Do bankers prefer married couples? Marital status and credit constraints in France*

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April 2011

Preliminary

Abstract

Are married couples more credit constrained than unmarried households? If the cost of separation increases the risk of default, banks might be willing to lend to stable couples. In presence of incomplete information, marriage could be used as a signal of the quality of the match. This paper investigates the link between marriage and credit constraints. I use matching methods to evaluate the impact of marriage on credit constraints. I find that married couples are more likely to be approved for their loan, but they bear higher costs of credit. The differences between married and unmarried couples can be attributed to selection in the marriage rather than to discrimination against unmarried couples.

Keywords: marriage, credit constraints, signal, matching estimator

JEL Classification : J12, R21, J71, D12

*This paper was started jointly with Arnaud Périgord when he was a PhD student. I am very grateful to Laurent Gobillon, Thierry Ly, Raúl Sampognaro, Maxime Tô, Yanos Zylberberg and to seminar participants at PSE for their thoughtful comments. All comments are welcome (leturcq@pse.ens.fr)

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1 Introduction

Encouraging access to property has been at the heart of political debates in France for the last decades. There are two main reasons keeping households away from ownership: households may not be willing to be owner or households may not be able to become owner. Political measures target the latter, providing state-supported loans (such as *Prêt aidé à l'accession à la propriété (PAP)* and a *Prêt conventionné* since 1977, a zero interest loan *Prêt à taux zéro* since 1995). Such measures clearly aim at making credit constraints less binding, by decreasing the cost of credit. It supports the idea that households are renters not because they chose it, but because they are not able to become owner.

Since the seminal work by Hall (1978), the literature has broadly investigated the idea that at least some households are credit constrained in the economy. This empirical question has important theoretical consequences: if households are credit constrained, they can not smooth their consumption over the life cycle, leading to a non optimal consumption path. It challenges the permanent income cycle hypothesis (PIH) and then the Ricardian equivalence which implies that macroeconomic stabilization policies are not effective.

Why are households credit constrained? Stiglitz and Weiss (1981) indicates that the lack of information on which entrepreneurs are likely to default could explain credit rationing. Banks are likely to discriminate among households those having a high probability to default. Because the bank does not know which households are more likely to default then it has to use proxies such as income and to impose a collateral. What can household do to make the constraints less binding? A strategy inspired by the signalling literature would be to find a signal that shows that the risk of default is low. If the risk of default is correlated to the risk of separation of the couple, then marriage could be used as a signal of the match quality and then lower credit constraints. The marriage is a good signal of the stability of the couple if it permits to separate stable from unstable couples. As a consequence, it has to be observable and costly. But the cost has to be higher for unstable couples. As marriage represents an additional cost in case of separation, it could be more costly for unstable couples than for stable couples. The idea of marriage as signal has not been investigated in the empirical literature on marriage, although it has been proposed in the theoretical literature on marriage since Bishop (1984). Other signal for the stability of the couple could be investigated, such as children or the duration since the formation of the couple. However, children also represents a cost for both married and unmarried couples, that could lower the chances to be approved for a credit and the duration since the formation of the couple is not observed by the bank. Moreover, the inactivity of the woman could be interpreted as a signal for the commitment of spouses and therefore for the stability of the couple. However, as children, the inactivity also represents a cost that could lower the access to credit.

But it could be interesting to investigate these other characteristics can be interpreted as signal of the stability of the couple.

This paper investigates the link between credit constraints and marriage. Identifying credit constrained households is challenging because credit constraints are not observed. Based on data from the 2001 housing survey in France, I study two types of credit constraints inspired by the literature on credit constraints. Using declarative credit constraints, I study constraints at the extensive margin: are married couples more able to get a loan? Then I turn to the terms of the credit: are married couples more able to get a better loan? The loan is described by 6 variables: value (expressed in level or in annual income), downpayment (expressed in level and in proportion of the value of the housing), total cost of the loan and required income. I cannot compare directly the outcomes of married and unmarried couples, as they have different observable and unobservable characteristics. I use matching methods to deal with the differences in observables between married and unmarried couples. The results do not exhibit stronger credit constraints for unmarried couples than for married couples. However, unmarried couples are more discouraged borrowers than married couples. That could be explained by selection in the marriage. On the contrary, married couples look disadvantaged on the credit market. This surprising result could be interpreted as a selection on unobservable characteristics.

The paper is structured as follows. Section 2 presents the existing theories of marriage contracts and section 3 describes how credit constraints are measured in the literature. To my knowledge, these two streams of the literature have never been jointly considered. Section 4 defines the data and the measure of credit constraints. Section 5 explains the estimation strategy and section 6 presents the results. Section 7 concludes.

2 Marriage as a signal

When Becker wrote his seminal work on marriage (**??**), he made no difference between married and unmarried couples. Following his path, marriage and household formation have been treated identically in models for decades. This can be explained by the fact that there were almost no cohabiting couples in the 1970s. The last decades witnessed a change in household formation, with the increase of cohabitation jointly with the increase in the age at the first marriage. As explained by Stevenson and Wolfers (2007), the increase in the number of cohabiting couples is led by two forces: marriage tends to be preceded by a period of cohabitation for a large part of couples and cohabitation tends to become a permanent state for a part of couples - although it is very difficult, if not impossible, to estimate the number of "permanent cohabitation". As a consequence, the number of cohabiting couples in a cross section sample tends to become larger than what it was in the 1970s, especially in Europe. Stevenson and Wolfers estimate that 10.8% of couples are cohabiting in France in 2003, which is twice higher than in the US at the same period. The dramatic increase in the number of cohabiting couples coincides with the increase of out-of-wedlock births in France. 37.2% of newborn babies in 1994 had unmarried parents, 44.7% in 2001 and more than a half since 2006 (INSEE, 2010). Therefore, marriage is not necessarily the stepping stone of the formation of the family in France.

This phenomenon raises many questions on the role of marriage in the couple's life cycle. The idea of marriage as the couple outset tends to disappear. The marriage analysis follows now a choice-based approach. Couples can choose to get married or not, and when they get married. Brien, Lillard, and Stern (2006) propose a model in which cohabiting is a necessary step to observe the quality of the couple in an uncertain environment. Matouschek and Rasul (2008) investigates three reasons of getting married: marriage provides an exogenous benefit, serves as a commitment device, and it is used as a signal toward the partner. Their analysis of the impact of unilateral marriage on divorce trends tends to support the commitment device hypothesis. It implies that marriage is used in a repeated game to ensure that partners play cooperative strategies.

In an early paper, Bishop (1984) proposes an alternative analysis of marriage: marriage as a signal towards the world. This analysis is also supported by Rowthorn (2002). The idea of marriage as a signal is in the same vein as the theory of signal by Spence (1973). As divorce is costly, the marriage can be viewed as a costly signal of the quality of the couple. The cost is not bear by the couple when getting married (investing in the signal) but if the couple breaks up. Therefore, it can be viewed as a signal of the quality of the couple as the (expected) cost of marriage is higher for poor quality couples. Marriage is a signal toward the rest of the world, whereas the signalling theory of marriage in Matouschek and Rasul suggests that marriage is a signal toward the other partner. But marriage could provide information to economic agents for whom the quality of the match does matter such as economic agents involved in a long term partnership with the couple. Indeed, in a context of uncertainty, before starting a long term partnership with the couple or one of the spouses, the agent could be willing to know if the partner/couple is reliable. Marriage could express the capacity to commit in a long term relationship. For example, marriage could prove the capacity of a partner to get involved, and impact her employability. Korenman and Neumark (1991) finds a wage gap between married and unmarried men, and attribute the "marriage premium" to a selection in marriage.

This paper studies the impact of marriage on credit constraints. When contracting a mortgage, the couple contracts a long term relationship with the bank or the mortgage broker (thereafter both of them are called with the generic word "bank"). If the bank has to pay some costs at bargaining a new loan in case of divorce, it is more likely to lend to stable couples. But stability is not directly observable, thus the banker requires a proxy for stability: marriage could be a such a proxy, especially as the duration since the couple formation is unobserved. In order to be a good signal, the marriage needs to be observed, which is obviously the case, and costly. But the cost of marriage has to be high enough to induce a separate equilibrium, i.e. stable couples get married and unstable couples do not. So the cost of the marriage should be linked to the risk of splitting. If this assumption is verified, it should avoid reverse causality. Indeed, if couples are aware that they are more likely to be approved for their loan if they are married, even unstable couples could contract a marriage. Therefore, the marriage induces a separate equilibrium if the cost of marriage is high enough to keep unstable couples away from marriage, i.e. if the *Individual Rationality* constraint is verified, indicating that couples reveal their type by getting married.

Of course, the bank is willing to discriminate couples based on their stability only if it is costly to lend to unstable couples. The cost for the bank might arise if the couple breaks up. Several reasons explain the cost of separation for the bank. First, a separation can be very costly, because of moving cost, lawyers, etc. Therefore, agents can be economically weak during the period of divorce, thus increasing the risk of default. The typology of households listed as having an excessive debt in 2001 by the Banque de France[1] indicates that 27% of excessively indebted households are divorced (or separated) whereas 6.5% of the population is divorced (Banque de France, 2002). Moreover, the debt became excessive after a divorce for 16% of them, and for an accumulation of credits for 48% of them. Therefore, even if the risk of default is low in France, it tends to increase after a divorce or a separation. If the couple is economically weak before a separation, the separation could increase the economic burden and then the risk of default. If the risk is large enough, the bank should favor stable couples, and so married couples, if marriage is consider as a signal.

The French survey on households' assets (*Enquête Patrimoine 1998*) provide information on which households declare having experienced financial problems during the past years. Table 1 shows that the proportion of respondants indicating that they experienced some problems is much bigger among households that split during the last years. Especially, 31.8% of respondant having broken up during the last year declare having experience financial problem during the last year, whereas only 8.4% of unseparated couples and 12.2% of singles had such problem. Similarly, 29.7% of respondants having

[1]When they cannot support their debt anymore, households can call the Banque de France to have their debt paid off by the Banque de France. They have then to pay off the Banque de France and they are listed as having an "excessive debt" (Loi Neiertz, 1989).

broken up during the last 5 years declare having experienced financial problem for several years. Tables 2 points that among respondants experiencing a separation, previously married individuals tend to experience more financial problems than previously unmarried individuals. Among respondants declaring that they experienced financial problems, separated individuals tend to attribute more their financial problems to "personal reasons" (that includes separation) than other couples especially among previously married couples. Although these descriptive statistics do not give clear results on the causality of separation of financial difficulties, they tend to support the idea that individuals are financially weak after a separation.

But, default is the worst case: the separation does not end up in default in most cases. Then, the separation can also be costly even if the couple does not default. There are two classic cases. First case, the couple sells the house when separating and pays off the debt, providing the housing situation gives the opportunity to sell the house. The bank can charge the couple for the penalties in that case[2]. It induces a cost (albeit low) for the bank in terms of time and bargaining when the debt is liquidated. Second case, one spouse wants to buy her part from the other spouse and to stay in the house. In that case, she has to renegotiate the credit with the bank and to contract a new one to buy the other partner's part. This induces some negotiation costs. In all cases, the bank could support indirect costs after a separation with the loss of a consumer. Consumers tend to be reluctant changing of bank, except when contracting a credit. As the housing credit are long term credits, they can be used by the bank to attract new consumers. Therefore, the separation and the liquidation of the credit increase the risk of loosing a consumer.

A marital-based discrimination is an important issue in a context of raising cohabitation. If couples have to wait for being married in order to borrow, they would postpone the investment decision. It makes it more difficult to smooth consumption over the life cycle. They could also bring forward their marriage. In an analysis of uncertain match quality *à la* Brien, Lillard, and Stern (2006), it could decrease the mean quality of married couples and then increase divorce rate on the long run. If the bank needs a signal of the quality of the couple, then a decrease in the marriage rate could introduce non optimality on the credit market.

[2]The penalties the bank can charge are restricted by the the law (Loi Scrivener, 1978 and 1979)

3 Measuring credit constraints

3.1 A general framework defining credit constraints

The definition of credit constrained is straightforward: a household is constrained if it cannot borrow as much as what would be optimal given its intertemporal utility. Therefore, its consumption path is not the optimal over the life cycle, because it cannot borrow the amount of debt that maximizes its intertemporal utility and smooth its consumption. So the determination of who is credit constrained and how much she is constrained requires the observation of how much the couple is willing to borrow. The optimal consumption path is determined by an intertemporal program of consumption. The model is defined in the classical life cycle permanent income model. However, this framework has been challenged since the pioneer papers by Hall (1978) and Hall and Mishkin (1982). They show that the Euler equations derived from the intertemporal model induced by the permanent income hypothesis are violated, supporting the idea that household are credit constrained. Euler equations simply states that the marginal rate of substitution between current and future consumption is set equal to the marginal rate of transformation, ie how much 1 unit of current money produces in the future.

There are several implications to Hall's finding. First it challenges the permanent income cycle hypothesis (PIH) traduces the Ricardian equivalence, implying that macroeconomic stabilization policies are not effective with PIH. But this hypothesis requires that households are able to smooth their consumption over the life cycle. As explained by Hayashi (1985a), the life cycle permanent income hypothesis need household to be unconstrained. Therefore, if at least some households are credit constrained, macroeconomic stabilization policies could be effective. So, if households are not equally subject to credit constraints, it could be efficient to make policies targeting credit constrained households. Challenging the PIH has been an important motivation in the literature. Then, credit constraints can also impact the housing market. If they are constrained, households cannot move easily and thus, they can not adjust their housing stock to their need. Gobillon and Le Blanc (2002) show that investment in housing is similar to the (s, S) as in classic investment models. Credit constraints decrease mobility on the housing market, inducing market frictions.

The idea of the paper is to explore if unmarried couples are more credit constrained than married couples. Differences in the access to credit between households imply a difference between households on the long run. If credit constraints are more stringent for unmarried households, then the impact of constraints is more important for couples choosing to postpone their marriage. Therefore, it introduces differences that could impact their saving and investment behavior on the long run. As a consequence, the rise of cohabitation could increase the differences between households and impact wealth accumulation during the life cycle.

My measure of credit constraints is inspired by Hayashi (1985b), defining credit constraints as (i) credit rationing, ie they are constrained on quantities: "they face some quantity constraint on the amount of borrowing" (ii) total cost of the loan is too high: "the loan rate available to them is higher than the rate at which they could borrow"

3.2 Identifying credit constrained households

Following the seminal paper by Hall (1978), Hall and Mishkin (1982) uses Euler equations to study how the consumption is related to the permanent income (using the panel data of the PSID[3]) and transitory shocks on income. They find that consumption is more volatile than income: 80% of consumption obeys the life cycle/permanent income hypothesis, while 20% of consumption is explained by transitory shocks on income. They attribute these 20% to credit constraints. However, they are not able to identify credit constrained households. Identifying who is credit constrained and the impact of credit constraints is difficult because it relies on an unobserved information: the expectation the household forms on its permanent income. As they are not observed, credit constraints have to be derived from proxies.

Proxies are given either by indirect criteria such as income and net-wealth of the household or directly from declarative self reported indicators of constraints. Linneman and Wachter (1989) derived credit constraints from the observation of wealth and the income which defines the maximum home purchase price the household can afford. This amount is compared to the actual value of the housing purchased by the household. If it is close to the maximal price the household can afford, then the household is said to be credit constraint. If not, it is said to be unconstrained. Using their definition of credit constraint, Linneman and Wachter find that 27% (resp. 15.5%) of household are credit constrained during the 1975-1977 (resp. 1981-1983) period in the United States. Hayashi (1985a) imposes the condition that the debt held by the household cannot exceed the value of assets that serves as a collateral. If it is, then the household is credit constrained. In an influential paper, Zeldes (1989) splits his sample into low assets and high assets households, arguing that households with large amount of wealth and large wealth-to-income ratio are not credit constrained. On the contrary, Jappelli (1990), Cox and Jappelli (1993), Duca and Rosenthal (1994) on US data,

[3]Panel Study of Income Dynamics

or Chivakul and Chen (2008) on data from Bosnia and Herzegovina consider as credit constrained households reporting they made a request for credit that was turned down. Wakabayashi and Horioka (2005) uses Japanese data on complaints against financial institutions to derive credit constrained households, and Gross and Souleles (2001) exploit data on credit card accounts and use changes in the credit limit and in interest rates to estimate dynamic effects of changes in credit on consumption, denoting binding credit constraints.

Identifying credit constrained households serves several purposes. The first purpose was to define if at least some households are credit constrained and how much households in the economy it represents. Hayashi (1985a) and Zeldes (1989) test if the Euler equation is likely to be violated for household likely to be constrained and not for the unconstrained household. Their consumption behavior tends to support the idea that at least some households are credit constrained. Jappelli (1990) uses declarative information on US data to proxy borrowing constraints. He defined as credit constrained a household whose request was turned down or not fully granted, or if the household did not apply to a credit because it thought that it could be turned down. He finds that 19% of the households are credit constrained. Using a similar proxy, Chivakul and Chen (2008) shows that around 80% of households are credit constrained in Bosnia and Herzegovina in 2001. The second purpose focuses on the impact of credit constraints on economic choices, such as access to ownership. Using US data, Linneman and Wachter (1989) and Duca and Rosenthal (1994) study the impact of borrowing constraints on access to owner occupied housing. Using different proxies identifying constrained households, both find high and significant impact of credit constrained on home ownership. Cox and Jappelli (1993) estimates the extra amount constrained households would like to borrow. They identify constrained households from replies to direct questions. They are able to model the desired amount of debt from the unconstrained group and extrapolate the result to estimate the extra amount of debt desired by constrained household. They find that highly constrained household would increase their liabilities by 75%. Grant (2003) jointly model supply and demand for credit using a canonical desequilibrium model. He estimates that 26-31% of households are credit constrained and would like to borrow up to 4,000 dollars more.

The goal of the paper is to estimate if unmarried and married couples face different credit constraints. Therefore, I use the classic Rubin framework of evaluation literature in econometrics. I consider marriage as a treatment and I analyze the impact of marriage on credit constraints using econometric tools of the evaluation literature. However, as for papers that study the impact of credit constraints, I don't observe which households are constrained or not. I use different proxies inspired by the literature to derive credit constraints. To derive constraints at the extensive margin, I use declarative responses to questions on rejected application as in Jappelli (1990). To proxy constraints at the intensive margin, I compare the maximum debt a household can afford to the actual debt held by the household, as in Linneman and Wachter (1989). If they are close, I consider that the household is constrained : therefore the amount of debt observed gives the supply side of the loan, because it gives what constrained households were able to get. Among constrained households, I compare how married and unmarried couples perform on the credit market. As this part only consider constrained households, the sample size is drastically reduced.

4 Descriptive statistics

4.1 Data: Housing Survey

4.1.1 The survey

The housing survey (*Enquête Logement*) is a national survey conducted by the INSEE[4] describing the housing stock in France. It is a cross section survey, repeated almost every 4 years since 1970. Information about credit constraints is available in 2001, therefore I use only one cross section of the survey[5]. It provides detailed information on housing characteristics together with a number of household characteristics such as housing status, income, and demographic features. New owners are also surveyed about their debts when they had to contract a loan for their investment. Only debts contracted for housing investment are described.

Macroeconomic forces drive the credit market, especially the interest rate and the housing price. The interest rate for long term housing loans can be approximate by the rate of national bonds (see figure 1). The 1997-2001 period witnessed a decrease in the long-term interest rate and an increase in the housing prices everywhere in France. In 2001, the credit market tends to be favorable to investment: the leading interest rate decreases and the monetary aggregate M3 increases, meaning that banks are likely to lend to economic agents. In this context, credit constraints tend to be less binding at the end of the studied period than at the beginning.

[4] Institut National de Statistiques et des Etudes Economiques www.insee.fr

[5] Other surveys provide information on debts, such as the survey on assets (Enquête Patrimoine) which is a national survey providing detailed information on households' assets, including debts and housing. The 1998 wave also surveys households on their credit constraints, but only during the last 2 years. I preferred working on the housing survey because the sample is 3 times larger and because the main interesting question for this paper focuses on credit constraints on a larger span (5 years) than the survey on assets (2 years), which increases the size of my subsample of interest. Panel data including information on households debts does not exist in France.

4.1.2 Subsample selection

The sample of the housing survey is representative of the French population. I select a subsample to address the issue of credit constraints on couples. Among the 32,156 households of the initial sample, I keep 2,398 households (or 2,315 with the strict definition of credit constraints - see below for the definitions). The subsample is selected step by step in order to focus on access to owner-occupied housing. First, I keep couples. In order to make sure that the application for a credit was not made by one spouse with another partner, I exclude couples such that one spouse was committed in an other couple 5 years ago. As I want to analyze access to owner occupied housing, I drop all owner couples that don't buy for the first time. Among the remaining sample, 40% rent and 60% are owner. But among renters, some have been credit constrained and other have not. The question on declarative credit constraints permits identifying credit constrained households among renters, during the last 5 years. Therefore I can study households that have been willing to invest in housing during the last 5 years: either they succeed then I identify them because they have a mortgage contracted less than 5 years ago or they failed and they say their application has been turned down. I can also identify discouraged borrowers who declare willing to invest but do not apply for a mortgage, thinking their application could be turned down. So I only keep households that have been willing to invest during the period 1997-2001 (have they fulfilled or not). There are a strict and a broad definition of being constrained. The strict definition only includes households whose application had been turned down. The broad definition adds discouraged borrowers. In my sample, 1,212 households are recent owners, 1,001 did not invest but were not constrained and 102 households (resp. 185) are constrained according to the strict (resp. broad) definition of credit constraints. I want to avoid couples with unknown collateral value. So I drop couples owner of other housing, because the value of the other housing is not surveyed. As I only observe mortgage, I do not know if the household holds other debts. In order to reduce the risk of measurement error, I drop households with at least one self-employed partner because they are more likely to hold professional debts, and because housing could also be used as a work place. The type of marital contract is likely to be relevant if the female is active. Indeed, if she is inactive, then the debt only relies on the male's income are they eventually getting divorced or not. So I drop couples with an inactive woman. Eventually, for matching reasons, I had to drop couples if the male does not work full time, high income household (more than 12,000 euros a month) and people such that the head of the household is older than 50. The sample selection process is described in table 3.

This subsample is very small compared to the whole sample, as it only represents 7.5% (7.2% for the strict definition of credit constraints). But this subsample is likely to be representative of the

French population. Indeed, the INSEE (2011) states that in 2000, 21.1% of households in France was refunding a loan. But this includes singles: in 1999, 58.8% of the population lives in couples. Moreover, keeping couples that have been willing to invest in housing once in the last five years reduces dramatically the sample size.

4.2 Credit constraints

Credit constraints can have two impacts on investment behavior of couples:

- at the extensive margin: couples do not borrow at all, either because what they can borrow is not enough to satisfy them or because the bank rejects their request
- at the intensive margin: couples borrow less than what they would like, because the price is too high or they are constrained on quantities

4.2.1 Declarative credit constraints (at the extensive margin)

Estimating the impact of marriage on credit constraints at the extensive margin requires the observation of rejected loan applications.

Credit constraints at the extensive margin are difficult to identify because one needs to distinguish among non borrowers those who actually applied for a loan and were rejected from those who did not. Figure 2 summarizes the application process. Couple may or may not want to invest in housing, but this is not directly observed in the data. This information can be derived from the observation of couples that declare having applied for a mortgage or having been discouraged. 60% of unmarried couples and 69% of married couples are willing to invest in housing. Most couples need to borrow at least part of the value of the housing: on the period 1997-2001, I do not observe any credits for only 4% of first owner couples, including both non response to the debt questionnaire and those who could afford their investment without borrowing. So application for a loan is considered as a necessary step of the investment. I refer as discouraged borrowers those couples that, while willing to invest in housing, don't apply because they think their loan could be rejected. Discouraged borrowers are answering "Yes" to the question *"Was there any time in the past 5 years that you (or your husband/wife) thought applying for a credit at a particular place but changed your mind because you thought you might be turned down?"*[6] The proportion of discouraged households is a bit higher for unmarried couples:

[6]Translation for: *"Au cours des 5 dernières années, y a-t-il eu un moment où vous/votre conjoint avez envisagé de demander un crédit auprès d'un organisme, mais ne l'avez pas fait parce que vous pensiez que ce crédit vous aurait été refusé ?"*

4% of them are identified as discouraged while 3.1% of married couples are discouraged borrowers. Among those applying for a credit, rejected applications can be identified. Constrained borrowers are those answering "Yes, rejected" to the question *"Was there any time in the past 5 years that you were rejected for a loan by a mortgage broker or a bank, or you were approved for a lower amount than what you asked?"*[7] The rejection rate (5.2%) is a bit higher among unmarried couples than among married couples (4.0%).

Credit constraints can be strictly defined as credit constraints directly induced by the mortgage broker, excluding the discouraged borrowers. Following Jappelli (1990), a broader definition of credit constraints includes direct rejected applicants and discouraged borrowers. Using this broad definition, 9.0% (resp. 7.0%) of unmarried (resp. married) couples are constrained. The strict definition is more appropriate to the goal of the paper, which is to estimate the direct impact of being married. However, as discouragement is indirectly bank-induced, the impact of marriage using the broader definition is also estimated.

Constrained and unconstrained couples are described in table 5. Whatever the definition of credit constraint, unconstrained couples tend to be richer, to work full time, to be more educated and the spouses more often work in the public sector than constrained couples. The differences are straightforward since the bank is more likely to approve the application of wealthier couples, who tend to work more and to be more educated because education increases income in the life cycle. Moreover, public employment is more stable than private employment. This results are confirmed by the regression of the dummy for credit constraints on the covariates presented in table 7: richer and educated households are less likely to be constrained, but hte sector of employment does not impact credit constraints.

4.2.2 Defining credit constraints at the intensive margin

Credit constraints at the intensive margin, i.e. how much couples can borrow compared to how much they would like to borrow are not directly observed. Even if the amount of money borrowed by the household is observed, this amount does not directly give how much the household is constrained. Indeed, it reflects how much unconstrained couples demand and how much constrained couples were given. Grant (2003) proposed to model the observed credit using a canonical desequilibrium model as in Fair and Jaffee (1972). The market for credit is composed of a demand side and a supply side. On the demand side, the household wants to borrow d_i. On the supply side, the bank agrees to lend

[7]Translation for *"Dans les cinq dernières années, est ce qu'un organisme de prêt, une banque , vous a refusé une demande de crédit, ou vous a accordé un crédit d'un montant inférieur à celui que vous demandiez ?"*

s_i to this household. The observed credit y_i is the minimum of them:

$$y_i = d_i + c_i(s_i - d_i) \text{ with } c_i = \mathbb{1}\{s_i < d_i\}$$

The estimation of such models requires excluded variables both for the supply and for the demand for credit. However, estimating the impact of marriage on credit constraints at the intensive margin does not require information on both sides of the market. It only requires the observation of how much the bank is likely to lend to a married couple compared to an unmarried couples. This difference could be studied if s_i were observed for married and unmarried couples. The supply side s_i might be observed for couples for whom the credit constraint is likely to be binding. Therefore, I use a classic splitting sample strategy in the literature, based on observed assets: I only examine households that I consider being constrained because they indicate how much a constrained household is able to get, so it indicates the terms of the loan for credit constrained household at the intensive margin.

When investing in housing, the household buys a house of value V, partly with its downpayment D and the mortgage M, such that $V = D + M$.

As explained in Linneman and Wachter (1989) and Gobillon (2008), credit constraints stem from a two-fold rule: on wealth and on income. First, households should have a downpayment D, which is greater than a part a of the value of the house. So $D \geq aV$. This constraint is binding if the household can not borrow more than $\overline{M}^D = \frac{1-a}{a}D$.

Second, the annual mortgage payment cannot be higher than a part $\overline{e}$ of the income. e is called the effort rate. When borrowing at a rate r, for a N-year mortgage, the household yearly refunds $R = \tilde{r}M$, with $\tilde{r} = r\frac{(1+r)^N}{(1+r)^N-1}$[8]. Denoting I the year income, this constraint imposes that $R \leq \overline{e}I$. It is binding if the household can not borrow more than $\overline{M}^I = \frac{\overline{e}I}{\tilde{r}}$. Taken together, the two constraints imply that the maximum value a household can borrow is:

$$\overline{V} = D + \max\left(\frac{1-a}{a}D, \frac{\overline{e}I}{\tilde{r}}\right)$$

For each household, I compute the maximum amount it can borrow when the constraint on income is binding. $\tilde{r}$ is computed using the mean r observed for the year the loan is contracted and using as N, the duration of the main loan (determined by the most important debt) hold by the household. $\overline{e}$ is fixed to an arbitrary value 0.3, which is the maximal effort rate approved by state-supported loans.

[8]The condition to determine the annual mortgage payment is that the sum of annual payment should be equal to the value of the loan the year it falls due. So, R is determined such as $R+(1+r)R+\cdots+(1+r)^{N-1}R = (1+r)^N M \Leftrightarrow \sum_{t=0}^{N-1}(1+r)^t R = (1+r)^N M \Leftrightarrow \frac{(1+r)^N-1}{r}R = (1+r)^N M$

Linneman and Wachter (1989) fix $\overline{e}$ to 0.28. Then I consider as likely credit constrained household those whose debt is higher than $0.85\overline{M}^I$. I chose 0.85 in order to satisfy two constraints: I want to keep couples likely to be credit constrained, but I need my subsample to be as great as possible. According to that definition, 33% of married couples and 31% of unmarried couples are credit constrained.

Table 6 summarizes the credit held by households, depending on their marital status. Notice that the number of indebted couples is lower than the number of unconstrained household detected before. This could be explained if some couples apply and are approved for a loan but they do not invest. Constrained households are more indebted than unconstrained household: they hold a higher debt and the debt represents 3.84 years of annual income, for 2.66 years for unconstrained households. The constraint on downpayment does not seem binding for all households: 22.2% of couples do not report any downpayment when contracting their mortgage. The downpayment represents 13.9% of the house value for constrained couples, but 21.4% for unconstrained couples. In France, the State supports access to owner-occupied housing by proving zero-rate loans (*Prêt à Taux Zéro*, denoted PTZ below). This loan is often considered as personal downpayment. It can be refund either directly or once the main mortgage is refunded. As so, it is considered as shifting personal savings over time. Including PTZ in downpayment decreases the proportion of couples without downpayment to 9.8% for constrained couples and 15.6% for unconstrained couples. Then, downpayments represent 24.4% of the housing value for constrained household and 26.3% for unconstrained households. The total cost of the loan represents the ratio of what is refunded on the initial debt. The cost is approximatively 1.5 and similar for constrained compared to unconstrained couples. By definition of credit constrained, the effort rate is much higher among constrained couples than unconstrained couples. Therefore, constrained households tend to borrow more than unconstrained households, with lower downpayment. But the cost of credit is similar for both types of couples. They contract more State supported loans.

Table 4 describes constrained and unconstrained households at the intensive margin. Among indebted households, constrained households are richer and are more educated, and females are less likely to work part time than unconstrained households. The constrained spouses less often work in the public sector. These results are confirmed in the regression of the characteristics of the debt on the households characteristics and the debts characteristics in the column (1) to (5) in the table 8 and table 9. Both tables describe the correlation between the outcome and the caracteristics of the household and the debt. They are different as the sets of characteristics are different. Table 8 uses discretized variables while table 9 uses continuous covariates.

The value of the debt is impacted positively by the income and the characteristics of the debt (column (1)). The cost of the debt is negatively impacted by the income, the percentage of downpayment and the number of children, but positively by the amount of the debt and if the female works part time. Men working in the public sector impact positively the cost, but women working in the public sector impact negatively the cost (column (3)). The amount of downpayment is positively correlated to a higher income and higher education of the women, but negatively by the number of children (column (4)). The percentage of the value paid with the downpayment is positively correlated to the amount of downpayment and to the number of children and negatively to the cost and to the amount of the debt (column (5)). Therefore, a higher income is correlated to a higher debt, but also to a higher downpayment. The higher the part of the value is explained by the downpayment, the lower the debt is. The total cost of the debt tends to decrease with the amount of the debt, and as a consequence with the percentage of downpayment.

4.3 Married and unmarried couples

Constraints at the extensive margin are measured on a different subsample than constraints at the intensive margin. Indeed, it includes all couples that are willing to invest in housing. Therefore, it includes constrained couples that are not able to access ownership. But it also includes households that eventually give up getting a loan or that have not contracted the loan to the date the survey is made. Therefore, I define two samples depending if constraints at the extensive or at the intensive margin are at stake.

Table 5 describes the characteristics of constrained and unconstrained households according to the strict and the broad definition of credit constraints at the extensive margin, depending on their marital status. Married couples tend to be older, richer, and have more kids than unmarried couples, are they constrained or not. The unmarried female works more full time and has higher diploma than her married counterpart. Among unconstrained couples, unmarried male are more educated than married. These characteristics are confirmed by columns (5) and (6) in table 7 that give the regression of a dummy "married" on the household and the debt characteristics.

Table 4 summarizes the characteristics of constrained couples at the intensive margin, depending on their marital status. Married couples tend to have similar income, be older and have more kids than unmarried couples. Both unmarried female, work more in the public sector and male are more educated than their married counterparts. This results are confirmed by column (6) in tables 8 and 9. It also denotes that married couples face higher costs of credit and are less indebted than unmarried couples.

As presented by figure 2 and table 6, married and unmarried couples tend to have similar access to mortgage although they have different observable characteristics. These characteristics are likely to impact credit constraints: income for obvious reasons, diploma impacting the permanent income and kids representing a cost for the couple. The analysis of characteristics impacting credit constraints in the above sections shows that married couples share characteristics that indeed impact credit constraints: higher income, lower education and older female.

The issue is then to understand if being married directly impact credit constraints, compensating differences in observable characteristics or if being married has no impact on credit constraints, as descriptive statistics suggest. The next section corrects for selection on observables using matching methods.

5 Estimation strategy

5.1 Roy-Rubin causal model

The goal is to estimate if married couples benefit from a reward that makes them less credit constrained than unmarried couples. The impact of marriage on credit constraints could be analyzed using the classic Roy-Rubin causal model, considering marriage as a non random treatment. Let y_i^1 be a measure of access to credit by a couple i when married, and y_i^0 the measure of access to credit if unmarried. Let m_i be a dummy that equals one if the couple is married. The impact of marriage on the access to credit is simply given by $y_i^1 - y_i^0$. A classic statement in this literature is that both y_i^1 and y_i^0 can not be observed at the same time, preventing from identifying the impact of marriage. Indeed, it is not possible to observe the *same* couple both married and unmarried. Only y_i is observed, with:

$$y_i = y_i^0 + m_i(y_i^1 - y_i^0)$$

y_i measures the access to credit. Therefore, when measuring credit constraints at the extensive margin, y_i is a dummy indicating if the application for a credit has been turned down by a mortgage broker (or, using the broad definition: if the application was rejected or if the couple is a discouraged borrower).

The measure of access to credit at the intensive margin can take different forms. Following Hayashi

(1985b), credit constraints could be defined as

(i) credit rationing, "they face some quantity constraint on the amount of borrowing", in which case constrained couples would be able to borrow a lower amount even if they face the same loan rate.

(ii) "the loan rate available to them is higher than the rate at which they could borrow", in which case the total cost of holding a debt is higher for a fixed amount of debt.

To these two measures, I also consider a third one:

(iii) the condition on the value of the required downpayment is made more binding for constrained households, i.e. they need a higher downpayment (or the loan-to-value ratio must be lower) for constrained couples, for the same mortgage.

The goal of the paper is to identify the impact of being married on the different outcomes describing credit constraints.

5.2 The statistical problem of selection on observables

Identification and counterfactual Estimating the impact of marriage can be framed within the potential outcome approach. The potential outcome y_i^0 (resp. y_i^1) is not observed for a married (resp. unmarried) couple. It makes it impossible to observe the individual effect of the marriage. Extremely strong assumptions are needed to infer individual effect, because it depends on the joint distribution of y_i^1 and y_i^0. At the contrary, the average effect of marriage could be derived under less stringent assumptions. The average treatment effect on married couples, $E(y^1 - y^0|m = 1)$ depends on the marginal distribution of the potential outcomes and not on the joint distribution. But $E(y^1 - y^0|m = 1) = E(y^1|m = 1) - E(y^0|m = 1)$ and $E(y^0|m = 1)$ can not be observed. The main idea is to approximate the counterfactual in the data. I present below the 8 approximations for the impact of credit constraints I have computed. (To make the discussion clearer, I identify each approximation computed in the result part in italic.)

The idea of the approach consists in constructing a suitable comparison group. A natural proxy for married couples is unmarried couples. The simplest estimator for the impact of marriage is thus a *simple difference* (est. 1) of the means of the outcomes between married and unmarried couples:

$$\overline{y^1} - \overline{y^0}$$

However, as explained in section 4.3, married and unmarried couples have different observable characteristics. This could be related to a life cycle description of the couple, explaining why married couples tend to be older (and then wealthier) and have more kids. Therefore, the simple difference estimator could attribute to the marriage an impact of covariates that are not equally distributed in the two subpopulations.

Unconfoundness As a consequence, the approach consists in defining a fixed set of covariates justifying the unconfoundedness hypothesis. As stated by Imbens and Wooldridge (2007), "unconfoundedness, a term coined by Rubin, refers to the case where (non parametrically) adjusting for differences in a fixed set of covariates removes biases in comparisons between treated and control units, thus allowing for a causal interpretation of those adjusting differences". So it refers to the possibility to embody all the difference in terms of potential outcomes, between married and unmarried in a fixed set of covariates. Of course, a marriage is not a social neutral institution, it is hard to believe that differences between married and unmarried couples could be cleaned up with a set of observed variables. But in terms of potential outcomes, it means that the joint distribution of potential outcomes is independent from the marital status conditional on other relevant characteristics for the bank, such as income or wealth. This assumption is more believable. It means that the banker, having observed relevant characteristics such as age, employment status, income, etc. determines the outcome for married and unmarried couples, without taking into account the unobserved reasons that make the married couples different from unmarried couples. This assumption does not hold if there is an unobserved characteristic relevant for the banker and highly correlated to the marital status - such as social background -, that are observed by the banker and not the econometrician.

The main idea of the identification strategy relies on the assumption that a set of fixed covariates X is observed by the econometrician and justifies the unconfoundedness assumption. This set of variable is such that

$$(y_i^0, y_i^1) \perp m_i | X_i \tag{1}$$

This equation traduces the "conditional independence assumption" (thereby named CIA) or ignorability assumption. This assumption is the cornerstone of the identification. Indeed, under the assumption 1, the average treatment effect on the treated (ATT) is identified:

$$
\begin{aligned}
ATT = E(y_i^1 - y_i^0|m_i = 1) &= E\big(E(y_i^1 - y_i^0|m_i = 1, X_i)\big) \\
&= E\big(E(y_i^1|m_i = 1, X_i) - E(y_i^0|m_i = 1, X_i)\big) \\
&= E\big(E(y_i^1|m_i = 1, X_i) - E(y_i^0|m_i = 0, X_i)\big)
\end{aligned}
$$

Similarly, the $ATU = E(y_i^1 - y_i^0|m_i = 0)$ (average treatment on the untreated) can be identified.

Control regression approach Under the assumption that the impact of the treatment is homogenous in the population, the *controlled regression* (est 2.) identifies the impact. Indeed, if $y_i^0 = \alpha + \beta X_i + \varepsilon$ and if the impact of marriage is supposed constant, then, y_i can be written $y_i = \alpha + \tau m_i + \beta X_i + \varepsilon$, assuming $\varepsilon \perp X_i$. This impact can be estimated by a simple OLS regression. But the OLS regression gives a parametric form for the impact of marriage, and it does not take into account the common support condition. Therefore, it extrapolates the impact of marriage on units that are not likely to be married (or unmarried). This condition is commented below. The two estimators proposed so far are classic in this literature, so I consider them as my baseline estimates.

Another approach addressing the question of the impact of a treatment in the literature is the *Oaxaca-Blinder decomposition* (est 3.). The idea is that the treatment do not have an impact *per se* but through different rewards of the same characteristics. So it proposes to disentangle in the determination of the outcome what comes from a difference in the distribution of the covariates (unmarried couples are younger) from a difference in the reward of the covariates (being 30 years old does not impact credit constraints the same way when married or unmarried). Different rewards of the covariates are often considered as a source of discrimination. It supposes that:

$$
\begin{aligned}
y_i^1 &= X_i^1\beta^1 + \varepsilon_i^1 \\
y_i^0 &= X_i^0\beta^0 + \varepsilon_i^0 \\
\overline{y^1} - \overline{y^0} &= \underbrace{\overline{X^1}(\beta^1 - \beta^0)}_{\text{rewards}} + \underbrace{(\overline{X^1} - \overline{X^0})\beta^0}_{\text{endowments}}
\end{aligned}
$$

The ATT could be approximate by the "rewards" part of the equation, because it represents the rewards of being married, keeping the characteristics constant.

Both approaches (controlled regression and Oaxaca Blinder) suppose constant treatment effect and extrapolate the relationship between the y_i and the m_i and X_i outside the common support.

Common support and matching The common support assumption states that both treated and untreated have to share common traits in order to estimate the impact of the treatment. The common support assumption requires that for each combination of X (strictly defined) there are married and unmarried couples. Indeed, if some values of X_i are only observed for $m_i = 1$ then the coefficient on m_i could be biased because part of the impact of X_i on y_i is captured by m_i. This problem is likely to bias the results if there is no variation in the marital status for some combination of the X_i, e.g. if wealthiest or oldest couples are all married. Therefore, the impact of marriage should be estimated on a subsample that provides variation in the treatment status for all combination of X_i. This problem sheds light on which units among treated and controlled (i.e. married and unmarried) should be compared. This implies adding an assumption of the joint distribution of the covariates and the marital status, called the common support assumption, often written as[9]:

$$0 < Pr(m_i = 1|X_i) < 1 \tag{2}$$

Indeed, if $Pr(m_i = 1|X_i) = 1$ I only observed some married couples for some combination of X. On the common support, I can observe married and unmarried couples for each combination of X.

In order to estimate the ATT, the approach of matching consists in reweighting the untreated units to make them similar to treated units. For the ATU, the approach consists in reweighting treated unit to make them similar to untreated units. The number of married couples is more important than unmarried couples. Therefore, the estimation of the outcome for treated units is likely to be more precise than the estimation of the outcome for untreated units.

Then, the idea is to compare a simple difference between the average outcome for treated and the weighted average outcome for untreated. There are different ways to compute the weights. The most intuitive way consists in a one to one matching of married couples to unmarried couples with the same characteristics and to give them a unit weight (zero for unmatched). Notice that under a strong definition of the ignorability assumption, this is suffisant to estimate the individual effect of marriage. Indeed:

[9]Only $Pr(m_i = 1|X_i) < 1$ is necessary to identify the ATT and $0 < Pr(m_i = 1|X_i)$ for the ATU. As I'm willing to estimate both of them, I imposes both restrictions at the same time.

$$
\begin{aligned}
\tau &= E(y_i^1 - y_i^0 | m_i = 1) \\
\tau(x) &= E(y_i^1 - y_i^0 | m_i = 1, X_i = x) \\
&= E(y_i^1 | X_i = x, m_i = 1) - E(y_i^0 | X_i = x, m_i = 0) \\
\tau &= E(\tau(x))
\end{aligned}
$$

However, this estimation is infeasible if the dimension of X is large - and the sample size is finite, because it requires to observe both married and unmarried couples in each cell defined by the X. It is possible to use a metric that measure the distance between two combination of X. The *Mahalanobis metric* (est. 4) matches units on a metric that measures the distance in terms of covariates between a treated and an untreated unit. It permits choosing the closest match in the sense of that metrics.

Propensity score matching Rosenbaum and Rubin (1983) showed that it is not necessary to condition on all covariates. Conditioning on the propensity score (i.e. $p(x) = P(m_i = 1 | X_i = x)$) is sufficient to remove the biases due to observable covariates, and unobservable characteristics, if they are perfectly correlated to observable characteristics. Therefore, the impact of the marriage can be estimated by comparing the outcome between a married couple and a matched unmarried couple, i.e. a couple having a similar values of the propensity score. The use of the propensity score makes the matching rely on less stringent conditions than the one to one matching, but there is still a need of common support of the propensity score: it means that each level of the propensity score is likely to be observed among married and unmarried couples. So even if there are only married or unmarried couples for some combination of X, there is enough overlap in the X to suppose that this combination could be observed among the other group.

The propensity score matching estimator compares the mean outcome of married couples to the mean outcome of matched counterfactuals. There are different methods to match individuals. In this paper I first use the *nearest neighbors matching* (est. 5), that uses for each treated unit the closest untreated units in terms of propensity score (five neighbors in this case). Then I use *kernel matching* (est 6.) that for each treated unit mimics a counterfactual attributing different weights to each untreated observation.

Which matching estimator should be chosen? The choice has to be led by the effectiveness in eliminating the bias and efficiency considerations. If the true propensity score is known, all methods are effective at eliminating the bias. However, when it is not known (as in most situation in applied economics), it has to be estimated (often using a logit or probit specification) and the efficiency is not clear. Hirano, Imbens, and Ridder (2003) (thereafter call HIR) proposes an efficient reweighted estimator based on the propensity score.

Reweighting estimators The methods presented so far are all based on the same idea: reconstruct for each treated unit a suitable comparison unit using untreated units. But as I am interested in moments, I can also use the propensity score as weights in order to create a balanced sample of married and unmarried observations, as suggested by HIR. The matching estimators presented above try to mimic the counterfactual for each treated unit. The reweighting method proposed by HIR reweights all untreated units in the sense that it mimics the mean of the distribution.

They show that the estimator

$$\widetilde{\tau}_{ATE} = \frac{1}{N}\sum_{i=1}^{N}\Big(\frac{m_i y_i}{\hat{p}(X_i)} - \frac{(1-m_i)y_i}{(1-\hat{p}(X_i))}\Big)$$

is an unbiased estimator of the average treatment effect, $ATE = E(y_i^1 - y_i^0)$, where $\hat{p}(X_i)$ is the estimated propensity score. As the weights for treated do not add up to one[10], they have to be normalized. Similarly, they have to be normalized for the untreated.

Similarly, the $ATT = E(y_i^1 - y_i^0|m_i = 1)$ can be approximated with:

$$\widetilde{\tau}_{ATT} = \sum_{i=1}^{N}\frac{\hat{p}(X_i)}{\sum_{j=1}^{N}\hat{p}(X_j)}\Big(\frac{y_i m_i}{\hat{p}(X_i)} - \frac{y_i(1-m_i)}{(1-\hat{p}(X_i))}\Big)$$

which is just a *reweighted simple difference* (est. 7). Hirano, Imbens, and Ridder (2003) show that this estimator is efficient, with a fully nonparametric estimator for the propensity score. The weights have to be normalized to add up to one for treated units and for untreated units. Therefore, the estimator can be rewritten:

$$\widetilde{\tau}_{ATT} = \sum_{i}^{N}\Big(\frac{m_i y_i}{\sum_{i=1}^{N} m_i} - \frac{W_i y_i}{\sum_{i=1}^{N} W_i}\Big)$$

with $W_i = \frac{(1-m_i)*p(X_i)}{1-p(X_i)}$

This is exactly similar as a WLS estimator of β is the model

$$y_i = \alpha + \beta m_i + \varepsilon$$

[10]In expectation, they do. But the sum is very likely to be different from 1 in finite samples.

with weights λ_i such as:

$$\lambda_i = \sqrt{\frac{1}{\sum_{j=1}^{N} \hat{p}(X_i)} \Big(m_i + \frac{\hat{p}(X_i) * (1 - m_i)}{(1 - \hat{p}(X_i))}\Big)}$$

This regression model could be extended adding covariates to the regression function to improve the precision (*weighted control regression*, est. 8), without loosing consistency.

The two estimators (including covariates or not) are based on the idea that the propensity score can be used to reweight outcomes in order to correct for the bias induced by the X. HIR show that this estimator is efficient. The ATU can be estimated similarly.

If the ignorability assumption is assumed to be true, why are estimation methods based on the propensity score (matching or reweighting) interesting compared to simple controlled regression? The crucial assumption is the common support assumption. The goal of the estimation of the propensity score is of course the estimation of a measure of how close are treated and untreated units, but also to get rid off "outliers" in terms of treatment. By trimming part of the support for which only treated or untreated units are observed, the econometrician drops observations that are not relevant in the sense that for this combination of X, there is no variation in the treatment status. Regression methods extrapolate the results to the off support observations relying heavily on parametric forms. Matching and weighting methods give a non parametric estimation of the impact of treatment, while the ignorability assumption gives a causal interpretation to the estimator. In practice, a parametric propensity score is although estimated, but the impact of the treatment on the outcome is not parametric.

Therefore, matching and reweighting are methods to correct the selection on observables. As explained in Heckman, Ichimura, Smith, and Todd (1998), there are three potential sources of bias in classical OLS regression when estimating the impact of a treatment on an outcome:

(i) Different support of X between controlled and treated units could induce bias.

(ii) The difference of the distribution of X between the two groups over its common support could induce bias

(iii) Selection on unobservables could of course induce bias. But this means that the CIA assumption does not hold in that case, challenging the required assumption of ignorability of the treatment.

All the estimators presented above tend to eliminate the bias due to (i) and (ii). As there is no clear reason why one estimator could be better at reducing the bias in finite sample than the others, I give estimates using all of them. I compare the results to the classic control regression models.

5.2.1 Basic assumptions

The basic assumptions necessary for a causal interpretation of the impact of treatment are ignorability and common support. I claim these assumptions are likely to be verified when studying the impact of marriage on credit constraints, providing that a set of relevant covariates is available. Relevant covariates mean here that the covariate are correlated to marital status and impact the credit decision of the banker.

Credit constraints result from the decision of the bank. Therefore, when addressing the question of ignorability, one has to think about the covariates that could matter for the decision of the bank. The main covariates are the income, the wealth and characteristics on employment (as stated previously in section 4.2), because the main preoccupation of the bank should be to avoid the risk of default. Ignorability means that the joint outcomes are independent from the choice of getting married of the couple, conditional on these covariates. In other words, what is important is that the unobserved part of the decision of the bank to approve the credit is not correlated to the unobserved part of the decision of the couple to get married. This assumption is likely to be violated if there are some omitted factors correlated to marital status, that matter for the decision of the bank, observed by the banker but not by the econometrician and which are not completely cleared up by the set of covariates. This kind of omitted factor could be the social background of the couple. There is no way to test for that kind of factors but they can be partly correlated to income, education and wealth, that are controlled for. More over, this is not clear that such a factor would influence the bank *per se*. This is more likely that they are other signal for the seriousness of the couple. But in that case, I interpret as an impact of the marriage the impact of this other factor.

The set of covariates used to study the impact of marriage on credit constraints at the extensive margin includes income and some demographic characteristics: male age, female age, annual income of the household (I cannot distinguish the male's from the female's income), number of kids, female education, male education, a dummy indicating if the female works part time, and dummies indicating if the spouses work in the public sector. The income is the current income, as it is not possible to measure the permanent income although the theory predicts that the bank takes into account the permanent income. However, the approximation is not bad if the current income reflects well the permanent income. Unfortunately, I observe downpayment only when the household gets its loan, so I don't observe it for rejected couples. So I do not have any proxy for the wealth of constrained households. This is likely to bias my results, as it is an important covariate. However, it will bias the result if it is highly correlated to the marital status. On the sample of new owners, I can compare the amount of downpayment for married and unmarried couples (table 6). The downpayment is similar for married and unmarried couples when not constrained, but unmarried couples tend to have an higher downpayment than married couples, among constrained couples (the difference is slightly significant at a 10% level, see table 18). This is not clear if the difference in downpayments between married and unmarried couples would be greater for constrained (at the extensive margin) than for constrained (at the intensive margin) couples. If so, it is likely to bias downward my results: downpayment should facilitate the credit and unmarried couples have a higher downpayment. Moreover, if the wealth is strongly correlated to the covariates including in the matching procedure, then the bias is removed by conditioning on the set of observable covariates. I do not include in the set of covariates the size of the life town because this is highly endogenous for those who access to ownership. I do not include neither some covariates that might seem important for the banker, such as the distribution of income among the partners that could be informative but it is not observed in the data. However, I included a dummy indicating if the female works part time as a proxy for a large difference in the male's and the female's income.

The set of relevant covariates to address the issue of credit constraints at the intensive margin depends on the outcome. Following Hayashi (1985b), I study six different outcomes

1. The total amount borrowed in level, in order to detect any restriction on quantities

2. The total amount borrowed, calculated in years of income

3. The value of the downpayment, in order to check if the second constraint is more binding for unmarried couples

4. The part of the value of the house financed by the downpayment, to check how binding the other constraint is

5. The level of income, in order to check if the required level of income is different for married and unmarried couples for a fix debt

6. The total cost of the loan, in order to detect any restriction in prices.

I define a set of covariates composed of demographic characteristics as well as education and employment status: a dummy if the female works part time, a dummy indicating if the male has a diploma higher than high school, same for female, number of kids, male's age, female's age, and dummies for the sector of activity. This set is common to all outcomes. As for the computation of the propensity score for the study of constraints at the extensive margin, the repartition of income among the household is not included in the sets of covariates. Each of the six outcomes (except the total amount borrowed, calculated in years of income) are included in the set of fixed covariates when it is not the explained variable. So the set of covariates included for the computation of the propensity score is different for each covariate. As this set of variables sums up all the key characteristics determining the access to credit, the ignorability hypothesis is likely to hold.

The common support would be unlikely if there was no variation in the life cycle among couples. For example, if all couples were to get married at age a. In that case, the common support assumption could not be verified because at age $a+1$, all couples are married and there are not unmarried couples. This means that the assumption requires some heterogeneity in the life cycle dynamic of couples, with some getting marrying older than other, having kids at different ages, etc. This assumption is likely to hold because marriage is not a neutral institution and there is heterogeneity in the preferences of couples toward marriage. But these preferences should not be correlated to the decision of the bank to approve a credit because it would violate the ignorability assumption.

6 Results

6.1 Estimation of the propensity score

As explained in section 5.2, all the estimators for the ATT or the ATU (matching kernel and nearest neighbors, weighted estimators) rely on the estimation of the propensity score, except the matching estimator based on the Mahalanobis metric. The propensity score is estimated parametrically, using a logit specification.

Two sets of covariates are being used. They include the same variables, but the first set (Set 1 thereafter) includes discretized continuous covariates (age, income) while the second set (Set 2) includes the continuous covariates. Introducing discrete covariates is useful because it allows for non linearities in the impact of X on m_i. For each outcome, I test both sets of variables.

The estimation of the propensity scores for the study of constraints at the extensive margin is given by tab 10. The estimation confirms what the descriptive statistics illustrates: married couples are richer, more educated, have more children, are a little older and more often works in the public sector. The estimation of the propensity scores for the study of constraints at the intensive margin is given by tab 11 and 12. The sample of indebted households likely to be constrained is very small compared to the sample of households willing to invest. As a consequence, the estimation of the propensity score gives less clear results. However, it confirms that constrained indebted married couples have more children, the male more often works in public sector and the female is older and they tend to be more educated than indebted unmarried couples.

In order to ensure the common support assumption (equation 2), I drop the extreme values of the common support, i.e. those observations which propensity score is greater than 95% or lower than 0.15%. Figure 3 draw the distribution of the propensity score (treatment=marriage) for married and unmarried couples. This propensity score is computed on the subsample used to study the credit constraints (strict definition). The propensity score for the study of the credit constraints (board definition) is not exactly the same because the population is not the same. Anyway, as the sets of covariates are strictly identical and the populations are very close, the distribution of the propensity score is very close to this one. Although the distribution is not identical, the common support assumption is clearly verified here, because for each level of the propensity score, there are both married and unmarried couples. The propensity scores obtained with each set of variables are very similar to each other.

The study of credit constraints at the intensive margin is based on an other subsample of households, the sample of indebted households. Figure 4 draw the distribution of the propensity score (treatment=marriage) for married and unmarried couples. This propensity score is computed on the subsample used to study the total cost of marriage (individual characteristics + debt, downpayment, % of downpayment). This figure only gives one distribution for one propensity score as an example, although I estimate one propensity score for each outcome. The common support assumption is verified for levels of the propensity score greater than 0.5. This is why I only keep observations having a propensity score greater then 0.5. Then, the distribution are quite similar. This tend to show that indebted couples are quite similar on observables, are they married or not. The shape of the propensity score depends on which covariates are included in the estimation. Therefore, as the set of included covariates depends on the explained outcome, the propensity score is different for each outcome. However, as the set of covariates is very similar in each case, there are similar to the propensity score presented in figure 4.

For each outcome, I compute two impacts of marriage: the average treatment effect on the treated, where being treated is being married (ATT), and the average treatment effect on the untreated, i.e on the unmarried (ATU). Matching estimators are non parametric estimators: the two impacts are not necessarily the same in both population with matching estimators. They are the same with simple difference and OLS estimation as these methods suppose constant treatment effects. The ATT gives the impact of marriage for those who got married, and the ATU gives the impact of marriage for the unmarried, if they were to get married. I expect that the ATT gives that married couples tend to have a greater access to credit and better terms. Similarly, I expect that the ATU indicates that unmarried couples would not benefit from being married.

The estimation of the propensity score is very important as it defines the weights attributed to the untreated units to make them similar to the treated unit. Then, the different estimators differ in the way they use the propensity score to compute the weights. So, any difference in the estimations comes from the different weights. Figure 5 and 6 compare the weights attributed to the untreated unit as a function of the propensity score by each estimator. For comparison reasons, the matching weights are normalized to sum up to one. The Mahalanobis weights are clearly less precise and give more weight to untreated units unlikely to be treated (for who the propensity score is low) than the estimators based on the propensity score. The HIR and kernel weights are very similar, except for high values of the propensity score. The HIR and the nearest neighbors weights are similar, but the nearest neighbors introduce more variation at each level of the propensity score.

The goal of the matching is to define weights that correct for the bias induced by the differences in the observable variables between married and unmarried couples. So a good test is to compare married to reweighted unmarried. The two population should be similar after reweighting. I perform a χ^2 test for the balancing of the two populations. As the set of covariates is different for each outcome, I have estimated a propensity score for each outcome. Moreover, the χ^2 test is weights specific, so I have to compute one test for each weight and propensity score. As a consequence, I have performed estimators using 128 set of weights: for each outcome: I need to test for the 2 outcomes at the extensive margin, because the population are different and for the 6 at the intensive margin because the set of covariates includes for each outcomes other features of the debt. I test 2 sets of variables (discrete and continuous), I compute 2 treatment effects (ATT and ATU), using 4 set of weights (nearest neighbors matching, kernel matching, mahalanobis metric, HIR weights). There is no reason *a priori* that the sample would be balanced for each of them after reweighting. Table 13 shows the p-value of the χ^2 tests of overall significance of the difference between covariates after reweighting. Although the reweighting sample is balanced in most cases, some differences remain for the first set of variables with nearest neighbors and mahalanobis weights for the study of credit constraints at the extensive margin and also with the mahalanobis weights with the second set of variables, whatever the outcome. A bad balancing prevents from interpreting the estimates because it means that differences in observables remain after the reweighting.

6.2 On declarative credit constraints: constraints at the extensive margin

Table 7 shows that the probability of being constrained (strict or broad definition) at the extensive margin decreases with annual income. The point estimate is larger for the definition including discouraged borrowers, meaning that income is a key criterion of self selection. Educated couples are less constrained: having a diploma decreases the probability of being constrained, and the female's education has a larger impact than male's education, for both definition of credit constraints. The point estimate of female's education is larger for credit constrained including discouraged borrowers, whereas the point estimate of the male's education is similar. It means that female's education could alter the decision to apply for a credit. Children and male's age do not impact credit constraints, but female's age do, especially for the measure including discourage borrowers. Having savings increases the probability of being constrained, when the discouraged borrowers are included.

Table 7 also shows that married couples have higher income, the male is more educated, but married female are less educated than their unmarried counterparts. They are older than unmarried couples. Therefore, the direction of the bias is not clear: married couples tend to share characteristics increasing credit constrained (female less educated and older) but also characteristics decreasing credit constraints (more income and more educated males).

Table 14 gives the results for the impact of being married using the strict definition. The simple difference indicates that among married couples there are 1.4% (in % points) less constrained couples than among unmarried couples, but the difference is not significant: on the subsample of couples on the common support, unmarried couples do not seem to be turned down more often than married couples. However, the sign of the coefficient is negative, meaning that married couples experience slightly less credit constraints than unmarried couples. Introducing controls does not alter this result. Matching and weighting estimators tend to decrease the point estimate, but the difference is not significant neither, both for the ATT and the ATU. The estimator based on the Mahalanobis metric gives a lower point estimate for the ATU than other estimators. The Mahalanobis metric tends to weight more couples that are unlikely to get married according to the propensity score. If those couples are unconstrained unmarried couples then it tends to decrease the difference between the two groups. The HIR weights give significant credit constraints with the second set of variables, indicating that being married decreases the risk of credit constraint by 1.7% (instead of 1.3% for simple difference). The

HIR weights are very close (in that case) to the kernel weights but the kernel estimator does not give significant results. The HIR weights give more weights to unmarried couples having a high propensity score than the kernel estimator: the difference in the point estimate could be explained by strong credit constraints for unmarried couples very similar to married couples. According to the nearest neighbors estimators, unmarried couples would experience 2.8% points less credit constraints were they married (with the first set of covariates), but other estimators do not support this result. Taken together, the estimators tend to conclude that if any, the impact of marriage on the probability of being turned down is very low in percentage point. But a back of the envelop calculation indicates that the impact is quite big: notice that 4.0% of married couples are credit constraints (at the extensive margin, strict definition). The HIR estimation indicates that if the impact of marriage for married couples on credit constraints reduces 1.7 percentage points the number of credit constraints household. So it corresponds to a decrease of 29.8% of credit constraints households among the married couples (1.7/(4+1.7)). Similarly, there are 5.2% of credit constraints households (strict definition) among the unmarried. The nearest neighbors estimators indicate that being married would decrease with 2.8 percentage points the probability of being constrained if married. So if all of got married, it would decrease the probability of constrained household among this population with 53.4% (2.8/5.2). The sign of the estimate is robust and remains negative for almost all estimators. The comparison between matching estimators shows that unmarried couples similar to married couples are more likely to be constrained.

Table 15 gives the results of the impact of marriage on credit constraints, including discouraged borrowers. The simple difference is negative and significant. It indicates that there are 2.2% (% points) more credit constrained household among unmarried couples than among married couples: unmarried couples seem more credit constrained than married couples. The matching estimators give larger (but not significant) point estimates than the simple difference. Because of a lower variance, the HIR weighing estimators give significant results: if they were not married, married couples would have experience an increase in their credit constraints from 2.4% to 3.0%, in % points (including controls). The HIR estimation of the ATU, however, is not significant: unmarried couples would not experience lower credit constraints if they were married. The nearest neighbors and the mahalanobis estimators indicate that unmarried couples would also experience significantly lower credit constraints if they were married. Higher point estimates mean that married couples have observable characteristics that would affect them if they were not married, such characteristics could be a less educated female. Notice that 7% of married couples are constrained at the extensive margin according to the broad definition, and 9% of unmarried couples. As a consequence, according to the

HIR weights, being married decreases the number of constrained household with 26.3% (2.5/(2.5+7)).

The difference between the strict definition of credit constraints and broad definition is the inclusion of discouraged borrowers. Of course, the ignorability assumption is likely to be violated in the case of discouraged borrowers. There might be some unobserved factors, such as the decision to form a household that are positively correlated to the intention to apply (so negatively to credit constraint) for a credit and marriage. This would bias downward the impact of marriage on credit constraints, and so increase the difference between married and unmarried. So, the difference between the results for the two definitions shows that married couples tend to be less discouraged, maybe because of the dynamic of the formation of the household. As the bank does not discriminate on the marital status, the results do not support the signalling assumption of marriage.

6.3 On the measure of credit constraints at the intensive margin

First of all, notice that approved couples for a loan do not necessarily contract a loan. Among approved couples, only 56% have indeed contracted a loan (1242 over 2231). It means that there is a selection, between approved couples, of who access to ownership. To study this selection, it would be interesting to observe the terms of the loan couples were approved for. As shows in fig. 2, the selection of approved couples is more important among unmarried couples than among married couples: 64% of married couples approved for a loan eventually contract a loan whereas only 40% of them eventually do.

On the subsample of credit constraints households (defined as in section 4.2.2), the impact of covariates on credit outcomes are presented in table 8 for the first set of covariates and table 9 for the second set of covariates. Controlled for the characteristics of the loan, the value of the debt does not seem to be correlated with other household covariates (column (1) and (2)). The total cost of the debt[11] is correlated to the characteristics of the loan, but also to the employment status of the woman: working part time is positively correlated to the cost of the loan and having two or more children is negatively correlated to the cost (column (3)). The downpayment is positively correlated to the education of the partners, and the female's age (column (4)). This could be explained by assets accumulation over the life cycle. The percentage of downpayment is mostly correlated to the characteristics of the debt, and positively to the employment status of the woman (column (6)). A higher income is correlated with a higher debt, higher downpayment and lower cost. But it is also negatively correlated to part time activity, education and children (column (7)).

[11] If the household borrows M and refunds $(1+c)M$, the total cost of the loan is c.

Married couples tend to be a bit different than unmarried couples: the woman is older, they have more children and the female is often less educated than unmarried counterparts. Their loan is similar to the loan of unmarried couples. The differences between married and unmarried couples justify using matching methods because they are likely to be correlated to credit constrants.

Table 16 shows that married couples tend to borrow 5248 euros (with set 1) less than unmarried couples, although the difference is slightly significant. The sign is robust to all estimators. The controlled OLS and the Oaxaca Blinder decomposition reinforce the impact of marriage (the controlled OLS regression give significant results for both set of covariates), while matching estimator do not give clear results. HIR weights confirm the simple difference estimation, indicating that married couples borrow less than unmarried couples (6840 euros for the set 1, 9895 for the set 2). This result is surprising because it does not support the main idea of the signalling theory.

However, this crude definition of the value of the debt might not be adapted: even if the income is controlled for, the relationship between income and debt could be different than linear. Instead, I consider measuring the debt in terms of annual income. Table 17 shows that married households are significantly less indebted than unmarried couples, and decrease their debt by 0.17 annual income. While the controlled OLS coefficient tends to support this result, the estimation based on matching and reweighting estimators tend to lower the point estimate for the ATT, which become not significant and to increase the coefficient for the ATU that remains significant. As a consequence, married couples would not lower the amount borrowed if they were not married, but unmarried couples would have a lower debt.

Married couples tend to have a lower downpayment than unmarried couples, although the simple difference is slightly significant, but there is no difference between couples in the downpayment expressed as a proportion of the value of the housing (tables 18 and 19). This is easily explained by the differences in the value of the debt. Matching and reweighted estimators tend to show that married couple would have even lower downpayment, have they not been married (than what indicates the simple difference) and unmarried couples would have decrease, although not significantly the value of their downpayment. The matching and reweighting estimators control for the value of the debt. Therefore, the differences in the value of the downpayment could be interpret as the reward of being married. The ATT tends to be significant with the HIR weights, meaning that married couples should bring more downpayment, would they be unmarried, but the ATU is not significant: unmarried couples would not benefit from such a reward. This difference could be explained by the female's employment status, which is the main difference in the observables between married and unmarried couples. The ATT is computed by reweighting the unmarried: therefore the significant difference means that the marital status could have an impact *per se* on the demanded downpayment when the woman is inactive. The ATU is computed by reweighting the married couples: when the woman is working full time, the marital status does not impact the value of the downpayment. The proportion of downpayment is not affected by the marital status (table 19). The simple difference in table 21 confirms that married couples are slightly wealthier than unmarried couples. Reweighting for demographic and debt characteristics does not reverse the sign of the coefficient: married households require the same income to borrow a fixed debt, keeping the downpayment and the cost of the loan constant.

Surprisingly, the table 20 points out a higher cost of credit for married couples. While the simple difference is not significant, controlled OLS and matching and reweighting estimator using the second set of variables give significant and even higher point estimates for the impact of marriage on the cost of credit. The first set of variables gives qualitatively similar results, but not significant (althought it stays close to be significant). Why is the cost higher for married couples? The description of the loans contracted by couples in table 4 shows that married couples contract lower debt and they contract less often a zero rate loan (prêt à taux zéro, PTZ). I have tested this assumption computing the cost of the loan without taking into account PTZ loans (results not showed here) and the total cost remains higher for married couples. The mean duration is similar for married (15.39) than unmarried couples (15.45) and the mean interest rates offered are very close, and a bit higher for unmarried (3.66% for married and 3.69% for unmarried). Therefore, the difference in the total cost must be explained by a different structure of the debt.

As a consequence, the overall results given by the analysis are quite surprising. Married couples do not seem to be advantaged on the credit market, if not disadvantaged: the cost of the loan is higher and they are approved for lower debts. These surprising results can be related to the self selection process highlighted above. Among unmarried, the discouraged borrowers could be those having the worst credit proposals, while married couples having the same proposals, are not discouraged because of some omitting factors, such as the willingness to form a household. The self selection is reinforced by the selection in the contract, because all approved borrowers did not eventually contract a loan. Therefore, even if the ignorability assumption is likely to hold when considering the credit supply, it is not likely to hold considering that what is observed is also conditional on couples agreeing on the conditions of the bank. So, high costs could have discouraged more elastic couples: unmarried couples are likely to be more elastic to the cost of the loan because of different unobservable characteristics.

7 Conclusion

This paper investigates the link between marriage and credit constraints, using the French housing survey in 2001. The leading idea is that marriage could be used as a signal toward the bank of the quality of the match. I estimate the impact of marriage on credit constraints using matching estimators to match married couples to unmarried couples. I propose different matching estimators. The comparison of matching estimators is interesting as a robustness check: for all outcomes, some estimators give significant results and some do not. This comparison highlights the sensitivity of the estimators to the choice of the set of covariates and to the weights attributed by the matching process. The HIR weights are taken as the most relevant as they give more efficient estimators.

The results tend to support the idea that married couples are less credit constrained at the extensive margin, when discouraged borrowers are included, but not when they are excluded. Therefore, it is difficult to interpret this result as the direct impact of marriage. It mostly supports the idea of selection in the marriage, that appeals couples willing to form a household. On the contrary, the results show the married couples are worst off on the credit market. This should not be seen as a negative impact of marriage but as the consequence of selection in the marriage. Married couples are more likely to accept less advantageous credits than unmarried couples. Therefore, the marriage is indeed correlated to outcomes on the credit market, although the hypothesis of marriage as signal is not verified. These results are interesting in a long run perspective. The number of cohabitant couples is increasing in France, because of the increase in cohabitation before marriage and of cohabitation as a permanent state. This evolution could have dilute the value of marriage as a signal. Therefore, it could be interesting to complete this study including older and more recent waves of the survey, in order to study the evolution of credit constraints. Moreover, it could be interested to investigate if other characteristics could be used as signal of the stability of the couple, such as children or labor supply of female. I leave the task of extending the study to incorporate evolution for future research.

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A Annexes

A.1 Financial difficulties

Table 1: Households experiencing financial difficulties, by matrimonial status

	Experienced Financial difficulties:			
	Never	Less than 1 y. ago	During the last years	Total
Single, never separated	74.4	12.2	13.3	100.0
Couple, not separated	76.5	8.4	15.1	100.0
Unmarried	*69.1*	*16.3*	*14.6*	*100.0*
Married	*78.2*	*7.0*	*14.8*	*100.0*
Separation <1 y. ago	51.8	31.8	16.4	100.0
Previously unmarried	*56.1*	*30.6*	*13.3*	*100.0*
Previously married	*48.3*	*36.0*	*15.7*	*100.0*
Separation]1,5] y. ago	55.1	15.1	29.7	100.0
Previously unmarried	*55.0*	*17.8*	*27.1*	*100.0*
Previously married	*55.5*	*13.6*	*30.9*	*100.0*
Total	73.1	10.2	16.8	100.0

Source: Assets survey 1998 *Enquête Patrimoine 1998* - The subsample excludes household with at least one self employed spouse.
Lecture: 56.1% of individuals that broke up from an unmarried couple less than one year ago never experienced financial difficulties.

Table 2: Main declared reason of financial difficulty

	Main declared reason of financial difficulty				
	Professional (e.g. unemployment)	Personnal (incl. separation)	Current expenses	Refund	Total Total
Single, never separated	39.9	11.5	42.7	5.9	100.0
Couple, not separated	45.0	8.2	40.5	6.3	100.0
Unmarried	*53.3*	*7.5*	*37.2*	*2.0*	*100.0*
Married	*42.7*	*7.6*	*42.6*	*7.2*	*100.0*
Separation <1 y. ago	28.3	50.9	20.8	0.0	100.0
Previously unmarried	*27.9*	*30.2*	*41.9*	*0.0*	*100.0*
Previously married	*37.0*	*58.7*	*4.3*	*0.0*	*100.0*
Separation]1,5] y. ago	40.8	29.3	28.0	1.9	100.0
Previously unmarried	*50.0*	*19.0*	*27.6*	*3.4*	*100.0*
Previously married	*37.6*	*32.9*	*28.2*	*1.2*	*100.0*
Separation >5 y. ago	37.9	21.4	38.3	2.4	100.0
Previously unmarried	*52.8*	*11.1*	*33.3*	*2.8*	*100.0*
Previously married	*33.5*	*23.9*	*40.0*	*2.6*	*100.0*
Total	42.2	14.3	38.4	5.1	100.0

Source: Assets survey 1998 *Enquête Patrimoine 1998* - The subsample excludes household with at least one self employed spouse.
Lecture: 27.9% of individuals that broke up from an unmarried couple less than one year ago declaring having experienced financial difficulties attribute them to professional issues.

A.2 Macro environnement and sub sample selection

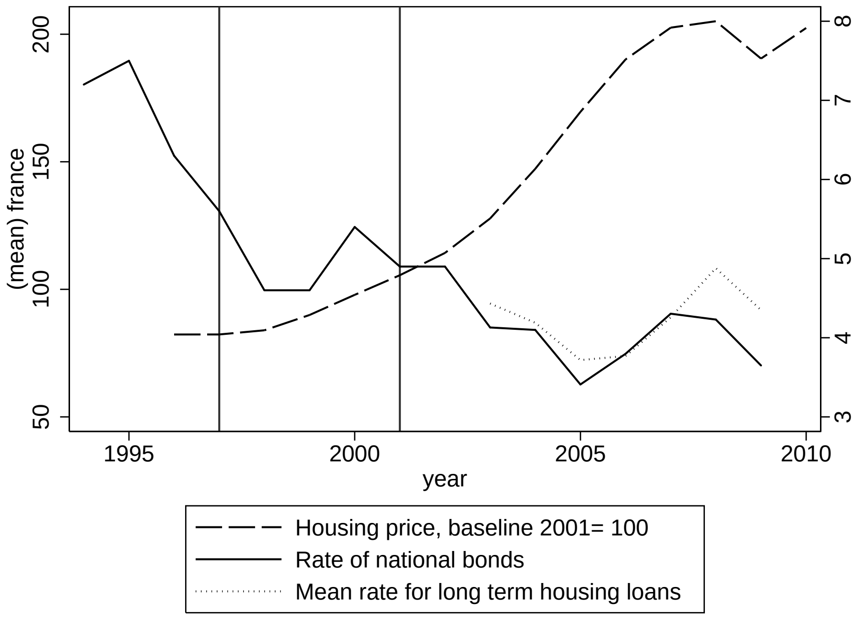


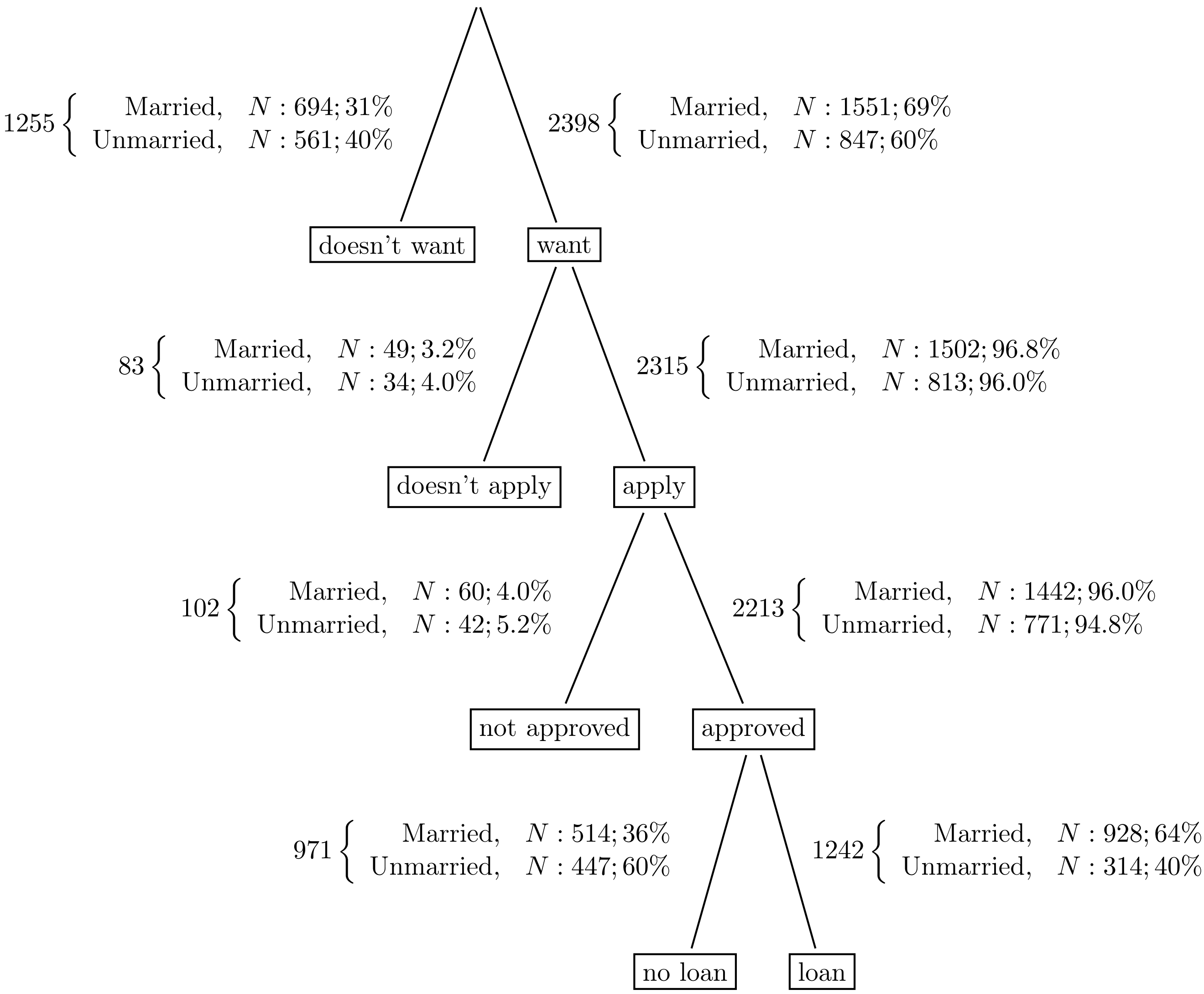
Figure 1: Macroeconomic variables

Table 3: Sub-sample selection

Selection	**N (remaining)**
Total sample	32,156
Keep couples	19,951
Was with another partner 5 years ago	19,776
Keep renters and recent owners	11,010
Drop owners having other goods	10,025
Drop self-employed	9,106
Drop if male does not full time	7,045
Drop if female inactive	5,353
Willingness to invest	2,410 (strict) 2,508 (broad)
Matching reasons	2,315 (strict) 2,398 (broad)

A.3 Application process

Figure 2: Getting a loan: process of application



Unconstrained household:	Want→Apply→Approved (2213 couples).
Strict definition of constrained household:	Want→Apply→Not Approved (102 couples).
Broad definition of constrained household:	Want→Doesn't apply + Want→Apply→Not Approved (102+83 couples)

A.4 Descriptive statistics

Table 4: Descriptive statistics - characteristics of indebted households, depending if they are credit constrained at the intensive margin

	Unconstrained			**Constrained**		
	Unmarried	Married	Total	Unmarried	Married	Total
Annual Income	38088	40028	39527	29633	30711	30459
Male age	32.88	35.8	35.05	32.47	34.62	34.11
Female age	31.4	34.07	33.38	30.63	32.93	32.39
Nb of kids	.72	1.42	1.24	.96	1.42	1.31
Female works part time	.2	.33	.3	.36	.42	.41
Male works in public sector	.2	.27	.25	.13	.21	.19
Female works in public sector	.29	.35	.33	.28	.28	.28
Male diploma						
No diploma	.09	.09	.09	.07	.08	.08
Up to High school	.52	.53	.52	.7	.66	.67
Some college	.4	.39	.39	.22	.25	.24
Female diploma						
No diploma	.05	.08	.07	.04	.09	.08
Up to High school	.42	.47	.46	.56	.63	.62
Some college	.53	.45	.47	.39	.27	.3
N	97	304	401	217	624	841

Table 5: Descriptive statistics, depending on constraint status at the extensive margin

	Unconstrained			**Constrained (strict)**			**Constrained (broad)**		
	Unmarried	Married	All	Unmarried	Married	All	Unmarried	Married	All
Annual Income	31924	35015	33938	24359	28035	26521	23306	27456	25751
Male age	31.23	35.16	33.79	31.64	35.28	33.78	31.41	35.89	34.05
Female age	29.66	33.45	32.13	29.83	32.7	31.52	29.92	33.92	32.28
Nb of kids	.63	1.39	1.13	.67	1.57	1.2	.79	1.59	1.26
Male works in public sector	.19	.24	.23	.17	.13	.15	.16	.16	.16
Female Activity									
works part time	.27	.38	.34	.38	.42	.4	.46	.46	.46
Unemployed	.08	.09	.09	.19	.18	.19	.25	.21	.23
Employed	.92	.91	.91	.81	.82	.81	.75	.79	.77
Female works in public sector	.29	.3	.3	.24	.25	.25	.25	.2	.22
Male diploma									
No diploma	.09	.11	.1	.36	.27	.3	.29	.23	.25
Up to High school	.62	.59	.6	.5	.58	.55	.57	.61	.59
Some college	.29	.3	.3	.14	.15	.15	.14	.16	.15
Female diploma									
No diploma	.06	.12	.09	.17	.35	.27	.18	.32	.26
Up to High school	.51	.52	.52	.69	.53	.6	.67	.5	.57
Some college	.43	.36	.39	.14	.12	.13	.14	.17	.16
N	771	1442	**2213**	42	60	**102**	76	109	**185**

Table 6: Descriptive statistics on credit

	Constrained			Unconstrained		
	Unmarried	Married	All	Unmarried	Married	All
Value (in years of income)	4.134	3.744	3.836	2.562	2.69	2.658
Total debt	98324	98186	98218	73416	78719	77357
Debt (by year of income)	3.466	3.246	3.298	1.986	2.017	2.009
Downpayment	23237	18312	19480	24856	25861	25603
% no downpayment	0.186	0.234	0.222	0.243	0.202	0.212
% of the value in downpayment	0.153	0.134	0.139	0.222	0.211	0.214
Downpayment (inc. PTZ)	33454	28671	29806	28209	30860	30179
% no downpayment (inc. PTZ)	0.062	0.109	0.098	0.173	0.15	0.156
% of the value in downpayment (inc. PTZ)	0.253	0.241	0.244	0.266	0.261	0.263
Cost	1.463	1.49	1.484	1.507	1.497	1.5
Effort rate	0.274	0.262	0.265	0.178	0.187	0.185
N	97	304	401	217	624	841

A.5 Impact of covariates on credit constraints and estimation of the propensity score

Table 7: Impact of covariates on credit constraints at the extensive margin - OLS regressions

	Credit Constrained (strict)		Credit Constrained (broad)		Married	
	(1)	(2)	(3)	(4)	(5)	(6)
Income: among 33-66%	-0.0332^a		-0.0667^a		0.0344	
	(0.0111)		(0.0140)		(0.0235)	
Income: among the top 33%	-0.0351^a		-0.0740^a		0.0823^a	
	(0.0129)		(0.0164)		(0.0275)	
Woman works part time	-0.0034	0.0003	0.0067	0.0126	0.0309	0.0263
	(0.0095)	(0.0094)	(0.0120)	(0.0119)	(0.0201)	(0.0198)
Male education: up to high school	-0.0577^a	-0.0597^a	-0.0543^a	-0.0573^a	0.0340	0.0427
	(0.0146)	(0.0146)	(0.0183)	(0.0184)	(0.0308)	(0.0307)
Male education: some college	-0.0497^a	-0.0512^a	-0.0458^b	-0.0449^b	0.0694^c	0.0838^b
	(0.0174)	(0.0175)	(0.0220)	(0.0222)	(0.0370)	(0.0370)
Female education: up to high school	-0.0488^a	-0.0519^a	-0.0753^a	-0.0796^a	-0.0676^b	-0.0496
	(0.0154)	(0.0154)	(0.0192)	(0.0193)	(0.0322)	(0.0322)
Female education: some college	-0.0744^a	-0.0777^a	-0.0987^a	-0.1011^a	-0.0978^a	-0.0685^c
	(0.0180)	(0.0180)	(0.0225)	(0.0226)	(0.0378)	(0.0378)
Has 1 child	-0.0108	-0.0129	-0.0005	-0.0032	0.1953^a	0.1970^a
	(0.0109)	(0.0108)	(0.0138)	(0.0137)	(0.0232)	(0.0230)
Has 2 children (or more)	-0.0027	-0.0036	0.0121	0.0132	0.3307^a	0.3334^a
	(0.0118)	(0.0117)	(0.0149)	(0.0148)	(0.0250)	(0.0246)
Male age: $\in [31, 35]$	0.0061		0.0181		0.0631^b	
	(0.0129)		(0.0163)		(0.0274)	
Male age: ≥ 36	0.0122		0.0281		0.0997^a	
	(0.0156)		(0.0197)		(0.0331)	
Female age: $\in [29, 33]$	-0.0180	-0.0179	-0.0366^b	-0.0332^b	0.0660^b	0.0557^b
	(0.0129)	(0.0121)	(0.0162)	(0.0154)	(0.0273)	(0.0257)
Female age: ≥ 34	-0.0334^b	-0.0294^c	-0.0494^b	-0.0374^c	0.0695^b	0.0214
	(0.0160)	(0.0158)	(0.0201)	(0.0200)	(0.0338)	(0.0334)
Man: Works in public sector	-0.0078	-0.0101	-0.0070	-0.0119	0.0585^b	0.0570^b
	(0.0106)	(0.0106)	(0.0135)	(0.0135)	(0.0227)	(0.0226)
Woman: Works in public sector	0.0113	0.0100	0.0069	0.0048	-0.0225	-0.0169
	(0.0099)	(0.0098)	(0.0126)	(0.0125)	(0.0211)	(0.0209)
Has savings	-0.0124	-0.0135	-0.0245^b	-0.0265^b	-0.0118	-0.0088
	(0.0088)	(0.0088)	(0.0111)	(0.0112)	(0.0187)	(0.0186)
Income		-0.0008^b		-0.0000^a		0.0000^c
		(0.0004)		(0.0000)		(0.0000)
Male's age		0.0002		0.0005		0.0117^a
		(0.0010)		(0.0013)		(0.0021)
Constant	0.1915^a	0.1973^a	0.2649^a	0.2828^a	0.3464^a	-0.0154
	(0.0192)	(0.0358)	(0.0240)	(0.0452)	(0.0403)	(0.0756)
Observations	2315	2315	2398	2398	2398	2398
R^2	0.040	0.038	0.056	0.052	0.170	0.175

Outcomes: (1) and (2)=1 if household constrained according to the strict definition
(3) and (4)= 1 if household constrained according to the board definition
(5) and (6)= 1 if married couple.
Standard errors in parentheses
^{c} p<0.1, ^{b} p<0.05, ^{a} p<0.01

Table 8: Impact of covariates on credit constraints at the intensive margin (set of discrete variables) - OLS regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Outcomes:			
	Debt (in 1000)	Debt (in an.inc.)	Total cost	Downp. (in 1000)	Downp. (in %)	Income (in 1000)	Married
Income: among 33-66%	13.3^a	-.465^a	-.0329	-3	-.0205		.0552
	(2.78)	(.0863)	(.025)	(3.47)	(.0184)		(.0577)
Income: among the top 33%	35.3^a	-.7^a	-.102^a	4.86	-.0443^c		.11
	(3.17)	(.0983)	(.0312)	(4.42)	(.0233)	(.0736)	
Downpayment:$\in[10\%, 30\%]$	4.3	.149	-.107^a	10^a		-.591	-.024
	(3.16)	(.0981)	(.0263)	(3.5)		(1.01)	(.0613)
Downpayment:$> 30\%$	-10.3^b	-.151	-.182^a	38.9^a		-2.97^b	-.042
	(4.34)	(.135)	(.0349)	(4.02)		(1.36)	(.0835)
Downpayment $\in]0, 16000[$	-5.88^b	-.291^a	-.00548		.0564^a	1.12	-.0142
	(2.99)	(.0928)	(.0254)		(.018)	(.945)	(.0578)
Downpayment ≥ 16000	9.91^a	-.0364	.0188		.212^a	4.94^a	-.0358
	(3.67)	(.114)	(.0312)		(.0185)	(1.16)	(.0711)
Total cost: among 33-66%	8.53^a	.14		-4.72	-.0621^a	-1.44	.0658
	(2.79)	(.0866)		(3.3)	(.0172)	(.881)	(.0545)
Total cost: among the top 33%	16.3^a	.438^a		-2.15	-.117^a	-3.04^a	.0962
	(2.95)	(.0915)		(3.61)	(.0182)	(.947)	(.0598)
Woman works part time	-1.56	.0547	.073^a	-1.47	.0251^c	-2.19^a	-.00839
	(2.44)	(.0758)	(.0204)	(2.84)	(.0149)	(.763)	(.047)
Man: Works in public sector	-4.08	-.108	.0486^c	-2.67	.0139	.609	.0889
	(3.05)	(.0946)	(.0256)	(3.54)	(.0187)	(.955)	(.0586)
Woman: Works in public sector	-2.16	.00434	-.0439^b	-.904	.000263	.12	-.0351
	(2.62)	(.0814)	(.0221)	(3.05)	(.0161)	(.827)	(.0504)
Male education: some college	4.73	-.109	-.0159	10.9^a	.00183	4.08^a	.0889
	(3)	(.0932)	(.0253)	(3.47)	(.0184)	(.938)	(.0578)
Female education: some college	3.13	.0185	.0514^b	9.03^a	-.00931	3.39^a	-.0823
	(2.9)	(.0901)	(.0244)	(3.36)	(.0177)	(.899)	(.0558)
Has 1 child	3.69	-.122	-.0276	-1.5	.00592	1.47	.141^b
	(3.15)	(.098)	(.0265)	(3.67)	(.0194)	(.996)	(.0607)
Has 2 children (or more)	5.7^c	-.14	-.0442^c	-2.24	.0294	2.2^b	.223^a
	(3.19)	(.099)	(.0266)	(3.69)	(.0195)	(1.01)	(.0613)
Male age: $\in [31, 35]$	-1.2	.054	.0416	-3.97	.011	.422	-.0144
	(3.24)	(.101)	(.0272)	(3.76)	(.0199)	(1.02)	(.0623)
Male age: ≥ 36	1.06	.122	-.0127	.779	.00674	.599	-.0434
	(3.74)	(.116)	(.0317)	(4.36)	(.023)	(1.18)	(.0722)
Female age: $\in [29, 33]$	-1.83	-.0436	-.00441	1.31	.00585	.579	.131^b
	(3.08)	(.0956)	(.026)	(3.57)	(.0189)	(.97)	(.0592)
Female age: ≥ 34	-3.02	-.105	.0418	7.58^c	.00046	1.31	.177^b
	(3.89)	(.121)	(.0329)	(4.47)	(.0238)	(1.23)	(.075)
Debt: among 33-66%			.071^a	1.27	.00722	4.53^a	-.0148
			(.0251)	(3.52)	(.0184)	(.881)	(.0585)
Debt: among the top 33%			.153^a	6.49	-.0186	10.6^a	-.109
			(.0301)	(4.32)	(.0227)	(.98)	(.0722)
Constant	70^a	3.72^a	1.53^a	-3.49	.187^a	21.7^a	.499^a
	(4.77)	(.148)	(.0359)	(5.31)	(.0269)	(1.5)	(.0926)
Observations	397	397	397	397	397	397	397
R^2	0.475	0.287	0.216	0.377	0.436	0.522	0.113

Standard errors in parentheses
^{c} p<0.1, ^{b} p<0.05, ^{a} p<0.01

Table 9: Impact of covariates on credit constraints at the intensive margin (set of continuous variables) - OLS regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Outcomes:			
	Debt (in 1000)	Debt (in an.inc.)	Total cost	Downp. (in 1000)	Downp. (in %)	Income (in 1000)	Married
Income	2.47^a	-.033^a	-7.6e-03^a	.881^a	-7.1e-05		9.3e-03^b
	(.113)	(4.5e-03)	(1.8e-03)	(.209)	(1.2e-03)		(4.1e-03)
% of downpayment	-25.9^a	-1.17^a	-.321^a	112^a		-.126	-.024
	(7.03)	(.281)	(.075)	(6.94)		(2.15)	(.175)
Downpayment	.03	4.5e-03^a	1.5e-04		3.6e-03^a	.051 ^{a}	-1.2e-03
	(.041)	(1.6e-03)	(4.3e-04)		(2.2e-04)	(.012)	(9.9e-04)
Total cost	24.9^a	.786^a		2.11	-.144^a	-6.05 ^{a}	.201^c
	(4.62)	(.185)		(6.02)	(.033)	(1.41)	(.117)
Woman works part time	.941	.022	.067^a	.396	.036^a	-1.6^a	-.014
	(1.9)	(.076)	(.02)	(2.39)	(.013)	(.567)	(.046)
Man: Works in public sector	-2.83	-.14	.062^b	-2.29	8.4e-03	1.37^c	.081
	(2.36)	(.095)	(.025)	(2.97)	(.017)	(.71)	(.058)
Woman: Works in public sector	-1.17	-.011	-.038^c	-.734	-3.2e-03	.409	-.031
	(2.04)	(.082)	(.022)	(2.57)	(.015)	(.616)	(.05)
Male education: some college	-2.32	-.071	8.0e-03	3.87	-9.8e-04	2.91^a	.077
	(2.36)	(.095)	(.025)	(2.97)	(.017)	(.696)	(.058)
Female education: some college	-2.26	5.3e-03	.053^b	8.18^a	-.023	2.32^a	-.089
	(2.27)	(.091)	(.024)	(2.83)	(.016)	(.676)	(.056)
Has 1 child	-.587	-.094	-.013	-3.71	.03^c	1.4 ^{c}	.135^b
	(2.43)	(.097)	(.026)	(3.05)	(.017)	(.729)	(.059)
Has 2 children (or more)	.274	-.065	-.025	-7.38^b	.052^a	1.54^b	.221^a
	(2.42)	(.097)	(.026)	(3.02)	(.017)	(.725)	(.059)
Male's age	.049	4.7e-03	-2.4e-03	.339	-1.9e-03	-.016	2.0e-03
	(.254)	(.01)	(2.7e-03)	(.319)	(1.8e-03)	(.077)	(6.2e-03)
Female's age	-.197	-6.1e-03	3.7e-03	.087	4.5e-04	.137^c	5.8e-03
	(.245)	(9.8e-03)	(2.6e-03)	(.309)	(1.8e-03)	(.074)	(6.0e-03)
Debt			2.8e-03^a	.047	-1.3e-03^a	.224^a	-2.9e-03^b
			(5.3e-04)	(.064)	(3.6e-04)	(.01)	(1.2e-03)
Constant	-2.06	3.49^a	1.45^a	-55.2^a	.526^a	10.3^a	.096
	(9.77)	(.391)	(.073)	(12)	(.064)	(2.89)	(.239)
Observations	397	397	397	397	397	397	397
R^2	0.674	0.263	0.221	0.547	0.524	0.729	0.106

Standard errors in parentheses
^{c} p<0.1, ^{b} p<0.05, ^{a} p<0.01

Table 10: Estimation of the propensity score (extensive margin) $P(m_i = 1|X_i)$ Probit estimation

Set of the outcome :	(1) Constraint (strict)	(2)	(3) Constraint (broad)	(4)
Income: among 33-66%	.0884 (.0745)		.107 (.0728)	
Income: among the top 33%	.249^a (.0881)		.257^a (.0865)	
Woman works part time	.116^c (.0655)	.102 (.0648)	.0995 (.0642)	.0838 (.0635)
Male education: up to high school	.114 (.0999)	.142 (.1)	.113 (.0968)	.139 (.0972)
Male education: some college	.24^b (.12)	.292^b (.121)	.228^c (.117)	.277^b (.118)
Female education: up to high school	-.261^b (.111)	-.213^c (.112)	-.236^b (.107)	-.181^c (.107)
Female education: some college	-.386^a (.128)	-.302^b (.128)	-.331^a (.123)	-.245^b (.124)
Has 1 child	.531^a (.0695)	.536^a (.0693)	.514^a (.0682)	.521^a (.068)
Has 2 children (or more)	1^a (.0801)	1.01^a (.0795)	.985^a (.0782)	.992^a (.0777)
Male age: $\in [31, 35]$	.142^c (.0843)		.157^c (.0824)	
Male age: ≥ 36	.3^a (.104)		.287^a (.102)	
Female age: $\in [29, 33]$	.158^c (.0835)	.102 (.0798)	.164^b (.0815)	.113 (.0781)
Female age: ≥ 34	.153 (.106)	-.00447 (.106)	.191^c (.103)	.027 (.104)
Man: Works in public sector	.187^b (.0738)	.181^b (.0739)	.19^a (.0726)	.186^b (.0727)
Woman: Works in public sector	-.0558 (.0672)	-.0438 (.067)	-.0768 (.0662)	-.0632 (.0661)
Has savings	-.0345 (.0596)	-.028 (.0597)	-.0319 (.0586)	-.024 (.0587)
Income		.00413 (.00265)		4.56e-06^c (2.61e-06)
Male's age		.0371^a (.00698)		.0369^a (.00683)
Constant	-.356^a (.135)	-1.5^a (.25)	-.399^a (.13)	-1.54^a (.244)
Observations	2315	2315	2398	2398

Standard errors in parentheses
^{c} p<0.1, ^{b} p<0.05, ^{a} p<0.01
For all estimation, the outcome is $m_i = 1$ if the couple is married.
Column (1) and (2): estimation of the propensity score for the population excluding discouraged borrowers
Column (3) and (4): estimation of the propensity score for the population including discouraged borrowers

Table 11: Estimation of the propensity score (intensive margin - Set 1) Probit estimation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
					Outcomes:		
	Debt (in 1000)	Debt (in an.inc.)	Total cost	Downp. (in 1000)	Downp. (in %)	Income (in 1000)	All
Income: among 33-66%	.144 (.189)	.144 (.189)	.137 (.201)	.18 (.203)	.186 (.205)		.189 (.205)
Income: among the top 33%	.144 (.212)	.144 (.212)	.257 (.252)	.349 (.258)	.375 (.259)		.366 (.26)
Downpayment:$\in$ $[10\%, 30\%]$	-.133 (.22)	-.133 (.22)	-.181 (.216)	-.156 (.211)		-.128 (.221)	-.119 (.222)
Downpayment:$>$ 30%	-.126 (.296)	-.126 (.296)	-.296 (.283)	-.243 (.24)		-.184 (.293)	-.155 (.296)
Downpayment $\in]0, 16000[$	-.0337 (.205)	-.0337 (.205)	-.0433 (.208)		-.0827 (.205)	-.0398 (.207)	-.0647 (.208)
Downpayment $\geq$ 16000	-.183 (.247)	-.183 (.247)	-.13 (.25)		-.203 (.209)	-.0936 (.247)	-.138 (.25)
Total cost: among 33-66%	.164 (.186)	.164 (.186)		.213 (.189)	.221 (.186)	.171 (.186)	.213 (.189)
Total cost: among the top 33%	.251 (.198)	.251 (.198)		$.357^c$ (.212)	$.389^c$ (.203)	.285 (.205)	$.359^c$ (.212)
Woman works part time	-.0296 (.167)	-.0296 (.167)	-.0204 (.165)	-.0374 (.167)	-.0477 (.166)	-.0678 (.166)	-.0374 (.167)
Man: Works in public sector	.36 (.222)	.36 (.222)	$.39^c$ (.221)	$.372^c$ (.223)	.361 (.223)	$.398^c$ (.221)	.365 (.223)
Woman: Works in public sector	-.144 (.176)	-.144 (.176)	-.169 (.177)	-.149 (.177)	-.147 (.176)	-.142 (.176)	-.151 (.177)
Male education: some college	.286 (.205)	.286 (.205)	.272 (.203)	.289 (.204)	.315 (.204)	$.336^c$ (.203)	.304 (.206)
Female education: some college	-.29 (.191)	-.29 (.191)	-.249 (.19)	-.287 (.191)	-.274 (.191)	-.232 (.187)	-.278 (.192)
Has 1 child	$.424^b$ (.201)	$.424^b$ (.201)	$.401^b$ (.2)	$.443^b$ (.202)	$.431^b$ (.202)	$.446^b$ (.202)	$.44^b$ (.202)
Has 2 children (or more)	$.733^a$ (.211)	$.733^a$ (.211)	$.715^a$ (.209)	$.756^a$ (.211)	$.734^a$ (.21)	$.752^a$ (.212)	$.747^a$ (.212)
Male age: $\in [31, 35]$	-.0562 (.211)	-.0562 (.211)	-.0399 (.211)	-.0525 (.211)	-.0504 (.211)	-.0205 (.211)	-.0505 (.212)
Male age: $\geq$ 36	-.192 (.252)	-.192 (.252)	-.166 (.254)	-.155 (.254)	-.156 (.253)	-.142 (.253)	-.157 (.254)
Female age: $\in [29, 33]$	$.4^b$ (.196)	$.4^b$ (.196)	$.384^c$ (.196)	$.393^b$ (.196)	$.397^b$ (.196)	$.407^b$ (.196)	$.395^b$ (.197)
Female age: $\geq$ 34	$.612^b$ (.261)	$.612^b$ (.261)	$.602^b$ (.262)	$.572^b$ (.259)	$.596^b$ (.262)	$.612^b$ (.262)	$.587^b$ (.263)
Debt: among 33-66%			.0286 (.203)	-.0309 (.205)	-.0521 (.205)	.064 (.19)	-.0421 (.208)
Debt: among the top 33%			-.237 (.242)	-.392 (.252)	-.391 (.254)	-.179 (.21)	-.387 (.258)
Constant	-.0109 (.316)	-.0109 (.316)	.218 (.285)	-.0502 (.3)	-.109 (.289)	.0237 (.317)	-.0286 (.321)
Observations	397	397	397	397	397	397	397
R^2							

Standard errors in parentheses - ^{c} p<0.1, ^{b} p<0.05, ^{a} p<0.01

Lecture: as the set of covariates is different for each outcome, there are as many estimations of the propensity score as final outcomes. But of course, as it is an estimation of the propensity score, the dependant variable is $m_i = 1$ if the couple is married. Column (1) gives the estimation of the propensity score when the set of covariate corresponds to the study of the final outcome: the value of the debt. The last column includes all covariates.

Table 12: Estimation of the propensity score (intensive margin - Set 2) Probit estimation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Outcomes:			
	Debt (in 1000)	Debt (in an.inc.)	Total cost	Downp. (in 1000)	Downp. (in %)	Income (in 1000)	All
Income	6.3e-03	6.3e-03	.023[c]	.027[b]	.032[b]		.032[b]
	(9.5e-03)	(9.5e-03)	(.014)	(.014)	(.015)		(.015)
% of downpayment	.209	.209	-.377	-.501		-.095	-.013
	(.654)	(.654)	(.608)	(.485)		(.632)	(.662)
Downpayment	-4.1e-03	-4.1e-03	-3.4e-03		-3.8e-03	-2.1e-03	-3.8e-03
	(3.3e-03)	(3.3e-03)	(3.1e-03)		(2.4e-03)	(3.1e-03)	(3.2e-03)
Total cost	.637	.637		1.01[c]	1.05[b]	.728	1.05[b]
	(.464)	(.464)		(.515)	(.5)	(.479)	(.521)
Woman works part time	-.076	-.076	-.013	-.07	-.071	-.117	-.071
	(.166)	(.166)	(.163)	(.166)	(.165)	(.165)	(.166)
Man: Works in public sector	.351	.351	.372[c]	.342	.331	.362[c]	.331
	(.219)	(.219)	(.218)	(.22)	(.221)	(.218)	(.221)
Woman: Works in public sector	-.114	-.114	-.163	-.127	-.128	-.119	-.128
	(.174)	(.174)	(.175)	(.176)	(.176)	(.174)	(.176)
Male education: some college	.298	.298	.262	.26	.279	.36[c]	.279
	(.204)	(.204)	(.203)	(.203)	(.205)	(.201)	(.205)
Female education: some college	-.277	-.277	-.247	-.32[c]	-.293	-.225	-.293
	(.19)	(.19)	(.188)	(.189)	(.19)	(.187)	(.19)
Has 1 child	.413[b]	.413[b]	.395[b]	.433[b]	.414[b]	.453[b]	.415[b]
	(.197)	(.197)	(.196)	(.197)	(.196)	(.196)	(.198)
Has 2 children (or more)	.735[a]	.735[a]	.717[a]	.793[a]	.762[a]	.791[a]	.763[a]
	(.205)	(.205)	(.205)	(.206)	(.205)	(.206)	(.207)
Male's age	9.4e-03	9.4e-03	8.6e-03	.01	.011	9.8e-03	.011
	(.022)	(.022)	(.022)	(.022)	(.022)	(.022)	(.022)
Female's age	.017	.017	.017	.014	.015	.02	.015
	(.021)	(.021)	(.021)	(.021)	(.021)	(.021)	(.021)
Debt			-7.2e-03[c]	-.011[b]	-.01[b]	-3.0e-03	-.01[b]
			(4.1e-03)	(4.4e-03)	(4.4e-03)	(2.9e-03)	(4.5e-03)
Constant	-1.67[c]	-1.67[c]	-.375	-1.66[c]	-1.95[b]	-1.44	-1.94[b]
	(.932)	(.932)	(.573)	(.938)	(.886)	(.915)	(.979)
Observations	397	397	397	397	397	397	397
R^2							

Standard errors in parentheses
[c] p<0.1, [b] p<0.05, [a] p<0.01
Lecture: as the set of covariates is different for each outcome, there are as many estimations of the propensity score as final outcomes. But of course, as it is an estimation of the propensity score, the dependant variable is $m_i = 1$ if the couple is married. Column (1) gives the estimation of the propensity score when the set of covariate corresponds to the study of the final outcome: the value of the debt. The last column includes all covariates.

Table 13: P-value of χ^2 test for balancing of covariates

Outcome	NN weights				Kernel weights				Mahalanobis weights				HIR weights			
	Set 1		Set 2		Set 1		Set 2		Set 1		Set 2		Set 1		Set 2	
	ATT	ATU	ATT	ATU	ATT	ATU	ATT	ATU	ATT	ATU	ATT	ATU	ATT	ATU	ATT	ATU
CC - strict def.	.17	.12	.89	.68	.38	.99	.19	.89	0	.93	0.01	.57	1	.9	1	.8
CC - broad def.	.19	.61	.95	.85	.43	.98	.27	.92	0	.29	0	.61	1	.94	1	.86
Debt	.91	1	.79	1	.98	1	.97	1	.15	.43	0.01	.98	1	1	1	.92
Downpayment	.94	1	.33	1	.99	1	.79	1	.7	.71	0.01	.99	1	1	1	.85
Income	.37	1	.5	1	1	1	.88	1	.63	.83	0.01	.93	1	1	1	.88
% of downp.	.9	1	.43	1	.99	1	.88	1	.64	.82	0.02	.87	1	1	1	.86
Total cost	.36	1	.04	1	.99	1	.98	1	.27	.74	0.04	1	1	1	1	.96
Debt (in annual inc.)	.91	1	.79	1	.98	1	.97	1	.15	.43	0.01	.98	1	1	1	.92

Set 1: Discrete variables; Set 2: Continuous variables

Each cell gives the P-value of a χ^2 test of overall balancing test.

Each row gives the tests for the matching procedure studying each outcome (the set of covariates is different for each outcome).

Lecture: the P-value of the χ^2 test of overall equality of covariates between the two population is 0.01 for the propensity score computed to study credit constraints (strict definition) reweighting unmarried to make them similar to married couples (ATT) using nearest neighbors weights.

A.6 Results

Table 14: Impact of marriage on credit constraints at the extensive margin - strict definition

	Credit constraints: strict definition			
	ATT		ATU	
Simple difference	-0.014 (0.009)	-0.013 (0.009)	-0.014 (0.009)	-0.013 (0.009)
OLS (with controls)	-0.009 (0.01)	-0.01 (0.01)	-0.009 (0.01)	-0.01 (0.01)
Oaxaca Blinder	-0.012 (0.012)	-0.013 (0.012)	-0.009 (0.01)	-0.008 (0.01)
Matching estimators				
Kernel (ana)	-0.011 (0.012)	-0.006 (0.012)	-0.007 (0.01)	-0.009 (0.011)
Kernel (bs)	-0.011 (0.011)	-0.006 (0.011)	-0.007 (0.012)	-0.009 (0.011)
Mahalanobis (ana)	-0.005 (0.015)	-0.005 (0.014)	-0.027 (0.018)	-0.023 (0.012) *
Nearest Neighbors (ana)	-0.003 (0.015)	-0.005 (0.013)	-0.006 (0.013)	-0.013 (0.012)
HIR weights estimators				
Simple difference	-0.01 (0.009)	-0.016 (0.009) *	-0.015 (0.012)	-0.014 (0.012)
WLS (with controls)	-0.012 (0.008)	-0.017 (0.009) *	-0.009 (0.015)	-0.008 (0.015)
Covariates	Discrete	Continuous	Discrete	Continuous
N	2259	2240	2259	2240

Standard errors into parenthesis. Ana means that the analytical variance is computed, bs means that the variance is estimated by bootstrap. Bootstrap variances: 250 replicates. Covariates include: male age, female age, annual income, number of kids, female education, male education, employment status of the female,

Table 15: Impact of marriage on credit constraints at the extensive margin - broad definition

	Credit constraints: strict definition			
	ATT		ATU	
Simple difference	-0.022 (0.011) *	-0.02 (0.012) *	-0.022 (0.011) *	-0.02 (0.012) *
OLS (with controls)	-0.021 (0.012) *	-0.021 (0.012) *	-0.021 (0.012) *	-0.021 (0.012) *
Oaxaca Blinder	-0.03 (0.014) **	-0.029 (0.015) **	-0.018 (0.013)	-0.017 (0.013)
Matching estimators				
Kernel (ana)	-0.022 (0.015)	-0.023 (0.015)	-0.015 (0.013)	-0.016 (0.013)
Kernel (bs)	-0.022 (0.014)	-0.023 (0.015)	-0.015 (0.014)	-0.016 (0.015)
Mahalanobis (ana)	-0.016 (0.022)	-0.024 (0.018)	-0.031 (0.02)	-0.043 (0.017) **
Nearest Neighbors (ana)	-0.015 (0.015)	-0.024 (0.017)	-0.01 (0.016)	-0.02 (0.015)
HIR weights estimators				
Simple difference	-0.024 (0.011) **	-0.027 (0.011) **	-0.021 (0.015)	-0.014 (0.016)
WLS (with controls)	-0.028 (0.011) **	-0.03 (0.011) ***	-0.022 (0.019)	-0.027 (0.02)
Covariates	Discrete	Continuous	Discrete	Continuous
N	2348	2321	2348	2321

Standard errors into parenthesis. Ana means that the analytical variance is computed, bs means that the variance is estimated by bootstrap. Bootstrap variances: 250 replicates. Covariates include: male age, female age, annual income, number of kids, female education, male education, employment status of the female,

Table 16: Impact of marriage on credit constraints at the intensive margin : debt

	Debt			
	ATT		ATU	
Simple difference	-5248 (3761)	-2655 (3615)	-5248 (3761)	-2655 (3615)
OLS (with controls)	-5241 (2748) *	-5513 (2013) ***	-5241 (2748) *	-5513 (2013) ***
Oaxaca Blinder	-1971 (3419)	-4116 (2725)	-5860 (3517) *	-5757 (2502) **
Matching estimators				
Kernel (ana)	-7122 (4597)	-5863 (4465)	-6375 (4468)	-3774 (4220)
Kernel (bs)	-7122 (4117) *	-5863 (3837)	-6375 (4353)	-3774 (4374)
Mahalanobis (ana)	-3447 (5440)	987 (5335)	-5543 (5770)	-529 (4887)
Nearest Neighbors (ana)	-8286 (0.015)	-6761 (5726)	-7564 (4881)	-5939 (4255)
HIR weights estimators				
Simple difference	-6840 (3326) **	-9895 (3637) ***	-3373 (6775)	-90 (6784)
WLS (with controls)	-2422 (2334)	-4891 (1559) ***	-5216 (5142)	-5474 (3678)
Covariates	Discrete	Continuous	Discrete	Continuous
N	360	366	360	366

Standard errors into parenthesis. Ana means that the analytical variance is computed, bs means that the variance is estimated by bootstrap. Bootstrap variances: 250 replicates. Covariates include: male age, female age, annual income, number of kids, female education, male education, employment status of the female, total cost, value of the downpayment, % of downpayment

Table 17: Impact of marriage on credit constraints at the intensive margin : value of debt in annual income

	Value of the debt expressed in annual income			
	ATT		ATU	
Simple difference	-0.163 (0.088) *	-0.174 (0.088) **	-0.163 (0.088) *	-0.174 (0.088) **
OLS (with controls)	-0.182 (0.078) **	-0.189 (0.076) **	-0.182 (0.078) **	-0.189 (0.076) **
Oaxaca Blinder	-0.053 (0.115)	-0.142 (0.115)	-0.213 (0.113) *	-0.196 (0.104) *
Matching estimators				
Kernel (ana)	-0.095 (0.105)	-0.133 (0.117)	-0.134 (0.106)	-0.195 (0.111) *
Kernel (bs)	-0.095 (0.089)	-0.133 (0.09)	-0.134 (0.118)	-0.195 (0.114) *
Mahalanobis (ana)	-0.009 (0.122)	0.014 (0.108)	-0.097 (0.128)	-0.229 (0.125) *
Nearest Neighbors (ana)	-0.078 (0.015)	-0.201 (0.104) *	-0.172 (0.113)	-0.188 (0.12)
HIR weights estimators				
Simple difference	-0.027 (0.068)	-0.125 (0.071) *	-0.127 (0.149)	-0.148 (0.143)
WLS (with controls)	-0.08 (0.057)	-0.177 (0.06) ***	-0.183 (0.127)	-0.194 (0.128)
Covariates	Discrete	Continuous	Discrete	Continuous
N	360	366	360	366

Standard errors into parenthesis. Ana means that the analytical variance is computed, bs means that the variance is estimated by bootstrap. Bootstrap variances: 250 replicates. Covariates include: male age, female age, annual income, number of kids, female education, male education, employment status of the female, total cost, value of the downpayment, % of downpayment

Table 18: Impact of marriage on credit constraints at the intensive margin : value of the downpayment

	Value of the downpayment			
	ATT		ATU	
Simple difference	-4107 (3559)	-4196 (3534)	-4107 (3559)	-4196 (3534)
OLS (with controls)	-4086 (2734)	-4473 (2418) *	-4086 (2734)	-4473 (2418) *
Oaxaca Blinder	-5044 (4588)	-3814 (3416)	-3658 (4373)	-3857 (3517)
Matching estimators				
Kernel (ana)	-5437 (5510)	-6645 (5277)	-4639 (5026)	-3891 (4960)
Kernel (bs)	-5437 (5428)	-6645 (4661)	-4639 (5471)	-3891 (5068)
Mahalanobis (ana)	-4221 (6617)	-254 (4363)	-456 (6602)	-7834 (5287)
Nearest Neighbors (ana)	-5332 (0.015)	-4952 (5238)	-4146 (5188)	-4857 (5070)
HIR weights estimators				
Simple difference	-7269 (3682) **	-9783 (4021) **	-5790 (5733)	-5642 (5510)
WLS (with controls)	-5188 (2503) **	-4910 (2352) **	-3521 (4187)	-4016 (3510)
Covariates	Discrete	Continuous	Discrete	Continuous
N	361	359	361	359

Standard errors into parenthesis. Ana means that the analytical variance is computed, bs means that the variance is estimated by bootstrap. Bootstrap variances: 250 replicates. Covariates include: male age, female age, annual income, number of kids, female education, male education, employment status of the female, total cost, value of the debt, % of downpayment

Table 19: Impact of marriage on credit constraints at the intensive margin : % of downpayment

	% of the downpayment			
	ATT		ATU	
Simple difference	-0.006 (0.019)	-0.009 (0.019)	-0.006 (0.019)	-0.009 (0.019)
OLS (with controls)	0.001 (0.013)	0.014 (0.009) *	0.001 (0.013)	0.014 (0.009) *
Oaxaca Blinder	0.001 (0.014)	0.003 (0.012)	0.002 (0.014)	0.019 (0.017)
Matching estimators				
Kernel (ana)	-0.002 (0.022)	0.006 (0.019)	-0.003 (0.02)	-0.003 (0.02)
Kernel (bs)	-0.002 (0.019)	0.006 (0.015)	-0.003 (0.02)	-0.003 (0.019)
Mahalanobis (ana)	-0.006 (0.025)	0.012 (0.025)	-0.014 (0.026)	-0.012 (0.025)
Nearest Neighbors (ana)	-0.004 (0.015)	0.014 (0.019)	0 (0.022)	-0.015 (0.022)
HIR weights estimators				
Simple difference	-0.016 (0.019)	-0.009 (0.016)	-0.02 (0.036)	-0.021 (0.033)
WLS (with controls)	-0.001 (0.011)	0.01 (0.007)	0.004 (0.024)	0.017 (0.012)
Covariates	Discrete	Continuous	Discrete	Continuous
N	360	360	360	360

Standard errors into parenthesis. Ana means that the analytical variance is computed, bs means that the variance is estimated by bootstrap. Bootstrap variances: 250 replicates. Covariates include: male age, female age, annual income, number of kids, female education, male education, employment status of the female, total cost, value of the debt, value of downpayment

Table 20: Impact of marriage on credit constraints at the intensive margin : total cost

	total cost			
	ATT		ATU	
Simple difference	0.035 (0.024)	0.04 (0.024) *	0.035 (0.024)	0.04 (0.024) *
OLS (with controls)	0.038 (0.021) *	0.046 (0.021) **	0.038 (0.021) *	0.046 (0.021) **
Oaxaca Blinder	0.038 (0.025)	0.057 (0.022) ***	0.039 (0.024)	0.044 (0.022) **
Matching estimators				
Kernel (ana)	0.045 (0.027) *	0.052 (0.026) **	0.032 (0.025)	0.051 (0.025) **
Kernel (bs)	0.045 (0.026) *	0.052 (0.022) **	0.032 (0.026)	0.051 (0.025) **
Mahalanobis (ana)	0.065 (0.03) **	0.075 (0.032) **	0.047 (0.039)	0.058 (0.039)
Nearest Neighbors (ana)	0.061 (0.015) **	0.055 (0.026) **	0.022 (0.026)	0.051 (0.026) **
HIR weights estimators				
Simple difference	0.041 (0.018) **	0.062 (0.018) ***	0.035 (0.043)	0.034 (0.044)
WLS (with controls)	0.035 (0.017) **	0.057 (0.016) ***	0.039 (0.039)	0.044 (0.04)
Covariates	Discrete	Continuous	Discrete	Continuous
N	362	367	362	367

Standard errors into parenthesis. Ana means that the analytical variance is computed, bs means that the variance is estimated by bootstrap. Bootstrap variances: 250 replicates. Covariates include: male age, female age, annual income, number of kids, female education, male education, employment status of the female, value of the debt, value of downpayment, % of dowpayment

Table 21: Impact of marriage on credit constraints at the intensive margin : annual income

	Annual income			
	ATT		ATU	
Simple difference	114 (1219)	1310 (1158)	114 (1219)	1310 (1158)
OLS (with controls)	715 (868)	1493 (601) **	715 (868)	1493 (601) **
Oaxaca Blinder	-286 (1301)	1085 (828)	996 (1216)	1694 (771) **
Matching estimators				
Kernel (ana)	-881 (1660)	373 (1451)	246 (1494)	1505 (1356)
Kernel (bs)	-881 (1409)	373 (1171)	246 (1591)	1505 (1460)
Mahalanobis (ana)	-471 (1763)	857 (1588)	-113 (1688)	2381 (1638)
Nearest Neighbors (ana)	-899 (0.015)	1788 (1235)	761 (1604)	2126 (1391)
HIR weights estimators				
Simple difference	-1042 (1130)	574 (1017)	-404 (2044)	827 (1891)
WLS (with controls)	-51 (783)	1303 (480) ***	620 (1437)	1365 (1029)
Covariates	Discrete	Continuous	Discrete	Continuous
N	360	367	360	367

Standard errors into parenthesis. Ana means that the analytical variance is computed, bs means that the variance is estimated by bootstrap. Bootstrap variances: 250 replicates. Covariates include: male age, female age, number of kids, female education, male education, employment status of the female, value of the debt, value of downpayment, % of dowpayment, total cost

A.7 Propensity score

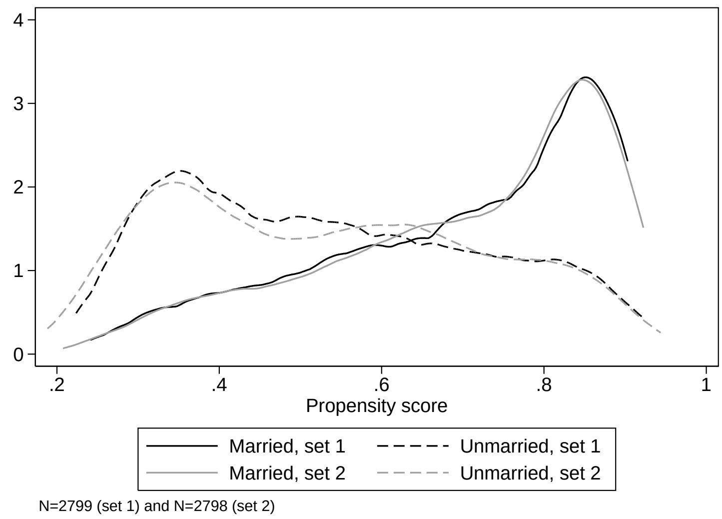


Figure 3: Distribution of the propensity score for $P(m_i = 1|X_i)$, for constraints at the extensive margin

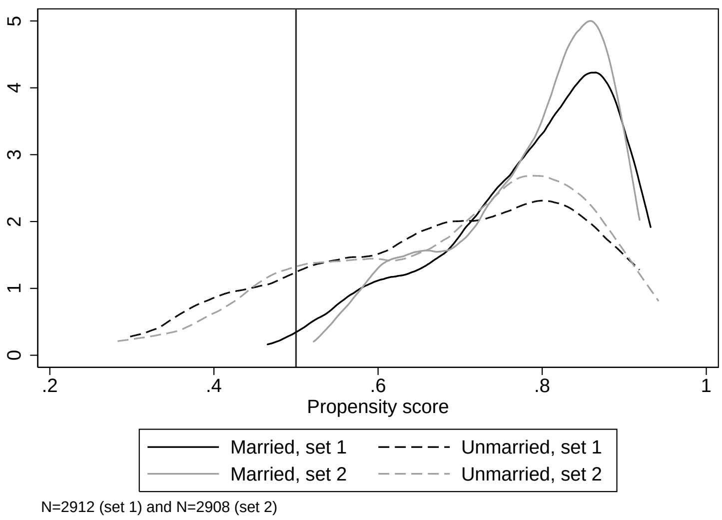


Figure 4: Distribution of the propensity score for $P(m_i = 1|X_i)$, for constraints at the intensive margin

A.8 Weights

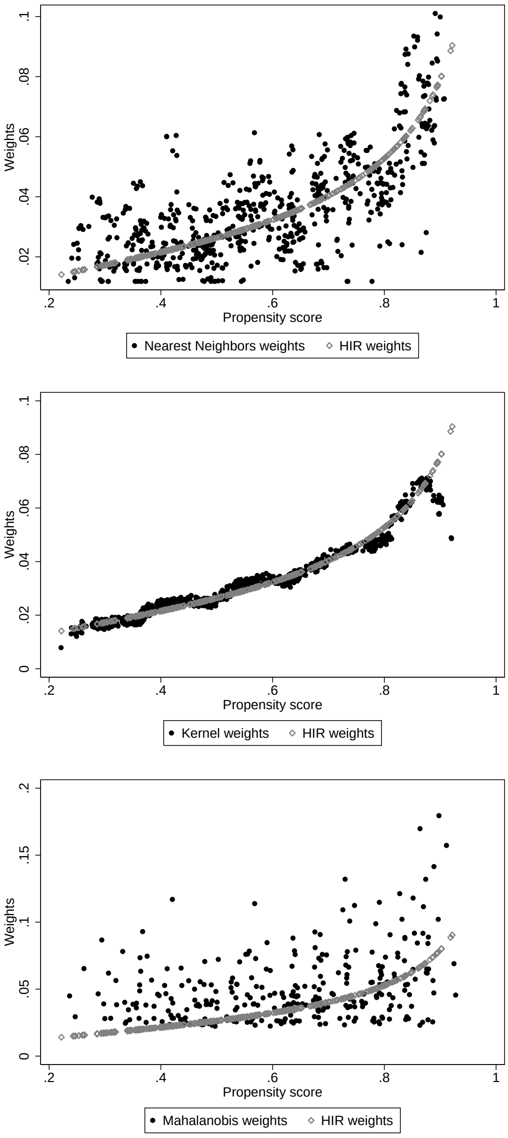


Figure 5: Comparison of weights - credit constraints at the extensive margin - Treatment=married

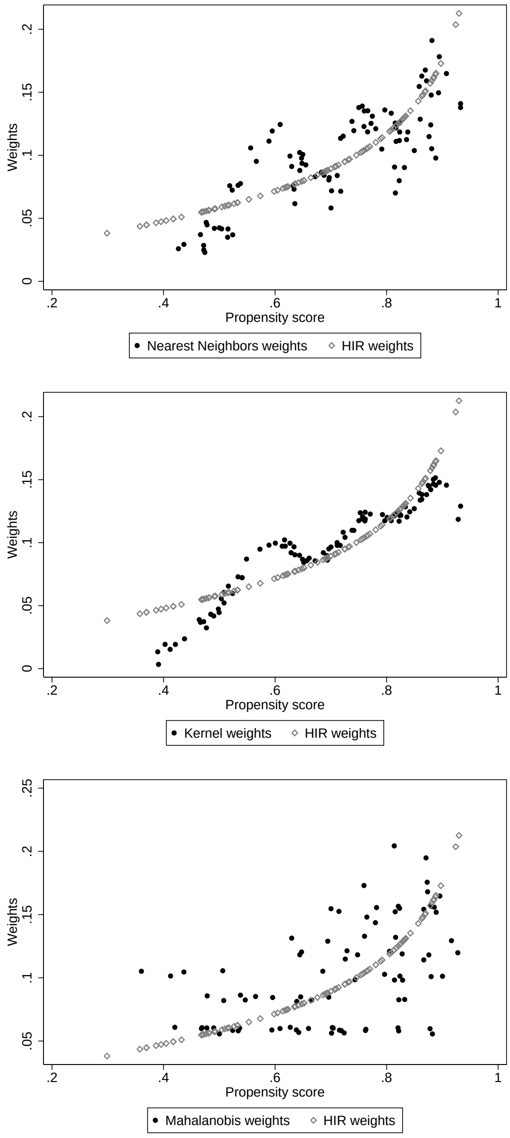


Figure 6: Comparison of weights - credit constraints at the intensive margin - Treatment=married