mean	sd	mean	sd	mean	sd
MissedMonthlyPayment	0.09	0.29	0.23	0.42				
MissedPaymentRate (%)					0.10	0.18	0.20	0.23
MissedThreePayments					0.20	0.40	0.41	0.49
Training hours	2.34	6.97	3.53	9.66	2.51	7.35	3.63	9.60
Consulting hours	25.76	27.09	17.10	23.68	29.93	30.22	21.95	26.95
Default ratio	0.19	0.30	0.24	0.35	0.22	0.34	0.28	0.38
Loan interest rate	0.07	0.03	0.07	0.04	0.08	0.02	0.07	0.03
Household income	2.45	2.00	1.76	1.28	2.60	2.12	1.71	1.24
Education year	15.29	2.46	14.25	2.40	15.49	2.56	14.14	2.42
College degree	0.81	0.39	0.71	0.45	0.82	0.38	0.72	0.45
Gender	0.33	0.47	0.37	0.48	0.36	0.48	0.33	0.47
Married	0.60	0.49	0.57	0.49	0.61	0.49	0.57	0.50
Credit score	698.04	47.47	554.30	45.33	699.68	47.61	554.87	43.14
Business courses	0.77	0.42	0.83	0.37	0.78	0.41	0.83	0.37
Business experience	3.12	5.09	3.28	5.05	3.09	5.18	3.23	4.76
Age	41.81	10.15	42.54	10.20	40.49	11.03	39.66	10.29
Distance	0.88	3.05	0.46	0.50	0.75	2.66	0.47	0.61
Membership years	2.84	2.29	3.40	2.54	3.26	2.04	3.45	2.42
N	8587		6931		420		310	

Table 2. 4 The impact of ancillary service on the monthly payment

	(1)	(2)	(3)	(4)	(5)	(6)
Training hours	0.00132***	0.00107***	0.00121***	0.000743**	0.000476	0.000204
	(0.000378)	(0.000368)	(0.000385)	(0.000372)	(0.000367)	(0.000358)
Consulting hours	-0.00130***	-0.000342**	-0.00159***	-0.000266**	-0.000771***	0.000161
	(0.000115)	(0.000134)	(0.000120)	(0.000132)	(0.000117)	(0.000128)
Default ratio			0.0914***	0.139***	0.0512***	0.0936***
			(0.0105)	(0.0110)	(0.0106)	(0.0112)
Loan interest rate			-0.484***	-0.981***	-0.307***	-0.643***
			(0.106)	(0.117)	(0.106)	(0.117)
Age			0.00391*	-0.000982	0.00371*	0.000800
			(0.00214)	(0.00211)	(0.00217)	(0.00214)
Age_square			-0.0000168	0.0000354	-0.0000247	0.00000544
			(0.0000240)	(0.0000237)	(0.0000245)	(0.0000241)
Credit score					-0.000763***	-0.000670***
					(0.0000345)	(0.0000353)
Edu years					-0.0158***	-0.0159***
					(0.00157)	(0.00155)
Edu college more					0.0966***	0.0931***
					(0.00933)	(0.00924)
Gender					0.0204***	0.0351***
					(0.00626)	(0.00621)
Married					-0.0217***	-0.0297***
					(0.00621)	(0.00610)
Number of Children					-0.0100***	-0.00797***
					(0.00264)	(0.00261)
Business course					-0.0359***	-0.0370***
					(0.00768)	(0.00750)
Year fixed effect		yes		yes		yes
Cons	0.183***	0.118	0.0717	0.231**	0.762***	0.759***
	(0.00408)	(0.0782)	(0.0462)	(0.0919)	(0.0571)	(0.0967)
N	15810	15810	15810	15810	15522	15522
R2	0.009	0.036	0.023	0.059	0.064	0.095

Standard errors in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01

Table 2. 5 The impact of ancillary service on the monthly payment, client fixed effect

	Whole sample	High score (620)	Low score (620)	High score (640)	Low score (640)	High score (680)	Low score (680)
Training hours	-0.00106	-0.00967***	-0.00111	-0.0117***	-0.000420	-0.00601*	-0.00100
	(0.00407)	(0.00339)	(0.00484)	(0.00362)	(0.00434)	(0.00340)	(0.00393)
Consulting hours	0.0000876	-0.000821**	0.00159**	-0.000825**	0.00160**	-0.000923**	0.00109*
	(0.000725)	(0.000394)	(0.000698)	(0.000387)	(0.000662)	(0.000365)	(0.000565)
Default ratio	0.0626	-0.000457	0.0836***	-0.0309	0.105***	-0.0343	0.0710***
	(0.0585)	(0.0228)	(0.0304)	(0.0229)	(0.0287)	(0.0282)	(0.0235)
Loan interest rate	1.154*	0.739***	1.264***	0.499**	1.224***	0.857***	1.151***
	(0.638)	(0.235)	(0.251)	(0.254)	(0.233)	(0.268)	(0.209)
Age	0.0904**	0.00825	0.135***	-0.0149	0.126***	-0.00266	0.113***
	(0.0356)	(0.0147)	(0.0211)	(0.0160)	(0.0186)	(0.0162)	(0.0163)
Age_square	-0.000538	0.000509***	-0.000987***	0.000760***	-0.000898***	0.000442***	-0.000753***
	(0.000429)	(0.000138)	(0.000165)	(0.000151)	(0.000143)	(0.000150)	(0.000129)
Year fixed effect	yes	yes	yes	yes	yes	yes	yes
Client fixed effect	yes	yes	yes	yes	yes	yes	yes
_cons	-2.781***	-1.489***	-3.665***	-0.983**	-3.434***	-0.871**	-3.251***
	(0.757)	(0.375)	(0.616)	(0.401)	(0.551)	(0.423)	(0.455)
N	15810	8688	7122	7491	8319	5000	10810
R2	0.049	0.070	0.054	0.065	0.058	0.051	0.054

Standard errors in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01

Table 2. 6 Means and standard deviations of ancillary service hours after the monthly payment

	One month on-time payment			One month missed payment			Two months missed payment		
	Obs	Mean	Sd	Obs	Mean	Sd	Obs	Mean	Sd
One month consulting	12893	0.39	1.33	2377	0.21	0.75	1320	0.16	0.66
Three month average consulting	11873	0.38	0.99	2330	0.18	0.52	1311	0.16	0.47
One month training	12893	0.03	0.34	2377	0.01	0.18	1320	0	0
Three month average training	11873	0.02	0.21	2330	0.01	0.09	1311	0	0.07

Table 2. 7 The impact of ancillary service after the last missed-payment on monthly payment

	OLS Whole sample	**Client fixed effect** Whole sample	**Client fixed effect** High score (620)	**Client fixed effect** Low score (620)
Training hours	-0.00323***	-0.00200	0.00128	-0.00399***
	(0.000319)	(0.00189)	(0.00130)	(0.00134)
Consulting hours	-0.00322***	-0.00311***	-0.00345***	-0.00278***
	(0.000140)	(0.000676)	(0.000269)	(0.000540)
Default ratio	0.110***	-0.252***	-0.186**	-0.346**
	(0.0109)	(0.0968)	(0.0858)	(0.154)
Loan interest rate	-0.491***	0.840**	0.698	1.239
	(0.115)	(0.394)	(0.765)	(1.039)
Age	0.00593***	0.0464	-0.0284*	0.123***
	(0.00211)	(0.0302)	(0.0162)	(0.0240)
Age_square	-0.0000542**	0.000180	0.000976***	-0.000521**
	(0.0000237)	(0.000348)	(0.000163)	(0.000218)
Credit score	-0.000511***			
	(0.0000347)			
Edu years	-0.0138***			
	(0.00152)			
Edu college more	0.0798***			
	(0.00911)			
Gender	0.0216***			
	(0.00613)			
Married	-0.0309***			
	(0.00601)			
Number of children	-0.0122***			
	(0.00258)			
Business course	-0.0219***			
	(0.00747)			
Year fixed effect	Yes			
Cons	0.513***	-2.367***	-0.859**	-4.092***
	(0.0960)	(0.679)	(0.402)	(0.660)
N	15522	15810	8688	7122
R2	0.125	0.061	0.085	0.057

Standard errors in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01

Table 2. 8 OLS regressions of the impact of ancillary service on MissedPaymentRate

	All	High	Low
Training hours	0.000692	-0.000551	0.00168
	(0.000819)	(0.000509)	(0.00128)
Consulting hours	-0.00103***	-0.000902***	-0.00118**
	(0.000238)	(0.000207)	(0.000501)
GDP growth rate	-0.0107*	-0.0167**	-0.00499
	(0.00579)	(0.00702)	(0.0103)
GDP growth rate next year	-0.0424***	-0.0545***	-0.0365***
	(0.00674)	(0.0112)	(0.00946)
Default ratio	0.0538**	0.0304	0.0734*
	(0.0229)	(0.0249)	(0.0406)
Loan interest rate	-0.144	0.219	-0.269
	(0.274)	(0.351)	(0.400)
Age	-0.000148	-0.0000291	0.000529
	(0.00398)	(0.00387)	(0.00905)
Age_squre	0.0000166	0.0000176	0.000000944
	(0.0000453)	(0.0000443)	(0.000107)
Credit score	-0.000595***	-0.000602***	-0.000564*
	(0.0000844)	(0.000151)	(0.000289)
Education year	-0.00369	0.0000619	-0.00921
	(0.00380)	(0.00371)	(0.00854)
Edu_college and more	0.0619***	0.0232	0.110**
	(0.0226)	(0.0237)	(0.0435)
Gender	0.0213	0.0169	0.0262
	(0.0157)	(0.0174)	(0.0321)
Married	-0.0340**	-0.0139	-0.0488
	(0.0147)	(0.0160)	(0.0318)
Business courses	-0.0238	0.00658	-0.0641*
	(0.0176)	(0.0169)	(0.0368)
_cons	0.656***	0.605***	0.706**
	(0.116)	(0.142)	(0.290)
N	731	420	311
R2	0.239	0.264	0.161

Standard errors in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01

Table 2. 9 Margins of Probit regressions of the impact of ancillary service on MissedThreePayments

	All	High	Low
Training hours	-0.000430	-0.00384	0.00107
	(0.00165)	(0.00243)	(0.00260)
Consulting hours	-0.00304***	-0.00306***	-0.00306***
	(0.000641)	(0.000803)	(0.000991)
GDP growth rate	-0.0351***	-0.0326***	-0.0375**
	(0.0101)	(0.0103)	(0.0182)
GDP growth rate next year	-0.0620***	-0.0604***	-0.0570***
	(0.0109)	(0.0167)	(0.0163)
Default ratio	0.0237	-0.0165	0.0432
	(0.0409)	(0.0480)	(0.0707)
Loan interest rate	-1.100**	0.271	-2.445***
	(0.515)	(0.773)	(0.753)
Age	-0.00106	0.0123	-0.0301*
	(0.00885)	(0.00993)	(0.0179)
Age_squre	3.49e-05	-0.000117	0.000389*
	(9.99e-05)	(0.000108)	(0.000213)
Credit score	-0.00101***	-0.00103***	-0.000116
	(0.000188)	(0.000373)	(0.000625)
Education year	-0.00451	0.00417	-0.00913
	(0.00824)	(0.00920)	(0.0154)
Edu_college and more	0.0888*	-0.0396	0.211***
	(0.0503)	(0.0605)	(0.0795)
Gender	0.0356	0.0509	-0.0193
	(0.0328)	(0.0361)	(0.0592)
Married	-0.0378	-0.00535	-0.0460
	(0.0315)	(0.0357)	(0.0576)
Business courses	-0.0768**	0.0233	-0.199***
	(0.0368)	(0.0375)	(0.0703)
N	731	420	311

Standard errors in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01

Table 2. 10 IV regressions of the impact of ancillary service on MissedPaymentRate

	All			High			Low		
	Second stage	First stage Training	First stage Consulting	Second stage	First stage Training	First stage Consulting	Second stage	First stage Training	First stage Consulting
Training hours	0.0105*	.		0.0136**			0.00752		
	(0.00568)	.		(0.00663)			(0.0182)		
Consulting hours	-0.00203**	.		-0.00198***			-0.00170		
	(0.000890)	.		(0.000660)			(0.00558)		
GDP growth rate	-0.0126**	0.195	0.118	-0.0185***	0.0453	0.115	-0.00645	0.448	-0.0738
	(0.00556)	(0.219)	(0.676)	(0.00669)	(0.258)	(0.863)	(0.0121)	(0.380)	(1.044)
GDP growth rate next year	-0.0387***	-0.348	0.899	-0.0567***	0.257	3.013***	-0.0325**	-0.818**	-0.696
	(0.00616)	(0.231)	(0.711)	(0.00869)	(0.326)	(1.092)	(0.0134)	(0.351)	(0.963)
Default ratio	0.0588***	0.528	10.84***	0.00233	2.445**	13.64***	0.0884	-1.479	7.606*
	(0.0226)	(0.868)	(2.679)	(0.0328)	(1.059)	(3.543)	(0.0808)	(1.462)	(4.013)
Loan interest rate	0.0484	-32.29***	-175.8***	0.283	-19.55	-209.7***	-0.128	-36.82**	-123.3***
	(0.320)	(10.81)	(33.35)	(0.422)	(14.49)	(48.49)	(0.468)	(16.66)	(45.73)
Age	0.00141	-0.104	1.653***	0.00423	-0.0790	2.666***	-0.00654	0.161	-1.418
	(0.00510)	(0.188)	(0.580)	(0.00580)	(0.205)	(0.686)	(0.0146)	(0.413)	(1.132)
Age_squre	-0.00000256	0.00159	-0.0188***	-0.0000372	0.00141	-0.0299***	0.0000961	-0.00216	0.0170
	(0.0000595)	(0.00217)	(0.00670)	(0.0000657)	(0.00229)	(0.00768)	(0.000181)	(0.00504)	(0.0138)
Credit score	-0.000490***	-0.00372	0.0710***	-0.000618***	0.00708	0.0932***	-0.000343	-0.0285**	0.00839
	(0.000121)	(0.00377)	(0.0116)	(0.000209)	(0.00772)	(0.0259)	(0.000636)	(0.0127)	(0.0349)
Education year	-0.00161	-0.173	0.429	0.00217	-0.164	0.547	-0.00676	-0.283	0.796
	(0.00432)	(0.165)	(0.509)	(0.00489)	(0.186)	(0.624)	(0.0132)	(0.316)	(0.867)
Edu_college and more	0.0487*	1.121	-3.145	-0.00276	1.917	-4.371	0.100**	0.701	-1.816
	(0.0268)	(1.019)	(3.143)	(0.0347)	(1.281)	(4.288)	(0.0500)	(1.704)	(4.676)
Gender	0.0405**	-1.692***	3.870*	0.0422*	-1.370*	3.199	0.0358	-2.471**	7.595**
	(0.0203)	(0.653)	(2.015)	(0.0227)	(0.758)	(2.536)	(0.0896)	(1.230)	(3.375)
Married	-0.0301*	-0.401	-0.266	-0.0167	0.483	-0.0993	-0.0439	-1.011	0.111
	(0.0158)	(0.628)	(1.939)	(0.0187)	(0.727)	(2.435)	(0.0336)	(1.183)	(3.248)
Business courses	-0.0257	0.937	6.599***	-0.00834	1.814**	13.24***	-0.0541	-1.420	-4.452
	(0.0204)	(0.799)	(2.466)	(0.0269)	(0.898)	(3.005)	(0.0374)	(1.516)	(4.163)
Distance		-0.943***	1.153		-1.016***	2.069**		-0.599	0.0883
		(0.247)	(0.761)		(0.283)	(0.948)		(0.468)	(1.286)
Membership years		0.643***	5.337***		0.384**	7.138***		0.992***	3.407***
		(0.138)	(0.425)		(0.177)	(0.594)		(0.219)	(0.602)
_cons	0.510***	11.26**	-74.89***	0.539***	-0.426	-128.0***	0.635	24.38**	32.45
	(0.164)	(5.029)	(15.51)	(0.198)	(7.341)	(24.57)	(0.396)	(11.70)	(32.12)
R2	0.085			-0.071			0.111		

Endogeneity Test										
Durbin (score)	chi2(2)	6.83049			8.55044			0.235017		
	p	0.0329			0.0139			0.8891		
Wu-Hausman	F	3.30567			4.06274			0.106181		
	p	0.0372			0.0179			0.8993		
Robust score	chi2(2)	5.46143			7.47694			0.222665		
	p	0.0652			0.0238			0.8946		
Robust regression	F	2.78298			3.98261			0.100895		
	p	0.0625			0.0194			0.9041		
Weak IV Test										
Minimum eigenvalue statistic		8.6			7.59			0.51		
Critical values (10%)		7.03			7.03			7.03		
Anderson-Rubin Wald test	F	3.09			7.25			0.14		
	p	0.046			0.0008			0.8714		
Anderson-Rubin Wald test	Chi-sq(2)	6.31			15.04			0.29		
	p	0.0426			0.0005			0.8653		
Stock-Wright LM S statistic	Chi-sq(2)	6.26			14.52			0.29		
	p	0.0438			0.0007			0.8654		
N		729	729	729	420	420	420	309	309	309

Standard errors in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01

Table 2. 11 Probit IV regressions of the impact of ancillary service on MissedThreePayments

	All			High			Low		
	Second stage	First stage Training	First stage Consulting	Second stage	First stage Training	First stage Consulting	Second stage	First stage Training	First stage Consulting
Training hours	0.0803*			0.0360			0.182		
	(0.0448)			(0.0584)			(0.191)		
Consulting hours	-0.0112			-0.0127*			-0.0424		
	(0.00729)			(0.00682)			(0.0587)		
GDP growth rate	-0.146***	0.448	-0.0738	-0.160***	0.448	-0.0738	-0.183	0.448	-0.0738
	(0.0421)	(0.380)	(1.044)	(0.0529)	(0.380)	(1.044)	(0.127)	(0.380)	(1.044)
GDP growth rate next year	-0.201***	-0.818**	-0.696	-0.301***	-0.818**	-0.696	-0.0625	-0.818**	-0.696
	(0.0473)	(0.351)	(0.963)	(0.0719)	(0.351)	(0.963)	(0.141)	(0.351)	(0.963)
Default ratio	0.0427	-1.479	7.606*	-0.258	-1.479	7.606*	0.712	-1.479	7.606*
	(0.182)	(1.462)	(4.013)	(0.308)	(1.462)	(4.013)	(0.846)	(1.462)	(4.013)
Loan interest rate	-0.339	-36.82**	-123.3***	2.666	-36.82**	-123.3***	-3.432	-36.82**	-123.3***
	(2.485)	(16.66)	(45.73)	(3.716)	(16.66)	(45.73)	(4.911)	(16.66)	(45.73)
Age	0.0107	0.161	-1.418	0.0564	0.161	-1.418	-0.150	0.161	-1.418
	(0.0411)	(0.413)	(1.132)	(0.0530)	(0.413)	(1.132)	(0.154)	(0.413)	(1.132)
Age_squre	-0.0000714	-0.00216	0.0170	-0.000555	-0.00216	0.0170	0.00194	-0.00216	0.0170
	(0.000480)	(0.00504)	(0.0138)	(0.000600)	(0.00504)	(0.0138)	(0.00191)	(0.00504)	(0.0138)
Credit score	-0.00323***	-0.0285**	0.00839	-0.00530***	-0.0285**	0.00839	0.00498	-0.0285**	0.00839
	(0.000985)	(0.0127)	(0.0349)	(0.00198)	(0.0127)	(0.0349)	(0.00672)	(0.0127)	(0.0349)
Education year	0.00395	-0.283	0.796	0.0247	-0.283	0.796	0.0659	-0.283	0.796
	(0.0349)	(0.316)	(0.867)	(0.0452)	(0.316)	(0.867)	(0.139)	(0.316)	(0.867)
Edu_college and more	0.205	0.701	-1.816	-0.240	0.701	-1.816	0.359	0.701	-1.816
	(0.216)	(1.704)	(4.676)	(0.314)	(1.704)	(4.676)	(0.527)	(1.704)	(4.676)
Gender	0.270*	-2.471**	7.595**	0.318	-2.471**	7.595**	0.579	-2.471**	7.595**
	(0.162)	(1.230)	(3.375)	(0.197)	(1.230)	(3.375)	(0.945)	(1.230)	(3.375)
Married	-0.0987	-1.011	0.111	-0.0455	-1.011	0.111	0.0383	-1.011	0.111
	(0.125)	(1.183)	(3.248)	(0.166)	(1.183)	(3.248)	(0.351)	(1.183)	(3.248)
Business courses	-0.359**	-1.420	-4.452	-0.0245	-1.420	-4.452	-0.466	-1.420	-4.452
	(0.162)	(1.516)	(4.163)	(0.242)	(1.516)	(4.163)	(0.395)	(1.516)	(4.163)
Distance	.	-0.599	0.0883		-0.599	0.0883		-0.599	0.0883
	.	(0.468)	(1.286)		(0.468)	(1.286)		(0.468)	(1.286)
Membership years	.	0.992***	3.407***		0.992***	3.407***		0.992***	3.407***
	.	(0.219)	(0.602)		(0.219)	(0.602)		(0.219)	(0.602)

_cons		1.803	24.38**	32.45	2.110	24.38**	32.45	-0.629	24.38**	32.45
		(1.313)	(11.70)	(32.12)	(1.808)	(11.70)	(32.12)	(4.180)	(11.70)	(32.12)
Endogeneity Test										
Wald test of exogeneity	chi2(2)	8.53				1.3		7.32		
	p	0.01				0.52		0.0258		
Weak IV Test										
Anderson-Rubin test (AR)	chi2(2)	4.02				3.5		3.78		
	p	0.1339				0.1738		0.1507		
F			5.1	19.99		3.25	19.64		3.8	4.9
N		729	309	309	420	309	309	309	309	309

Standard errors in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01

Chapter 1 Appendices

Table A1. 1 Maternity costs for female employees in China

Three periods	Length	Cost involved
Pregnancy	Ten months	Reduce work time and labor intensity; The prenatal examination time is included in the labor time. Overall cost of temporary replacement staff. Pregnant women's lounge.
Maternity	98 days onward	Maternity wage. Maternity subsidy and medical expenses for childbirth or abortion[30]. The overall cost of the temporary replacement staff.
Breastfeeding	12 months	One hour or more of breastfeeding time per day. Nursing room. Reduce work time and labor intensity

Source: The Special Rules on the Labor Protection of Female Employees (2012)

[30] For female employees who do not participate in maternity insurance.

Table A1. 2 Estimate the policy effect on the new childbirth (0 to 1-year-old) by pooled data

Dependent variable	**Second child**	**Any child**
One single-child parent	0.000803	-0.0406
	(0.0294)	(0.0319)
Neither single-child parent	-0.00356	-0.0734**
	(0.0309)	(0.0343)
Year 2014	0.00292	-0.00800
	(0.0143)	(0.0162)
Year 2016	0.0272	0.0113
	(0.0288)	(0.0324)
Two-child policy	-0.0155	0.264***
	(0.0274)	(0.0424)
Two-child policy*child before two-child policy		-0.345***
		(0.0329)
Linear combinations of parameters		
Policy effect on the second child		-0.081**
		(0.031)
Control variables		
Age	0.667***	0.163
	(0.221)	(0.279)
Age groups (3 years)	Yes	Yes
Age*age groups (3 years)	Yes	Yes
Edu years	0.000312	0.00229
	(0.00272)	(0.00309)
Edu years*collegesome	-0.00292**	-0.000284
	(0.00120)	(0.00144)
52 to 69 years old family member (dummy)	0.0274*	0.0248
	(0.0143)	(0.0155)
Family income (yuan)	-4.69e-09	-4.92e-08
	(7.43e-08)	(8.43e-08)
Location_rural	0.0601***	0.0369**
	(0.0137)	(0.0153)
First child gender (boy=1)	-0.0479***	-0.0458***
	(0.0123)	(0.0136)
Cons	-12.63***	-2.439
	(4.193)	(5.518)
N	2418	2618
Adj. R^2	0.102	0.241

Note: Sample is married women, 18 to 42 years old.
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A1. 3 Gender of the newborn first child before and after the two-child policy

		Obs	Mean
First child boy	Before policy	176	0.61
	After policy	87	0.55
Pairwise comparisons of means with equal variances			
Contrast		-0.056	
Std. Err.		0.0646	
Unadjusted 95% conf. Interval		[-0.1834, 0.071]	

Table A1. 4 Median regression of the extent of labor participation of married women, 18 to 42 years old

	Recent Usual Days/Month			Recent Usual Hours/Week		
Variable	**Zero Child**	**One Child**	**Two Children**	**Zero Child**	**One Child**	**Two Children**
Wage (1000 yuan/day)	-3.934	-9.634***	-14.30	16.97	-2.341*	-2.157
	(6.695)	(1.722)	(27.91)	(26.44)	(1.268)	(60.51)
Wage square	3.324	3.873	1.826	-9.606	1.171	-1.443
	(10.09)	(3.896)	(36.34)	(46.51)	(0.824)	(67.77)
Edu years	-0.334**	-0.222***	-0.0802	-0.984**	-0.339***	0.0119
	(0.155)	(0.0399)	(0.111)	(0.482)	(0.0807)	(0.350)
Collegesome	-1.291	-1.519***	-2.263**	-1.976	-5.636***	-8.540***
	(1.172)	(0.276)	(0.914)	(3.019)	(0.815)	(2.466)
Age	0.300	0.128	0.509	-0.329	0.0560	-0.147
	(0.736)	(0.149)	(0.427)	(2.095)	(0.599)	(1.874)
Age_sq	-0.00415	-0.00267	-0.00849	0.00641	-0.00222	-0.00154
	(0.0120)	(0.00223)	(0.00655)	(0.0337)	(0.00850)	(0.0279)
Health	-0.147	-0.120	-0.310	-0.425	-0.396**	-1.324
	(0.349)	(0.0791)	(0.238)	(1.058)	(0.193)	(0.811)
Family income	0.140	-0.0443	0.537	-0.279	-0.0627	0.135
	(0.295)	(0.0734)	(0.330)	(0.686)	(0.190)	(1.025)
Preschool children	-1.211	-0.625***	-0.0645	-2.459	-0.470	-1.468
	(2.669)	(0.155)	(0.280)	(5.826)	(0.403)	(1.061)
Location_rural	0.687*	0.849***	-0.300	1.882	0.534	-2.430
	(0.407)	(0.172)	(0.546)	(2.233)	(0.905)	(1.717)
Year2014	0.00347	0.336**	-0.387	1.994	-0.0474	-3.426*
	(1.441)	(0.164)	(0.606)	(2.763)	(0.414)	(1.760)
Year2016	-0.882	0.133	-0.562	-3.512	-0.925*	-5.625**
	(0.974)	(0.230)	(0.721)	(2.906)	(0.520)	(2.531)
Year2016-Year2014	-0.89	-0.203	-0.17	-5.51	-0.88**	-2.20
	(1.58)	(0.192)	(0.56)	(3.80)	(0.425)	(2.51)
Cons	23.48**	28.30***	17.06**	65.21*	54.60***	64.90*
	(11.19)	(2.542)	(7.930)	(33.24)	(10.41)	(36.41)
N	186	1771	1185	186	1771	1184

Note: Sample is women who worked last year.
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0$.

Table A1. 5 Linear probability estimation of female labor participation of married women, 18 to 38 years old

	Zero child	**One child**	**Two children**
Wage (1000 yuan/day)	-0.0106	0.00583	-0.00926
	(0.0864)	(0.0212)	(0.0264)
Wage square	-0.0163	-0.0581***	-0.0530***
	(0.0320)	(0.00956)	(0.0120)
Years of edu	-0.00939	0.00115	0.00158
	(0.0120)	(0.00290)	(0.00240)
College	0.154*	0.0615***	0.0448*
	(0.0801)	(0.0201)	(0.0259)
Age	0.0446	0.0490**	-0.0282
	(0.0632)	(0.0219)	(0.0224)
Age_sq	-0.000605	-0.000774**	0.000506
	(0.00102)	(0.000346)	(0.000359)
Health	-0.000282	0.00560	-0.0202**
	(0.0190)	(0.00737)	(0.00919)
Family member income	-0.0146	-0.0109*	-0.0213***
	(0.0210)	(0.00657)	(0.00784)
Fchildage_0to5	0.0288	-0.0571***	-0.0287**
	(0.0308)	(0.0152)	(0.0143)
Location_rural	-0.0436	0.0117	-0.0268
	(0.0455)	(0.0135)	(0.0182)
Year2014	0.147***	0.184***	0.256***
	(0.0434)	(0.0158)	(0.0276)
Year2016	0.109**	0.185***	0.212***
	(0.0521)	(0.0215)	(0.0290)
Year2016-year2014	-0.038	0.002	-0.044**
	(0.044)	(0.014)	(0.017)
_cons	0.308	0.139	1.449***
	(0.976)	(0.349)	(0.358)
N	179	1439	855
Adj. R2	0.099	0.390	0.367

Notes: These estimates use the imputed wage for women that did not work in the previous year.
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A1. 6 OLS estimation of the extent of labor participation of married women, 18 to 38 years old

	Recent usual days/month			Recent usual hours/week		
Variable	**Zero child**	**One child**	**Two children**	**Zero child**	**One child**	**Two children**
Wage (1000 yuan/day)	-7.127	-13.95***	-8.778**	31.64	-3.352	-4.939
	(6.780)	(2.744)	(3.460)	(24.46)	(6.133)	(7.047)
Wage square	4.978	4.391**	0.827	-32.52	1.081	-0.846
	(8.167)	(1.922)	(0.668)	(30.39)	(3.102)	(1.431)
Years of edu	-0.395***	-0.0226	-0.00301	-1.315**	-0.576*	0.228
	(0.142)	(0.0828)	(0.0888)	(0.637)	(0.304)	(0.292)
College	0.130	-1.174**	-0.713	-0.407	-4.720***	-4.585
	(1.015)	(0.539)	(0.940)	(3.648)	(1.773)	(3.430)
Age	0.640	0.492	1.511	1.756	-0.596	2.722
	(0.854)	(0.623)	(0.996)	(3.254)	(2.013)	(2.517)
Age_sq	-0.00937	-0.00814	-0.0268*	-0.0266	0.00591	-0.0523
	(0.0142)	(0.00986)	(0.0158)	(0.0551)	(0.0316)	(0.0407)
Health	0.113	-0.158	-0.0187	0.758	-1.730***	-1.487
	(0.386)	(0.190)	(0.299)	(1.319)	(0.622)	(1.031)
Family income	0.357	0.0998	-0.0557	0.0938	-0.207	0.195
	(0.296)	(0.199)	(0.277)	(1.291)	(0.654)	(0.966)
Child age 0 to 5	-0.503	-0.877**	-0.517	-4.046	-0.936	-2.772**
	(2.567)	(0.398)	(0.423)	(5.492)	(1.273)	(1.228)
Location_rural	-0.352	-0.312	-1.413***	-0.484	-1.658	-2.120
	(0.703)	(0.352)	(0.503)	(2.490)	(1.176)	(1.811)
Year2014	-0.255	0.895**	-0.644	0.484	-1.883	-2.306
	(0.883)	(0.355)	(0.585)	(3.610)	(1.226)	(2.193)
Year2016	-1.419	-0.231	-1.143	-3.244	-5.441***	-7.780***
	(1.163)	(0.565)	(0.779)	(4.119)	(1.854)	(2.888)
Year2016-year2014	-1.16	-1.13**	-0.50	-3.73	-3.56**	-5.47**
	(1.33)	(0.52)	(0.81)	(4.82)	(1.66)	(2.73)
Cons	15.93	18.38*	7.347	29.06	78.60**	22.43
	(12.79)	(9.908)	(15.57)	(47.04)	(31.98)	(39.51)
N	165	1290	760	165	1290	760
Adj. R2	0.130	0.112	0.051	0.061	0.062	0.018

Note: Sample is women who worked last year.
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Chapter 2 Appendices

Table A2. 1 Statistical summary of characteristics for service participants and non-participants (disaggregated performance)

	Whole sample		Only training		Only consulting		Both training and consulting		Training or consulting		Neither training or consulting	
	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
MissedMonthlyPayment [a]	0.16	0.36	0.15	0.36	0.14	0.35	0.15	0.36	0.15	0.35	0.20	0.40
Training hours [c]	2.87	8.29	8.22	14.02			8.99	12.12	3.52	9.06		
Consulting hours [d]	21.79	25.87			25.68	21.33	37.39	32.07	26.73	26.25		
Default ratio [e]	0.21	0.32	0.08	0.23	0.21	0.31	0.27	0.34	0.22	0.32	0.16	0.35
Loan interest rate	0.07	0.03	0.09	0.03	0.07	0.03	0.06	0.03	0.07	0.03	0.10	0.03
Household income [f]	2.14	1.75	1.45	1.04	2.41	2.00	1.76	1.23	2.12	1.76	2.24	1.68
Education year	14.82	2.49	14.38	2.05	14.96	2.44	14.65	2.80	14.81	2.53	14.88	2.30
College degree	0.76	0.42	0.70	0.46	0.81	0.39	0.70	0.46	0.77	0.42	0.75	0.43
Gender	0.35	0.48	0.17	0.37	0.41	0.49	0.31	0.46	0.36	0.48	0.29	0.45
Married	0.58	0.49	0.46	0.50	0.63	0.48	0.59	0.49	0.60	0.49	0.52	0.50
Number of children	1.16	1.19	1.28	1.52	1.20	1.16	1.23	1.20	1.22	1.21	0.88	1.02
Credit score [g]	633.74	85.26	605.93	74.63	650.30	84.02	628.80	85.68	639.49	84.93	608.42	82.03
Business courses	0.80	0.40	0.93	0.26	0.81	0.39	0.82	0.38	0.83	0.38	0.68	0.47
Business experience	3.19	5.07	2.07	2.58	3.57	5.32	3.19	4.13	3.31	4.79	2.67	6.12
Age [h]	42.14	10.18	38.24	9.92	41.89	10.33	42.27	9.28	41.65	10.05	44.28	10.46
Distance [i]	0.69	2.30	0.34	0.28	0.86	2.66	0.35	0.35	0.65	2.09	0.86	3.06
Membership years [j]	3.08	2.42	3.05	1.87	2.67	1.91	4.49	3.13	3.26	2.48	2.31	1.93
N	15441		1220		7555		3808		12583		2858	

Table A2. 2 Statistical summary of characteristics for service participants and non-participants (Aggregated performance)

	Whole sample		Only training		Only consulting		Both training and consulting		Training or consulting		Neither training or consulting	
	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
MissedPaymentRate (%) [a]	0.16	0.22	0.17	0.24	0.14	0.21	0.16	0.21	0.15	0.21	0.22	0.24
MissedThreePayments [b]	0.33	0.47	0.31	0.47	0.32	0.47	0.35	0.48	0.33	0.47	0.34	0.47
Training hours [c]	3.09	8.43	6.68	12.86	0	0	9.11	12.11	3.72	9.12	0	0
Consulting hours [d]	23.83	26.81	0.00	0.00	29.82	25.22	34.23	28.65	28.7	26.94	0	0
Default ratio [e]	0.19	0.34	0.14	0.33	0.18	0.32	0.22	0.35	0.19	0.33	0.18	0.36
Loan interest rate	0.08	0.03	0.10	0.02	0.07	0.03	0.07	0.03	0.07	0.03	0.1	0.02
Household income [f]	2.16	1.77	1.84	1.22	2.37	2.01	1.84	1.48	2.14	1.8	2.24	1.61
Education year	14.93	2.51	14.71	1.80	15.09	2.44	14.82	2.97	14.96	2.59	14.79	2.13
College degree	0.79	0.41	0.78	0.42	0.82	0.38	0.74	0.44	0.79	0.41	0.78	0.42
Gender	0.34	0.47	0.11	0.32	0.42	0.49	0.31	0.47	0.36	0.48	0.25	0.44
Married	0.58	0.49	0.47	0.50	0.63	0.48	0.59	0.49	0.6	0.49	0.49	0.5
Number of children	1.14	1.19	0.87	1.14	1.24	1.18	1.22	1.29	1.2	1.22	0.88	1.01
Credit score [g]	635.72	85.23	619.64	77.34	655.22	81.85	621.95	90.01	640.64	85.86	611.64	78.08
Business courses	0.80	0.40	0.93	0.25	0.79	0.41	0.82	0.39	0.81	0.39	0.77	0.42
Business experience	3.00	4.88	1.60	2.22	3.55	5.23	2.86	4.09	3.14	4.69	2.32	5.66
Age [h]	40.19	10.65	36.62	11.56	40.12	10.18	40	10.29	39.77	10.37	42.23	11.74
Distance [i]	0.63	2.06	0.28	0.13	0.88	2.94	0.33	0.29	0.64	2.24	0.58	0.69
Membership years [j]	3.24	2.13	3.14	1.62	2.96	1.37	4.5	2.9	3.5	2.17	1.98	1.35
N	613		45		289		175		509		104	

Table A2. 3 Means and standard deviations of characteristics for High (>620) and Low(≤620) credit score

	Monthly				Aggeragated			
	High credit score		Low credit score		High credit score		Low credit score	
	mean	sd	mean	sd	mean	sd	mean	sd
MissedMonthlyPayment	0.10	0.29	0.23	0.42				
MissedPaymentRate (%)					0.11	0.19	0.23	0.24
MissedThreePayments					0.24	0.43	0.44	0.50
Training hours	2.33	6.94	3.53	9.67	2.43	6.88	3.92	10.00
Consulting hours	25.62	26.92	17.05	23.67	26.02	25.99	21.06	27.61
Default ratio	0.19	0.30	0.24	0.35	0.16	0.31	0.22	0.36
Loan interest rate	0.07	0.03	0.07	0.04	0.08	0.03	0.07	0.03
Household income	2.45	2.00	1.76	1.28	2.49	2.02	1.73	1.26
Education year	15.29	2.46	14.25	2.40	15.40	2.47	14.34	2.44
College degree	0.81	0.39	0.71	0.45	0.83	0.38	0.74	0.44
Gender	0.33	0.47	0.37	0.48	0.36	0.48	0.32	0.47
Married	0.60	0.49	0.57	0.50	0.60	0.49	0.56	0.50
Number of children	1.09	1.21	1.24	1.15	1.06	1.25	1.25	1.11
Credit score	698.00	47.46	554.32	45.35	699.43	47.82	555.32	44.13
Business courses	0.77	0.42	0.83	0.37	0.77	0.42	0.84	0.37
Business experience	3.12	5.09	3.28	5.05	2.84	4.90	3.21	4.85
Age	41.81	10.15	42.54	10.20	40.89	11.17	39.31	9.90
Distance	0.88	3.05	0.46	0.50	0.75	2.70	0.48	0.61
Membership years	2.83	2.28	3.40	2.54	3.05	1.79	3.50	2.47
N	8535		6906		420		310	

Table A2. 4 Monthly payment and ancillary service, OLS, linear terms

	(1)	(2)	(3)	(4)	(5)	(6)
Training hours	0.00132***	0.00107***	0.00122***	0.000754**	0.000479	0.000207
	(0.000381)	(0.000370)	(0.000387)	(0.000374)	(0.000369)	(0.000360)
Consulting hours	-0.00129***	-0.000344**	-0.00159***	-0.000270**	-0.000767***	0.000160
	(0.000117)	(0.000136)	(0.000121)	(0.000134)	(0.000119)	(0.000130)
Default ratio			0.0944***	0.140***	0.0538***	0.0943***
			(0.0105)	(0.0110)	(0.0107)	(0.0112)
Loan interest rate			-0.490***	-0.984***	-0.314***	-0.647***
			(0.106)	(0.117)	(0.106)	(0.118)
Age			0.00386*	-0.00102	0.00363*	0.000745
			(0.00215)	(0.00212)	(0.00218)	(0.00215)
Age_square			-0.0000161	0.0000359	-0.0000237	0.00000614
			(0.0000241)	(0.0000238)	(0.0000246)	(0.0000242)
Credit score					-0.000765***	-0.000673***
					(0.0000346)	(0.0000354)
Edu years					-0.0159***	-0.0160***
					(0.00158)	(0.00155)
Edu college more					0.0970***	0.0937***
					(0.00938)	(0.00929)
Gender					0.0204***	0.0351***
					(0.00629)	(0.00624)
Married					-0.0215***	-0.0296***
					(0.00623)	(0.00613)
Housechild					-0.0100***	-0.00794***
					(0.00265)	(0.00262)
Business course					-0.0358***	-0.0370***
					(0.00771)	(0.00753)
Year fixed effect		yes		yes		yes
Cons	0.183***	0.118	0.0732	0.232**	0.767***	0.765***
	(0.00410)	(0.0782)	(0.0464)	(0.0920)	(0.0574)	(0.0969)
N	15732	15732	15732	15732	15445	15445
R2	0.009	0.036	0.023	0.059	0.065	0.094

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2. 5 Monthly payment and ancillary service, OLS, linear terms, client fixed effect

	Whole sample	High score (620)	Low score (620)	High score (640)	Low score (640)	High score (680)	Low score (680)
Training hours	-0.00119	-0.0112***	-0.00115	-0.0117***	-0.000574	-0.00606*	-0.00116
	(0.00434)	(0.00366)	(0.00485)	(0.00364)	(0.00459)	(0.00342)	(0.00413)
Consulting hours	0.000105	-0.000775*	0.00159**	-0.000827**	0.00160**	-0.000927**	0.00109*
	(0.000734)	(0.000402)	(0.000701)	(0.000392)	(0.000668)	(0.000371)	(0.000570)
Default ratio	0.0630	-0.000589	0.0844***	-0.0312	0.106***	-0.0351	0.0714***
	(0.0589)	(0.0229)	(0.0305)	(0.0231)	(0.0289)	(0.0287)	(0.0236)
Loan interest rate	1.157*	0.747***	1.261***	0.504**	1.221***	0.862***	1.150***
	(0.639)	(0.237)	(0.252)	(0.256)	(0.233)	(0.269)	(0.210)
Age	0.0913**	0.00830	0.136***	-0.0151	0.126***	-0.00323	0.114***
	(0.0358)	(0.0148)	(0.0212)	(0.0161)	(0.0187)	(0.0163)	(0.0163)
Age_square	-0.000541	0.000515***	-0.000988***	0.000768***	-0.000899***	0.000451***	-0.000757***
	(0.000431)	(0.000139)	(0.000165)	(0.000153)	(0.000144)	(0.000152)	(0.000130)
Year fixed effect	yes	yes	yes	yes	yes	yes	yes
Client fixed effect	yes	yes	yes	yes	yes	yes	yes
_cons	-2.806***	-1.496***	-3.685***	-0.987**	-3.453***	-0.863**	-3.280***
	(0.761)	(0.377)	(0.618)	(0.404)	(0.553)	(0.427)	(0.457)
N	15732	8635	7097	7442	8290	4967	10765
R2	0.049	0.070	0.054	0.065	0.058	0.051	0.054

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2. 6 OLS regressions (MissedPaymentRate)

	All	High	Low
Training hours	0.000488	-0.000809	0.00133
	(0.000902)	(0.000678)	(0.00136)
Consulting hours	-0.00128***	-0.00140***	-0.00115**
	(0.000299)	(0.000300)	(0.000489)
GDP growth rate	-0.0104*	-0.0155**	-0.00507
	(0.00576)	(0.00696)	(0.0104)
GDP growth rate next year	-0.0370***	-0.0493***	-0.0291***
	(0.00668)	(0.0118)	(0.00953)
Default ratio	0.122***	0.0760**	0.153***
	(0.0274)	(0.0348)	(0.0424)
Loan interest rate	-0.307	0.0493	-0.522
	(0.286)	(0.390)	(0.398)
Age	-0.000982	0.00383	-0.0115
	(0.00440)	(0.00471)	(0.0101)
Age_squre	0.0000290	-0.0000227	0.000154
	(0.0000496)	(0.0000520)	(0.000124)
Credit score	-0.000642***	-0.000681***	-0.000606**
	(0.0000943)	(0.000186)	(0.000297)
Education year	-0.00668	0.00156	-0.0177*
	(0.00446)	(0.00480)	(0.00904)
Edu_college and more	0.0776***	0.0221	0.145***
	(0.0258)	(0.0288)	(0.0494)
Gender	0.0274	0.0302	0.0113
	(0.0183)	(0.0213)	(0.0345)
Married	-0.0280*	-0.00811	-0.0303
	(0.0164)	(0.0187)	(0.0341)
Business courses	-0.0278	0.00413	-0.0560
	(0.0193)	(0.0186)	(0.0391)
_cons	0.741***	0.565***	1.049***
	(0.130)	(0.172)	(0.283)
N	614	342	272
R2	0.266	0.281	0.213

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2. 7 Margins of Probit regressions (MissedThreePayments)

	All	High	Low
Training hours	-0.000856	-0.00639*	0.000493
	(0.00191)	(0.00349)	(0.00269)
Consulting hours	-0.00298***	-0.00329***	-0.00291***
	(0.000693)	(0.000928)	(0.000984)
GDP growth rate	-0.0370***	-0.0349***	-0.0393**
	(0.0108)	(0.0116)	(0.0186)
GDP growth rate next year	-0.0586***	-0.0579***	-0.0468***
	(0.0118)	(0.0195)	(0.0171)
Default ratio	0.134***	0.0773	0.170**
	(0.0463)	(0.0588)	(0.0725)
Loan interest rate	-1.255**	0.0882	-2.840***
	(0.573)	(0.880)	(0.785)
Age	-0.000104	0.0148	-0.0410*
	(0.0100)	(0.0120)	(0.0218)
Age_squre	1.45e-05	-0.000145	0.000511*
	(0.000113)	(0.000130)	(0.000269)
Credit score	-0.00106***	-0.00138***	-0.000428
	(0.000210)	(0.000458)	(0.000658)
Education year	-0.00523	0.0109	-0.0203
	(0.00952)	(0.0117)	(0.0164)
Edu_college and more	0.0963*	-0.0748	0.277***
	(0.0581)	(0.0734)	(0.0861)
Gender	0.0444	0.0768*	-0.0519
	(0.0380)	(0.0449)	(0.0635)
Married	-0.0314	0.00246	-0.0220
	(0.0358)	(0.0430)	(0.0617)
Business courses	-0.0880**	0.0211	-0.221***
	(0.0418)	(0.0433)	(0.0760)
N	614	342	272

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2. 8 IV regressions (MissedPaymentRate)

	All			High			Low		
	Second stage	First stage Training	First stage Consulting	Second stage	First stage Training	First stage Consulting	Second stage	First stage Training	First stage Consulting
Training hours	0.0134*			0.0214*			0.0101		
	(0.00767)			(0.0121)			(0.0199)		
Consulting hours	-0.00292**			-0.00335**			-0.00250		
	(0.00148)			(0.00145)			(0.00571)		
GDP growth rate	-0.0129**	0.177	-0.0361	-0.0172**	-0.00278	-0.0115	-0.00855	0.476	-0.0933
	(0.00616)	(0.223)	(0.650)	(0.00810)	(0.247)	(0.791)	(0.0133)	(0.406)	(1.076)
GDP growth rate next year	-0.0321***	-0.375	0.502	-0.0537***	0.305	2.491**	-0.0237*	-0.828**	-0.892
	(0.00706)	(0.239)	(0.695)	(0.0112)	(0.326)	(1.043)	(0.0140)	(0.378)	(1.003)
Default ratio	0.126***	0.490	7.378**	0.0262	2.539**	10.30***	0.173**	-1.157	5.045
	(0.0280)	(1.019)	(2.963)	(0.0502)	(1.231)	(3.942)	(0.0684)	(1.693)	(4.492)
Loan interest rate	-0.0874	-33.24***	-172.9***	-0.0638	-12.51	-200.0***	-0.289	-38.23**	-123.4**
	(0.385)	(11.46)	(33.33)	(0.572)	(14.64)	(46.89)	(0.532)	(18.35)	(48.68)
Age	0.00241	-0.0585	1.777***	0.0139	-0.183	3.295***	-0.0163	0.270	-1.658
	(0.00628)	(0.203)	(0.590)	(0.00950)	(0.212)	(0.680)	(0.0183)	(0.476)	(1.263)
Age_squre	-0.0000102	0.000895	-0.0193***	-0.000130	0.00201	-0.0354***	0.000215	-0.00329	0.0209
	(0.0000719)	(0.00233)	(0.00677)	(0.000104)	(0.00234)	(0.00750)	(0.000230)	(0.00587)	(0.0156)
Credit score	-0.000488***	-0.00413	0.0589***	-0.000822***	0.0131	0.0891***	-0.000325	-0.0268*	0.0280
	(0.000155)	(0.00413)	(0.0120)	(0.000300)	(0.00822)	(0.0263)	(0.000780)	(0.0141)	(0.0374)
Education year	-0.00495	-0.0531	0.435	-0.00240	0.199	0.782	-0.0137	-0.230	0.826
	(0.00505)	(0.185)	(0.539)	(0.00699)	(0.205)	(0.657)	(0.0134)	(0.351)	(0.932)
Edu_college and more	0.0693**	0.480	-1.051	0.0208	0.234	-2.537	0.136***	0.562	0.285
	(0.0309)	(1.141)	(3.319)	(0.0446)	(1.368)	(4.381)	(0.0486)	(1.942)	(5.151)
Gender	0.0569**	-1.526**	6.570***	0.0688**	-1.107	6.028**	0.0420	-2.690*	8.565**
	(0.0274)	(0.724)	(2.106)	(0.0331)	(0.798)	(2.555)	(0.105)	(1.408)	(3.736)
Married	-0.0210	-0.637	-0.827	-0.00304	-0.0866	-0.438	-0.0229	-1.139	-1.015
	(0.0189)	(0.688)	(2.002)	(0.0249)	(0.756)	(2.423)	(0.0344)	(1.330)	(3.529)
Business courses	-0.0323	0.805	3.331	-0.0248	1.995**	9.996***	-0.0493	-1.660	-7.143
	(0.0239)	(0.882)	(2.565)	(0.0365)	(0.926)	(2.966)	(0.0432)	(1.765)	(4.681)
Distance	.	-0.906***	0.407		-0.718**	1.390		-0.808	-0.580
	.	(0.276)	(0.804)		(0.304)	(0.972)		(0.542)	(1.438)
Membership years	.	0.614***	4.215***		0.501**	5.688***		0.858***	3.303***
	.	(0.160)	(0.464)		(0.216)	(0.692)		(0.243)	(0.645)
_cons	0.522**	10.14*	-65.32***	0.539*	-6.980	-138.3***	0.880**	21.81*	27.47
	(0.205)	(5.591)	(16.27)	(0.281)	(7.908)	(25.33)	(0.435)	(13.14)	(34.86)
R2	614	614	614	342	342	342	272	272	272
	0.008			-0.344			0.072		

Endogeneity Test										
Durbin (score)	chi2(2)	6.83049			8.55044			0.235017		
	p	0.0329			0.0139			0.8891		
Wu-Hausman	F	3.30567			4.06274			0.106181		
	p	0.0372			0.0179			0.8993		
Robust score	chi2(2)	5.46143			7.47694			0.222665		
	p	0.0652			0.0238			0.8946		
Robust regression	F	2.78298			3.98261			0.100895		
	p	0.0625			0.0194			0.9041		
Weak IV Test										
Cragg-Donald Wald F statistic		5.22			3.59			0.46		
Critical values (15%)		4.58			4.58			4.58		
Anderson-Rubin Wald test	F	2.65			5.03			0.15		
	p	0.0716			0.0071			0.86		
Anderson-Rubin Wald test	Chi-sq(2)	5.43			10.52			0.32		
	p	0.0663			0.0052			0.85		
Stock-Wright LM S statistic	Chi-sq(2)	5.38			10.2			0.32		
	p	0.0679			0.0061			0.85		
N		614	614	614	342	342	342	272	272	272

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2. 9 Probit IV regressions of the impact of ancillary service on MissedThreePayments

		All	High	Low
Training hours		0.0933*	0.0596	0.183
		(0.0563)	(0.0874)	(0.204)
Consulting hours		-0.00971	-0.00853	-0.0369
		(0.0110)	(0.0108)	(0.0587)
GDP growth rate		-0.142***	-0.152***	-0.192
		(0.0445)	(0.0557)	(0.136)
GDP growth rate next year		-0.168***	-0.274***	-0.0320
		(0.0515)	(0.0803)	(0.144)
Default ratio		0.402*	0.0127	0.942
		(0.209)	(0.373)	(0.704)
Loan interest rate		-0.0842	2.710	-3.929
		(2.804)	(4.180)	(5.493)
Age		-0.00112	0.0555	-0.225
		(0.0470)	(0.0705)	(0.191)
Age_squre		0.0000553	-0.000522	0.00284
		(0.000541)	(0.000775)	(0.00239)
Credit score		-0.00301***	-0.00700***	0.00448
		(0.00116)	(0.00233)	(0.00802)
Education year		-0.00638	0.0248	0.0208
		(0.0379)	(0.0527)	(0.138)
Edu_college and more		0.257	-0.271	0.653
		(0.232)	(0.336)	(0.504)
Gender		0.264	0.391*	0.470
		(0.203)	(0.237)	(1.080)
Married		-0.0547	0.0223	0.0830
		(0.139)	(0.182)	(0.352)
Business courses		-0.366**	-0.128	-0.523
		(0.178)	(0.273)	(0.450)
Distance				
Membership years				
_cons		1.882	3.137	1.513
		(1.533)	(2.116)	(4.506)
Endogeneity Test				
Wald test of exogeneity	chi2(2)	9.34	2.67	7.54
	p	0.01	0.2638	0.023
Weak IV Test				
Anderson-Rubin test (AR)	chi2(2)	3.85	0.82	3.9
	p	0.146	0.66	0.14
F				
N		614	342	272

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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"Causal analysis on urban and rural education gap and income gap in China," *Economy and Management*, 2014, 28(06): 29-33.
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"The influence of marketing strategies on consumer behavior of organic vegetables*," Market Weekly (Theoretical Research*), 2014(09): 50-51. (with R. Shen, Y. Zhang)
"A review of the research on agriculture feminization in China,"*Jingchu Academic Journal*, 2014, 15(02): 37-40.
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