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RUNNING HEAD: Effect of Marital Status on Homeownership

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ABSTRACT

This research examines whether lower-income married renters are more likely to become homeowners than comparable single renters. Using data from the Community Advantage Panel Study, we use discrete-time survival analysis with propensity score matching to explore this relationship. Results indicate married couples have higher odds of buying a home, and do so at faster rates, than their unmarried counterparts. These findings were robust to the control of selection bias between the married and unmarried groups using propensity score matching. The findings suggest efforts to encourage marriage among low-income couples may be associated with subsequent economic mobility through homeownership.

Keywords: homeownership, assets ownership, marriage, low-income families, propensity score matching

The Effect of Marital Status on Homeownership Among Low-Income Households

Among the most challenging goals of social policy is determining the best way to help disadvantaged families move up the economic ladder. Over the last two decades, asset building as an anti-poverty strategy has been gaining substantial ground in both policy and research arenas. One of the main sources of assets is homeownership. Understanding the factors that influence the transition to homeownership has important implications for policy makers seeking to improve family well-being. In this study, we examine the potentially causal role that marriage plays in the decision to buy a home.

Homeownership is highly valued in the United States and considered part of the American dream among many households. Research suggests that homeownership is associated with considerable benefits for individuals, families, and their communities. For example, evidence supports that owning a home is associated with increased savings and wealth levels (Skinner 1989; Di, Yang, and Liu 2003). Further, research has established an association between owning a home and the household's greater social and civic involvement in local activities such as voting, volunteer work, and neighborhood associations (Drier 1994; DiPasquale and Glaeser 1999; Manturuk, Lindblad, and Quercia 2009). Studies have also shown a link between homeownership and positive child outcomes such as higher educational attainment (Boehm and Schlottmann 1999; Haurin, Parcel, and Haurin 2002), lower teenage pregnancy, and fewer behavioral problems (Haurin et al., 2002).

Like homeownership, marriage is associated with upward mobility and prosperity and is perceived by many as a normative life course milestone with numerous associated benefits (Waite 1995; Waite and Gallagher 2000). Evidence suggests that married couples in high quality relationships are more likely to have positive psychological outcomes (Williams 2003; Frech and Williams 2007), fewer health complications (Hughes and Waite 2009), and greater economic stability and wealth (Wilmoth and Koso 2002; Lupton and Smith 2003; Grinstein-Weiss, Zhan, and Sherraden 2006). Additionally, the socioeconomic benefits of marriage include an increased likelihood of higher income, greater affluence, and less material hardship (White and Rogers 2000; Lerman 2002; Hirschl, Altobelli, and Rank 2003).

In recent years, public policy initiatives have focused on separately promoting homeownership and marriage as part of an effort to improve family well-being; however, little attention has been given to the relationship between the two. Specifically, the extent to which marriage affects the transition from renting to homeownership remains unclear among low- and moderate-income households. This is an important social policy question because low-income individuals are especially disadvantaged with regard to homeownership due to poor credit, unstable job histories, lack of capital for a down payment, and racial discrimination (Haurin, Herbert, and Rosenthal 2007).

Several government sponsored homeownership programs have been designed to help address some of these barriers through subsidies and mortgage loans and by promoting asset and savings accumulation that could be used for homeownership, education, and business development (Sherraden 1991). To help homeownership and asset building programs tailor their strategies to meet the needs of low-income households, and to understand the role marriage may play in transitioning to homeownership, this study examines the effect of marital status in the tenure change process. To address this topic, we use propensity score matching and survival analysis to answer the following question: To what extent does marital status influence whether and when low- and moderate-income individuals purchase a home?

This research makes two major contributions to the literature. First, the study employs an innovative and rigorous approach to answer the research question by using discrete-time survival analysis with propensity score matching. In addition, the study examines important covariates affecting the selection into marriage compared to remaining unmarried and controls for these covariates through a series of matched samples using several approaches. The application of propensity score matching improves on the conventional covariance control approach by reducing the bias caused by selection effects in observational studies (Guo and Fraser 2009).

The second contribution stems from the sample of low-income households used in the study, which is of particular interest to policy makers. Low-income households are the primary population targeted by social policies aimed at increasing rates of both marriage and homeownership. Poverty reduction strategies that encourage marriage (e.g., Healthy Marriage Initiative) and assets building strategies that support homeownership (e.g., Assets for Independence) continue to be major priorities in the current administration as part of an effort to strengthen and support society's most disadvantaged families. Consequently, this study has important implications for these homeownership and family formation policies.

Homeownership in a Policy Context

Despite the advantages associated with owning a home, homeownership remains unattainable for many individuals in society (Withers 1998), and government programs have tended to favor middle- and upper-income households over low-income households through the favorable tax treatment of homeownership (Olsen 2007). Significant housing inequalities exist between low-income and higher income groups because of barriers including lack of wealth, lower income, inadequate knowledge about the homeownership process, and higher levels of debt. To address this gap, policy makers over the last two decades have promoted homeownership as a way of increasing the assets of low-income and minority households (Scanlon 1998; Shlay 2006). In part, these programs helped drive the increase in the rate of homeownership among low-income individuals in the 1990s (Belsky and Duda 2002); however, criticism against expanding homeownership opportunities has become more pronounced in light of the dramatic increase in foreclosures during the recent housing crisis. Some researchers have argued that the high rate of foreclosures is due to sub-prime, high cost mortgages, which were marketed to low-income borrowers who did not qualify for traditional mortgages (Gaines et al., 2009). Anne Shlay (2006) argues, given the obstacles facing low-income individuals, homeownership as an asset investment is more risky and may have fewer benefits than for moderate-income homeowners.

Despite these criticisms, several subsidy and mortgage loan programs have proven successful in assisting disadvantaged families become homeowners. For example, the U.S. Department of Housing and Urban Development has increased low-income homeownership opportunities through its Home Investment Partnerships Program (HOME). Since 1992, over three billion dollars in HOME funds have been used to help 270,000 low-income households purchase homes in various communities around the country (Turnham et al., 2004). A second example is the Assets for Independence program, which provides funds to non-profit organizations and government agencies for asset-based programs to help families accumulate savings that can be used for homeownership, post-secondary education, and small business opportunities (U.S. Department of Health and Human Services 2007). A third example is the Community Advantage Program (CAP), a secondary home loan mortgage program for low- and moderate-income households. CAP provides households with homeownership opportunities by working with traditional lenders to secure 30-year, fixed-rate prime loans that would otherwise be considered too risky to offer. Over 28,000 families have purchased homes as a result of CAP, and the on-going evaluation of the program indicates that the purchasers have accumulated significant equity (Riley, Freeman, and Quercia 2009).

Marriage in a Policy Context

Given the potential benefits to marriage, social policy efforts stemming from the Personal Responsibility and Work Opportunity Reconciliation Act of 1996 focused on supporting low-income families through the promotion of marriage and responsible fatherhood programs (Ooms, Bouchet, and Parke 2004). The Temporary Assistance for Needy Families Reauthorization Bill, passed in February 2006, appropriated up to $750 million to support such programs. Since then, over two hundred Healthy Marriage Initiative contracts have been awarded to service providers and researchers in states around the country working to strengthen and sustain marriages and relationships. Examples of the activities allowed under these grants include public service campaigns, high school education with a focus on marriage values and relationships, marital and relationship skills programs, premarital services, and marriage enhancement classes (U.S. Department of Health and Human Services 2006).

The link between marriage, economic well-being, and self-sufficiency continues to be the focus of current public policy efforts at the federal level today. President Obama’s Department of Health and Human Services 2011 budget includes $500 million for a new Fatherhood, Marriage, and Families Innovation Fund geared to replace the current Healthy Marriage Initiative. The goal of the fund is to build an evidence base about the type of interventions that successfully improve family functioning, parenting capacity, and employment opportunities. These policy efforts exemplify the government’s role in promoting marriage and family stability in the public domain.

Conceptual Framework

There are two dominate perspectives often used to explain the role that marriage plays in the decision to purchase a home. Sociological theory suggests there are several attributes that may make homeownership more likely among married couples compared to their unmarried counterparts. First, married couples may feel less transitional than singles and therefore more willing to make lasting, long-term decisions. Additionally, married couples are more likely to be financially stable compared to singles and are less likely to anticipate moving again in the near future. As such, they tend to be more willing to commit to the idea of purchasing a home (Clark, Deurloo, and Dieleman 1994; Mulder and Wagner 2001). Second, there are expectations inextricably tied to married life that influence important decisions including how many children to have and whether to purchase a home (Lupton and Smith 2003). Generally, householders have strong preferences for homeownership but prefer to wait until they have achieved stability not only in income but in their family situation as well (Clark, Deurloo, and Dieleman 1994). This stability often comes in the form of marriage, which in turn, is linked to higher levels of commitment (Smits and Mulder 2008). Additionally, households with more highly committed members are more likely to seek appropriate housing in anticipation of future events such as having children (Feijten and Mulder 2002). Third, people often change from renting to homeownership after experiencing a significant life transition (Clark, Deurloo, and Dieleman 1994; Deurloo, Clark, Dieleman, 1994). It is expected that a life event such as marriage could have this type of triggering effect.

From an economic perspective, there are financial reasons why married couples may be more apt to buy a home than single people. First, married couples have greater financial capability – higher assets and income – that can increase the probability of purchasing a home

(Plaut, 1987; Linneman and Wachter 1989; Hendershott et al., 2009). Second, married couples are able to save more and have higher levels of net worth because of labor market specialization and economies of scale from sharing expenses and purchasing goods and services in efficient sizes (Grinstein-Weiss et al., 2006). Third, married men generally earn more than unmarried men. Fourth, marriage can be associated with increased social capital resulting in opportunities that lead to saving. Finally, married couples commonly have access to benefits, like health and life insurance, that promote savings and therefore homeownership opportunities (Lupton and Smith 2003; Grinstein-Weiss et al., 2006).

The literature on the transition from renting to homeownership suggests that marriage, in addition to income, education, race, number of children, and age, is associated with the move from renting to owning (Mulder and Wagner 1998; Andrew, Haurin, and Munasib 2006). Few studies, however, have examined the effect of marriage on the transition to homeownership using data from low-income populations, leaving us uncertain about the relationship between low-income households and homeownership. Furthermore, some researchers suggest that marriage in low-income groups manifests itself differently than it does in higher income groups possibly suggesting that its influence on the decision to buy a home may operate differently in these two groups. Kathryn Edin and Maria Kefalas (2005) discovered that marriage in low-income communities has different standards and is viewed as an *end* goal – something that comes *after* obtaining a home, finishing school, finding a job, and having children. If this is true, homeownership among the unmarried low-income group in this study might be less likely to occur given the reduced likelihood of life events that having taken place given their socioeconomic status.

Taken together, the literature on marital status and homeownership is fragmented. No single study that we could find explicitly examined the effect of marriage on tenure change with a low-income U.S.-based sample using a rigorous analytical approach. The purpose of this research is to address this gap and to improve our understanding of how policies should be targeted to meet the needs of low- and moderate-income renters seeking homeownership. We hypothesize that married couples will be more likely to transition from renting to homeownership and will do so at faster rates than their unmarried counterparts.

Method

Data

This study uses data collected for the Community Advantage Program (CAP). CAP began as a secondary mortgage market program developed to underwrite 30-year fixed-rate mortgages for families who might have otherwise received a sub-prime mortgage or been unable to purchase a home. In order to qualify for the program, participants had to meet one of the following criteria: 1) earn an annual income of no more than 80% of the area median income (AMI); 2) be a minority with an income not in excess of 115% of AMI; 3) purchase a home in a high-minority (>30%) or low-income (<80% of AMI) census tract; and 4) earn an income not in excess of 115% of AMI. By the end of 2004, 28,573 families had purchased homes through CAP.

In 2004, the Community Advantage Panel Study (CAPS) was initiated to determine what impact homeownership had on the lives of CAP participants. In order to facilitate this analysis, a random sample of CAP borrowers was selected to participate in annual surveys. Once the sample of homeowners was recruited, a comparison group of renters was matched to the homeowners based on neighborhood and income. This matching was limited to the 30 metropolitan areas in the United States with the highest number of CAP owners. The renter sample was obtained by randomly selecting respondents who lived within the same census blocks[1] as already-enrolled homeowners based on public telephone directory lists. Like the CAP homeowners, the renters had to meet income or racial criteria. Respondents had to be between 18 and 65 years old, pay rent to the owner of their residence, and have an annual income of less than 80% AMI or 115% AMI in a predominantly-minority neighborhood. The final year-one sample was comprised of 3,743 homeowners and 1,530 renters. Since this study is examining the transition in to homeownership, we include only the 1,530 renters in our analysis.

This analysis used five waves of data from the CAPS renter panel collected annually from 2004 to 2008. As with any longitudinal survey, CAPS experienced sample attrition. As of 2008, the CAPS renter panel consisted of 923 (60%) of the original 1,530 respondents. Of those 923 cases, 642 had complete data on marital status and important predictors of homeownership such as income, race, and age. Applying the multiple imputation approach (Schafer 1997; Little and Rubin 2002), this study imputed missing data for the 281 subjects who had values on one or more independent and matching variables. The final analytic sample size used for propensity scoring and discrete-time analyses was 923. Using the five multiple imputed files, the study achieves a relative efficiency of 90%.

Measures

The key outcome measure in this study is time to home purchase. Because each respondent began the study as a renter, we measured our outcome variable in discrete units (1-4) as the number of data waves that elapsed before a respondent purchased a home.

The key independent variable of this study is marital status. In CAP, marital status was recorded with six categories: "*Living with a partner, Married, Widowed, Divorced, Separated, or*

[1] When eligible renters could not be found within the census block, the radius was expanded up to four miles.

Never married." Respondents who indicated they were separated were excluded from the analysis because it was not clear whether to classify them as married or not. The remaining respondents were classified as either married or not married. Not married respondents included those who were divorced, widowed, cohabiting, or never married. We chose to include cohabiting respondents in the unmarried group because previous research has shown that cohabitors do not typically pool sources of income, are unable to accumulate levels of wealth similar to that of married couples, and few have legally binding agreements about their joint economic resources (Wilmoth and Koso 2002). As such, they would more likely behave as other unmarried respondents with regard to homeownership decisions.

All models include socio-demographic control variables. Characteristics used in propensity score matching are measured at year one of CAP participation. Respondents self-reported gender (1 = *female*, 0 = *male*) and race. Race was measured using four categories that simultaneously captured race/ethnicity and entered models as indicator variables for African American, Hispanic, and Other. Caucasian was the reference category. Age at baseline was measured in years and recorded as an integer. CAP collected data on education by level of education completed. This variable is treated as an ordinal variable in the analysis because small cell counts for some tiers made indicator variables problematic in models. Education level answers ranged from (1) "*11th grade or less*" to (8) "*graduate degree.*" Four respondents who indicated their education was "non-traditional" were recoded to missing. Number of children in the household was constructed using the respondent reported household roster, which included a count of all child household members aged 0 to 17 years. Employment was recoded into an indicator variable (1 = *employed*, 0 = *non-employed*) from four response categories: employed, unemployed, out of labor force, retired. Income was measured in thousands of nominal dollars.

The analysis controlled for characteristics of the respondent's Census tract at baseline including median tract house value, median tract rent, and tract disadvantage score. The tract neighborhood disadvantage score was constructed from several other tract level items in the 2000 Census: percent unemployed, percent in poverty, percent on public assistance, and percent single-headed households with children (Sampson, Raudenbush, and Earls 1997). A well-established relationship exists between neighborhood characteristics and an individual's decision to purchase a home. We included tract-level characteristics to enable isolation of the effect of marriage on homeownership from the effect of neighborhood context. Although most of the variables discussed above are fixed characteristics, income and employment change over time. For the logistic models used to create the propensity scores, we measured all characteristics at baseline. For the subsequent survival analysis, we used time-varying measures of employment, number of children, and income.

The data were imputed using multiple imputation through chained equations (Rubin 1987; van Buuren, Boshuizen, and Knook 1999; Royston 2005). Imputation helps to reduce bias caused by item-nonresponse to survey questions (Raghunathan 2004). Using multiple imputation rather than single imputation allows researchers to include variability from the imputation in the analyses. The imputation model included all variables in the analytic model. Imputed values of the dependent variable were deleted after imputation (von Hippel 2007). Given the fraction of missing data, five imputed data sets were created.

Analysis

The research hypothesis central to this study aimed to test a potentially causal relationship: Does marital status have a net and strong correlation with transition into homeownership after important covariates available to the study are taken into consideration? In the past 30 years, researchers have recognized the need to develop more efficient approaches for assessing treatment effects from studies based on observational data. This growing interest in seeking consistent and efficient estimators of causal effects led to a surge in work focused on estimating average treatment effects under various sets of assumptions (e.g., Heckman 1978, 1979; Rosenbaum and Rubin 1983).

Researchers have found that the conventional covariance control approach has numerous flaws and should be replaced by more rigorous methods to draw causal inference. For instance, Michael Sobel (1996) criticized the common practice in sociology that uses a dummy variable (i.e., treatment versus nontreatment) to evaluate the treatment effect in a regression model (or a regression-type model) using survey data. In this paper, we use the term “treatment” and “nontreatment/control” in a broad sense; that is, they are used under the setting of observational studies and refer to conditions associated with the central “cause” being studied. More specifically, treatment in this study denotes being married, and nontreatment or control denotes not being married. The primary problems of covariance control approach discussed in the literature may be summarized as follows: 1) the dummy treatment variable is specified by these models as exogenous, but it is not; determinants of incidental truncation or sample selection should be explicitly modeled first, and selection effects should be taken into consideration when estimating causal impacts on outcomes (Heckman 1978, 1979); 2) the strongly ignorable treatment assignment assumption (i.e., conditional upon covariates, the treatment assignment is independent from outcomes under both treatment and control conditions) is prone to violation in observational studies; under such condition, the presence of the endogeneity problem leads to a biased and inconsistent estimation of the regression coefficient (Rosenbaum and Rubin 1983;

Berk 2004; Imbens 2004); and 3) covariance control does not automatically correct for nonignorable treatment assignment (Guo and Fraser 2009).

To draw valid causal inference, this study applies the Neyman-Rubin counterfactual framework (Neyman 1923/1990; Rubin 1974, 1990, 2006; Morgan and Winship 2007) as a conceptual model to guide the data analysis. Under this setting, a counterfactual is a potential outcome or would have happened in the absence of the cause (Shadish, Cook, and Campbell 2002); and a *counterfactual framework* emphasizes that individuals selected into either the treatment or the nontreatment group have potential outcomes in both states. For example, the setting in which they are observed and the one in which they are not observed. The Neyman-Rubin framework offers a practical way to evaluate counterfactuals. Working with data from a sample that represents the population of interest, the standard estimator for the average treatment effect is seen as the difference between two estimated medians from the sample data as:

$$\hat{\tau} = Median\ (\hat{T}_1 \mid w = 1) - Median\ (\hat{T}_0 \mid w = 0),$$

where $\hat{T}_1$ is the survival time under the treated condition; $\hat{T}_0$ is the survival time under the control condition; and w is binary variable indicating treatment receipt (i.e., w = 1, treatment; and w = 0, control).

Specifically, this study used the following methods to balance data to examine net association and to draw a valid inference concerning causality: (a) a discrete-time survival analysis applied to the original sample without matching; (b) a propensity score greedy matching (i.e., the nearest neighbor within caliper matching) followed by a discrete-time survival analysis; (c) a propensity score optimal pair matching that uses the generalized boosted modeling (GBM) to estimate the propensity score and a follow-up discrete-time survival analysis; (d) a propensity score optimal full matching that uses GBM to estimate the propensity score and a follow-up

Hodges-Lehmann aligned rank test; and (e) all analyses were conducted on five files that multiply imputed missing data of independent and matching variables; results from these datasets were then aggregated using either the Rubin's rule or procedures developed for multivariate models (Schafer 1997; Allison 2002; Little and Rubin 2002; Graham 2009). Since several approaches employed by this study are relatively new, and have not been seen in social welfare research, we provide a detailed description of the analytic methods in the appendix.

Findings

After missing data imputation, the analytic sample contained 923 participants. Of those, 224 (24.3%) participants were married; that is, they were either married at baseline or married during the four-year study period. The remaining 699 (75.7%) participants were not married at any point during the study period.

<See Table 1>

Table 1 presents sample descriptive statistics and imbalance checks before and after matching. As it shows, the overall sample before matching is not balanced on various covariates. For example, the table shows that the original sample contains more married males than married females, and the difference is statistically significant ($p < .001$). Other significant covariates predicting differences on marital status include race, age, education, number of children, employment status, income, and participant's census tract disadvantage score. Table 1 also shows statistically significant results of chi-square tests for categorical covariates and an independent sample *t* test for continuous covariates. Had these differences in marital status not been taken into consideration in causal inference about marital status on the transition to homeownership, the findings would be biased.

The sample sizes after greedy matching and optimal matching are also presented in Table 1. Greedy matching paired 215 married participants with 215 unmarried participants. After optimal pair matching, the matched sample contained 224 married participants and 224 paired or matched unmarried participants. Note that the optimal pair matching employed all married participants and did not lose any married subjects. Optimal full matching retained all 224 married and 699 unmarried participants and grouped these participants in matched strata. The ratio of treated (married) participants to control (unmarried) participants varied by stratum, but the married participants within each stratum shared a propensity score similar to that of the unmarried participants within the stratum. Note that the optimal full matching employed all subjects from the original sample.

As indicated in Table 1, both greedy matching and optimal matching improved sample balances. After greedy matching, none of the 10 covariates showed significant differences. Before optimal matching, the absolute standardized difference in covariate means before optimal matching (i.e., d_X) generally has a higher value than the index after optimal matching (i.e., d_{Xm}). Taking gender as an example, before optimal matching, d_X of gender was 0.299, meaning that the treated and control groups were 29.9% of a standard deviation apart on gender. After optimal pair matching, d_{Xm} of the same covariate is 0.125, meaning that the difference between the two groups is 12.5% of a standard deviation for gender. After optimal full matching, d_{Xm} of gender is 0.164, meaning that the difference between the two groups is 16.4% of a standard deviation for gender. The value of most covariates decreases from d_X to d_{Xm}, suggesting that optimal matching indeed improves balances. The worst-case scenario for the optimal pair matching occurs for the covariate “Census tract median house value” where d_X equals .044 and d_{Xm} equals .110 (i.e., matching creates more imbalance). The worst-case scenario for the optimal full matching occurs for the same covariate where d_{Xm} equals .103. Given that these imbalances can be considered small (i.e., the two groups differ on the covariate by only about 10% of a standard deviation), we concluded that matching improved sample balances and all matched samples were acceptable.

When conducting propensity score matching, it is important to take into account whether the treatment (married) and control (unmarried) groups have a similar distribution on propensity scores. Similarity in these is an important aspect of matching because the two groups must have sufficient overlap in their propensity scores in order to match cases and create a matched sample. Figure 1 shows the distribution of propensity scores we estimated using binary logistic regression. The two groups had a sizable common support region; as a result of this similarity, the greedy matching procedure produced only a small reduction in the matched sample. Figure 2 shows the box-plots and histograms of the estimated propensity scores derived using generalized boosted modeling. As the figure indicates, the two groups differed on the distribution of estimated propensity scores, sharing a very narrow common-support region. This narrow region of common-support is especially problematic; if we applied nearest-neighbor matching within caliper or other types of greedy matching, the narrow common-support region would produce a great loss of matched participants. This is not a problem when using optimal matching, however; both pair matching and full matching created matches for all 224 married participants. Further, the reduction of the sample size occurred only with the number of unmarried participants in the pair matching where, by design, each participant matches only one control.

<See Figure 1 and Figure 2 >

Table 2 presents results of the survival analysis. For this study, all four models estimating differences in timing of house purchase between married and unmarried people show consistent findings. The estimated odds ratio of purchasing a home for the original unmatched sample is

2.948 ($p < .001$), indicating the odds of homeownership for married participants was 194.8% higher than the odds of homeownership for unmarried participants [i.e. (2.948-1)*100=194.8%]. Similarly, the odds ratio of house purchase for the matched sample created by greedy matching was 2.711 (171.1% higher; $p < .001$). Matching is 2.579 (157.9% higher; $p < .001$) for the matched sample created by the optimal pair; both findings indicate that married participants purchased houses during the study period at a faster speed than the unmarried participants.

<See Table 2 >

Using the optimal full matched sample, we found the length of time married participants took to purchase a house was 0.373 year shorter (approximately 4.48 months shorter) than the unmarried participants. The Hodges-Lehmann aligned rank test showed that this was a statistically significant difference ($p < .001$).

Other significant predictors of timing of house purchase included participant's age at baseline ($p < .05$ for the overall sample), educational attainment, ($p < .05$ for the overall and matched samples), and income ($p < .001$ for the overall and matched samples). In general, participants who were younger and attained higher levels of education and higher income than their study counterparts were also more likely to purchase houses at a faster time-to-event rate.

In summary, this study confirms the research hypothesis and shows a positive impact of marriage on homeownership. This conclusion is valid given that the models include important covariates affecting the selection between getting married and not getting married. We control for these covariates through a series of matched samples using various propensity score analytic approaches.

Discussion

Using five years of data from the Community Advantage Panel Study, this study addressed the question of whether marital status causes more frequent and faster transitions into homeownership. Our findings indicate that even after using propensity score matching to control for selection bias between married and unmarried groups, low- to moderate-income married couples have higher odds of buying a home and purchase homes at faster rates than their nonmarried counterparts.

Our findings support the theoretical framework of this research. Economic and sociological perspectives suggest that married individuals are more apt to purchase a home because of fewer borrowing constraints (Linneman and Wachter 1989) and attributes that they may have which differ from single householders (Lupton and Smith 2003) that make owning more likely. Further, unmarried households are less likely to buy a home because of the transitory nature of their lives and the reduced need for large living quarters (Hendershott et al., 2009).

Part of the reason married couples are more likely than single people to buy homes is that they have more potential wage-earners within the home; however, we argue that there are other factors at work as well. First, we contend that our results reflect the strong normative pressures exerted on individuals within our society to time life course events in specific patterns. There is an expectation that marriage precedes home purchase in the sequence of life stages (Townsend 2002). Individuals respond to this social pressure by shaping their expectations, their aspirations, and ultimately, their behavior.

Second, institutional and environmental factors condition the ability of unmarried people to purchase homes relative to that of married couples. For example, unmarried individuals may have more difficulty receiving mortgage loans or may receive less attractive loan terms because mainline banking institutions are more likely to perceive unmarried persons as less responsible and less credit-worthy than their married peers. Similarly influenced by social norms, real estate agents may be less likely to show desirable properties to unmarried clients, and instead interact with them in ways that discourage home purchase. Finally, given that homeowners are usually married, the housing stocks may be more closely aligned with the tastes and needs of married couples, thus leaving a portion of unmarried individuals unable to find a suitable property. Any of these scenarios reduce the likelihood of homeownership for unmarried persons relative to married persons beyond the measured individual characteristics.

It is equally important to consider what aspects of the marital relationship drive our findings. Few would suggest that the legal proceedings defining marriage make a couple more likely to buy a home. Instead, we suggest that the changing social status and life course position of the relationship alter the social norms faced by the couple and their expectations of life in the future. In addition, common attributes of marriage, such as stability and commitment, may be the crucial determinate that explains our results rather than the marriage ritual itself.

A limitation to our study is worth acknowledging. Propensity score matching fails to correct for selection bias due to unmeasured variables. Unlike randomized clinical trials that balance data on both measured and unmeasured variables, propensity score matching cannot correct for hidden selection bias (Guo and Fraser 2009). Thus, if there are important variables predicting marriage omitted in our matching process, our study findings are prone to errors. The fact that our findings are consistent across all matched and unmatched samples is not uncommon in observational studies where the cause has a strong impact on effect. Although it is likely that the matched studies may have missed important covariates affecting sample selection, therefore, the findings from the matched studies are still prone to bias (precisely, prone to hidden selection bias), the results of the impact of marital status on transition into homeownership for this low-income sample are revealing.

Because of the limitation of propensity score analysis that fails to balance study conditions that are due to unmeasured variables, we cannot claim causality between marriage and the transition into homeownership. The analytic methods this study employed, however, are carefully chosen to overcome limitations of the conventional covariance control approach (particularly, its violation of the ignorable treatment assignment assumption), and therefore, permit the study to draw the conclusion about a net association between the study variables on a more solid and rigorous ground.

Our study makes three substantial, unique contributions to the field. First, it offers one of the first attempts to address self-selection into marriage using propensity score analysis. Most studies on the impact of marriage fall short because they not only fail to model the choice individuals make to be married but also fail to model how that choice affects the outcome of interest. Instead of the conventional covariance control approach, which cannot adjust for selection bias, we used an innovative and rigorous method that allows us to draw causal inference between marital status and the transition to homeownership. The second major contribution of this study is our focus on a low- and moderate-income population. This population is of great interest to policy makers and has been the core recipient of social policies aimed at increasing and sustaining both marriages and homeownership; however, no study to date has examined the relationship between marriage and homeownership among lower-income households.

Third, our findings have important implications for asset-building policy and marriage promotion initiatives. While the past decade has witnessed an increasing number of calls to promote marriage as a poverty reduction strategy among the poor, critics have countered that the benefits of marriage have been oversold, and marriage promotion has not translated to reductions in poverty (Solot and Miller 2007). Further, women's increasing economic independence and access to employment opportunities have been cited as evidence that promoting marriage is an outdated approach to asset building (Seefeldt and Smock 2004).

Although this study focused specifically on homeownership rather than asset-building in general, we nonetheless conclude that one benefit of marriage is its function as a catalyst to homeownership for lower-income families. Previous studies have provided strong evidence that responsible homeownership can yield meaningful wealth returns, even for low-income families, when purchased as a long-term investment (Riley, Freeman, and Quercia 2009). Given the social and economic gains that may be gleaned from marriage, and in turn from homeownership, policy makers may want to formulate well-coordinated policies aimed at concurrently increasing marriage and homeownership opportunities. Such policies could be of significant benefit to disadvantaged families who struggle to achieve economic and familial stability.

Appendix A:
Discrete-Time Survival Analysis in Conjunction with Propensity Score Matching

The Discrete-Time Survival Model. The outcome variable in this study (i.e., timing to house purchase) is a time-to-event variable that involved data censoring. That is, within the four-year study period, we knew the window of time of homeownership for only a portion of the study participants, and the remainder of the event times was known only to exceed (or to be less than) the maximum four years. Specifically, our study data were interval censored (Hosmer and Lemeshow 1999), because study participants were contacted every 12 months, and time was accurately measured only in multiples of 12 months. To analyze this type of censored data, we used the discrete-time survival model (Allison 1982), rather than the popular Cox proportional hazards model that assumes a continuous event time. In accordance with the censoring pattern embedded in the data collection, we used one year as a discrete time unit. The probability of house purchasing based on the person-time data is a proxy of hazard rate of house purchasing.

In this study, participant's employment status, number of children, and income were analyzed as time-varying covariates. In addition, the discrete-time model specifies the following time-fixed covariates: age at baseline; gender; dummy variables measuring race (i.e., the dummy variable "African American" and the dummy variable "Hispanic and Others"), with Caucasian used as a reference; education; median house value of the participant's neighborhood at baseline; median rent value of the participant's neighborhood at baseline; the disadvantage score of the participant's neighborhood at baseline; and the key variable to test the research hypothesis, which was the binary marital status. In this study, all neighborhood variables refer to the Census tract where a study participant was living at baseline.

The discrete-time survival model is the key analytic approach for studying the outcome difference between married and unmarried people. This model is applied to the original unmatched sample as well as to matched samples designed to correct for selection bias. When applied to the original sample, the method is the survival model using traditional covariance control. When applied to matched samples, the effect of marital status on timing of house purchasing more accurately represents the causal impact of interest.

The optimal pair matching strategy used in this study creates multiple pairs or strata, and each pair/stratum contains one married and one non-married participant. Therefore, study participants in the matched sample are also nested within matched pairs. This study follows John Kalbfleisch and Ross Prentice (2002) to control for "*pairwise dependency*" (or within-pair correlated survival times) and employs the Huber-White method to estimate robust standard errors for the logistic regression model. The participant's pair membership is specified as a cluster variable.

Propensity Score Greedy Matching

To create valid counterfactuals for treated participants, this study used the propensity score greedy matching technique (Rosenbaum and Rubin 1983, 1985), which involved the following steps.

First, it uses the binary logistic regression to estimate propensity score of receiving treatment (i.e., being married). By definition, a propensity score is a conditional probability of a participant receiving treatment given observed covariates. More precisely, the propensity score is a balancing score representing a vector of covariates or the so-called "conditioning variables." The advantage of the propensity score matching is its reduction of dimensions: the conditioning variables the study aims to match may include many covariates. The propensity score approach reduces all this dimensionality to a one-dimensional score. In doing so, it eases the burden of finding matches within the study sample. Following Paul Rosenbaum and Donald Rubin (1985), this study employs the logit of the predicted probability from the logistic regression as a propensity score

$$(\text{i.e., } \hat{q}(x) = \log[(1-\hat{e}(x))/\hat{e}(x)]$$

where $\hat{e}(x)$ is the predicted probability from the logistic regression) because the distribution of $\hat{q}(x)$ approximates to normal. The logistic regression employs the same set of independent variables as those used in the discrete-time model, except the three time-varying variables (i.e., participant's employment status, number of children, and income) are specified as time-fixed variables and measured at the time point of baseline.

Second, it matches the treated participants to controls on the estimated propensity scores to make the estimate of counterfactuals (i.e., outcome values of the comparison group) more valid. This study employs the nearest neighbor within a caliper matching (Rosenbaum and Rubin 1985). The method selects a control participant *j* as a match for treated participant *i*, if and only if the absolute distance of propensity scores between the two participants (i.e., the difference between propensity scores P_i and P_j) meets the following condition:

$$\| P_i - P_j \| < \varepsilon,$$

where ε is a prespecified tolerance for matching or a caliper. Rosenbaum and Rubin (1985) suggest using a caliper size of a quarter of a standard deviation of the sample estimated propensity scores (i.e., $\varepsilon \leq .25\sigma_P$, where σ_P denotes standard deviation of the estimated propensity scores of the sample).

Finally, based on the matched sample, the study conducts the discrete-time model to study outcome difference between treated and control participants. As depicted earlier, this analysis is expected to provide a more valid estimate of causal effect because it utilizes a sophisticated control of selection bias.

Propensity Score Optimal Matching

As discussed by Shenyang Guo and Mark Fraser (2009), a greedy matching method has several limitations. In dividing matching into a series of discreet decisions, it fails to account for the effect of a given match on the overall efficiency of matching; it can sometimes produce too many unmatched cases or too many inexactly matched cases; and finally, it requires a sizable common supported region to work efficiently. To overcome these limitations, this study applies the optimal matching method (Rosenbaum 2002).

The optimal matching method uses the network flow theory to optimize the creation of matched sample. A primary feature of network flow is that it concerns the cost of using b for a as a match, where a *cost* is defined as the effect of having the pair of (a, b) on the total distance of propensity scores.

Initially, we have two sets of participants: the treated participants are in set A and the controls are in set B, with $A \cap B = \varnothing$. The initial number of treated participants is $|A|$ and the number of controls is $|B|$, where $| . |$ denotes the number of elements of a set.

For each $a \in A$ and each $b \in B$, there is a distance, δ_{ab} with $0 \leq \delta_{ab} \leq \infty$. The distance measures the difference between a and b in terms of their observed covariates such as their difference on propensity scores. Matching is a process to develop S strata ($A_1, ...A_s; B_1, ...B_s$) consisting of S nonempty, disjoint participants of A and S nonempty, disjoint subsets of B, so that $|A_s| \geq 1$, $|B_s| \geq 1$, $A_s \cap A_{s'} = \varnothing$ for $s \neq s'$, $B_s \cap B_{s'} = \varnothing$ for $s \neq s'$, $A_1 \cup \ldots \cup A_S \subseteq A$, and $B_1 \cup \ldots \cup B_S \subseteq B$.

By this definition, a matching process produces S matched sets, each of which contains $|A_1|$ and $|B_1|$, $|A_2|$ and $|B_2|$, ...and $|A_S|$ and $|B_S|$. Notice, by definition, within a stratum or matched set, treated participants are similar to controls in terms of propensity scores. Depending on the structure (i.e., the ratio of number of treated participants to control participants within each stratum) the analyst imposes on matching, we may classify matching into the following three types: pair matching, matching using a variable ratio, and full matching. Optimal matching is the process of developing matched sets ($A_1, \ldots A_s; B_1, \ldots B_s$) with size of ($\alpha$,$\beta$) in such a way that the total sample distance of propensity scores is minimized. Formally, optimal matching minimizes the total distance Δ defined as

$$\Delta = \sum_{s=1}^{S} \omega(|A_s|,|B_s|)\delta(A_s, B_s),$$

where $\omega(|A_s|,|B_s|)$ is a weight function.

Using the R program *optmatch* (Hansen 2007) and following the guidelines suggested by Rosenbaum (2002), this study employs optimal pair matching and optimal full matching. Using the matched sample created by optimal pair matching, we conducted the discrete-time survival analysis as previously described. Next, using the matched sample created by optimal full matching, we conducted the Hodges-Lehmann aligned rank test, which is described later in this article.

Generalized Boosted Modeling

Our analyses also used generalized boosted regression (GBM) to estimate the propensity scores (McCaffrey, Ridgeway, and Morral 2004) created using a program developed by Matthias Schonlau (2007) for the optimal matching. One of the problems with the binary logistic regression is specifying an unknown functional form for each predictor. If specifying functional forms can be avoided, the search of a best model involves fewer subjective decisions, and therefore, may lead to a more accurate prediction of treatment probability.

GBM is a general, automated, data-adaptive algorithm that fits several models by way of a regression tree and then merges the predictions produced by each model. As such, GBM can be used with a large number of pretreatment covariates to fit a nonlinear surface and predict treatment assignment. GBM is one of the latest prediction methods that has been rapidly adopted by the machine learning community as well as mainstream statistics research (Guo and Fraser 2009). From a statistical perspective, the breakthrough in applying boosting to logistic regression and exponential family models was made by Jerome Friedman, Trevor Hastie, and Robert Tibshirani (2000).

Checking Covariate Imbalance

An important task for propensity score matching is to check covariate imbalance before and after matching. The analyst hopes that after matching, most study covariates are balanced between treated and control groups. This study employs chi-square test and independent sample *t* test to check covariate imbalance before and after greedy matching and the imbalance indexes developed by Amelia Haviland, Daniel Nagin, and Paul Rosenbaum (2007) to check covariate imbalance before and after optimal matching. The study employs a Stata ado program *imbalance* developed by Guo (2008*a*) to conduct this analysis. d_X and d_{Xm} are the two statistics generated by the imbalance check and can be interpreted as the difference between treated and control groups on X in terms of standard-deviation unit of X. d_X indicates imbalance on X before matching, and d_{Xm} indicates imbalance on X after matching. Typically, the analyst expects to have $d_X > d_{Xm}$, because she or he expects the need to correct for imbalance before matching, and the sample balance improves after matching.

The Hodges-Lehmann Aligned Rank Test

The outcome analysis following optimal full matching is complicated because the survival model analyzing event times for a matched sample needs to consider correlated survival times within matched stratum. Ideally, the analyst might use a frailty model that included random effects to represent extra heterogeneity of the unit that gives rise to the dependence of event times (Hougaard 2000; Kalbfleisch and Prentice 2002). Although a frailty model is fruitful in matched studies with a randomized experiment, that approach has not yet been developed for observational studies such as the current study. Thus, we used the Hodges-Lehmann aligned rank test (Hodges and Lehmann 1962) to evaluate outcome differences between treated and control participants for the sample generated by the optimal full matching.

The aim of the Hodges-Lehmann aligned rank test is to produce a crude estimate of the difference on the time-to-event data between study groups and to gauge whether that difference is statistically significant. The Hodges-Lehmann approach has three inherent limitations, however: (a) it treats the length of time-to-event as uncensored; (b) it analyzes mean difference rather than differences of other statistics that better account for skewed distribution of survival times; and (c) it is bivariate and fails to control for covariates of the survival times.

Using the Hodges-Lehmann method, we evaluated the sample average treatment effect by assessing a weighted average of the mean differences between treated and control participants of all matched sets, as:

$$\hat{\delta} = \sum_{i=1}^{b} \frac{n_i + m_i}{N} \left[\bar{T}_{0i} - \bar{T}_{1i} \right],$$

where i indexes the b matched strata, N the total number of sample participants, n_i the number of treated participants in the i^{th} stratum, and m_i the number of controls in the i^{th} stratum, and $\bar{T}_{0i}, \bar{T}_{1i}$ the mean survival times corresponding to the control and treated groups in the i^{th} stratum.

The Hodges-Lehmann aligned rank test (Hodges and Lehmann 1962; Lehmann 2006) further tests whether this average treatment effect differs to a statistically significant degree. The study employs a Stata ado program *hodgesl* developed by Guo (2008*b*) to conduct this analysis.

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Table 1. Sample Description and Imbalance Check before and after Matching

Covariate	% of Married People or Mean (*SD*) of the Covariate by Group[a]: Overall Sample before Matching (N = 923)	% of Married People or Mean (*SD*) of the Covariate by Group[a]: Sample after Greedy Matching (N = 430)	Absolute Standardized Difference in Covariate Means before Matching (d_x)	Absolute Standardized Difference in Covariate Means after Matching (d_{xm}): Sample after Optimal Pair Matching (N = 448)	Absolute Standardized Difference in Covariate Means after Matching (d_{xm}): Sample after Optimal Full Matching (N =923)
Number of married people	224	215		224	224
Number of non-married people	699	215		224	699
Number (%) of married people lost after matching		9(4.0%)		0(0%)	0(0%)
Gender			.299	.125	.164
Male	33.6%***	51.5%			
Female	20.9%***	47.6%			
Race					
Caucasian	25.7%**	49.1%			
African American	17.2%**	51.9%	.294[b]	.075[b]	.107[b]
Hispanic	34.1%**	50.0%	.243[b]	.057[b]	.045[b]
Other	33.3%**	50.0%			
Age at baseline			.428	.118	.113
Married people	36.25(11.5)***	36.40(11.43)			
Non-married people	41.55(13.19)**	36.23(11.68)			
Education at baseline (measured as an ordinal variable)			.202	.042	.027
Married people	3.44(2.07)**	3.43(2.05)			
Non-married people	3.05(1.86)**	3.46(2.02)			
Number of children at baseline			.254	.074	.035
Married people	.80(1.11)***	.76(1.09)			
Non-married people	.54(.94)***	.67(1.07)			
Employment status at baseline			.246	.052	.053
Working	27.7%**	48.2%			
Not working	18.6%**	54.7%			
Income at baseline (in $1,000)			.446	.126	.277
Married people	24.85(13.75)***	24.05(13.11)			
Non-married people	19.06(11.76)***	23.79(12.62)			
Census tract's median house value			.044	.110	.103
Married people	92521.9(37496.4)	92859.1(37937.1)			
Non-married people	90889.7(36912.4)	90471.2(36102.1)			
Census tract's median rent value			.142	.142	.131
Married people	482.76(129.38)	481.56(130.41)			
Non-married people	464.18(131.66)	478.07(122.49)			
Census tract's disadvantage score			.215	.101	.101
Married people	.09(.55)**	.09(.56)			
Non-married people	.22(.64)**	.11(.54)			

[a]Each entry is the percent of married people in the categorical covariate, or the mean [SD] of the continuous covariate by group;

***p < .001, **p < .01, *p < .05, chi-square test or independent-sample t test two-tailed.

[b]Race is recoded as two dummy variables (i.e., African American, Hispanic and Others) using Caucasian as a reference.

Figure 1(a). Histograms of Propensity Scores Estimated by Logistic Regression

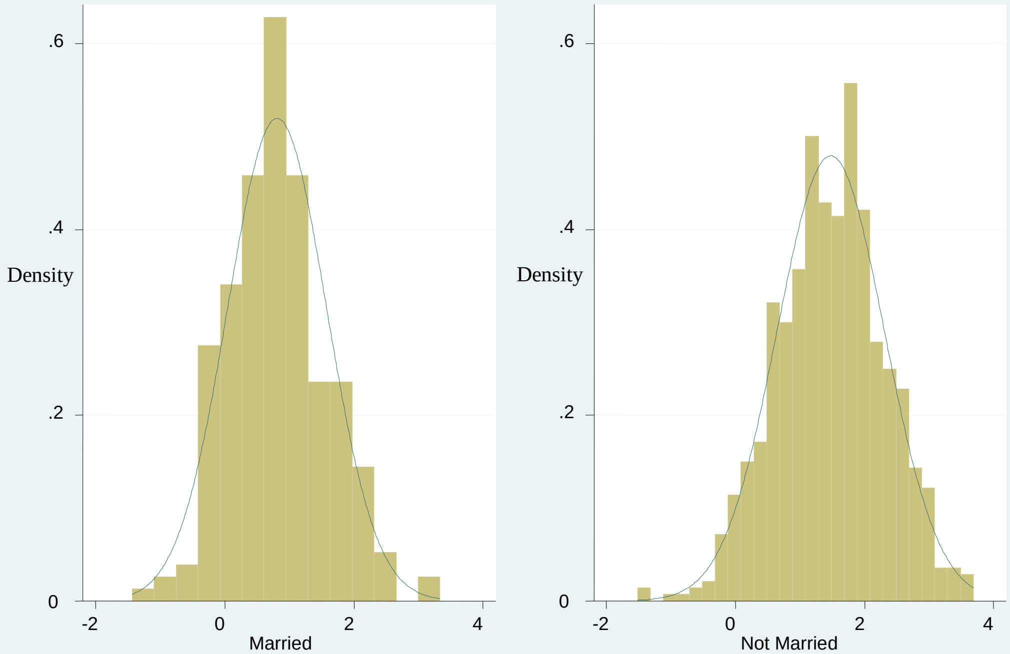

Figure 1(b). Boxplots of Propensity Scores Estimated by Logistic Regression.

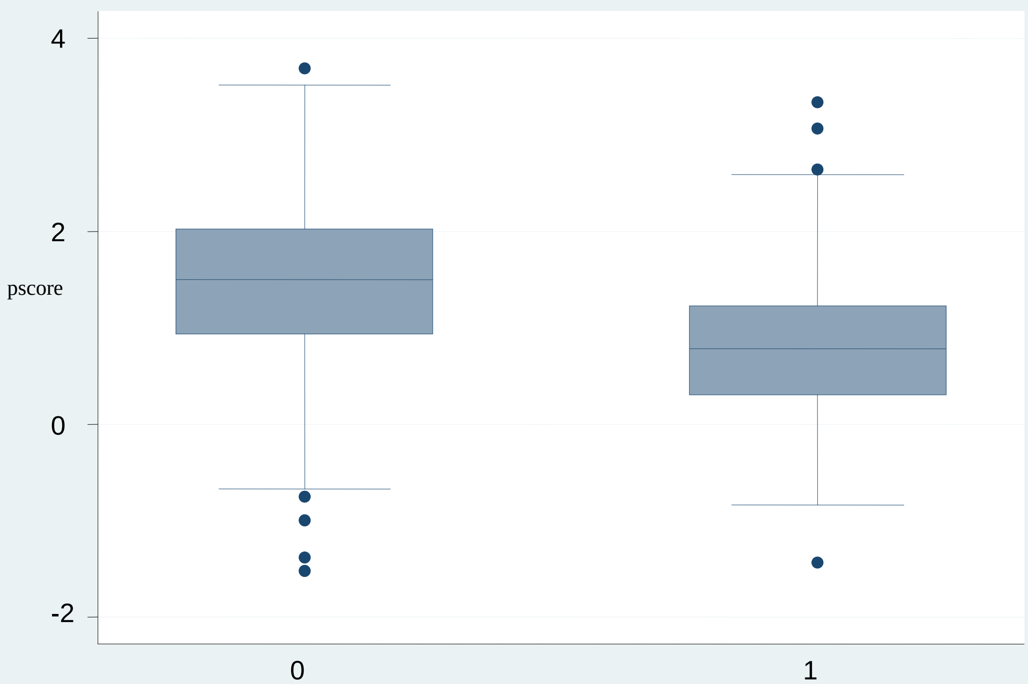

Figure 2(a). Histograms of Estimated Propensity Scores by GBM

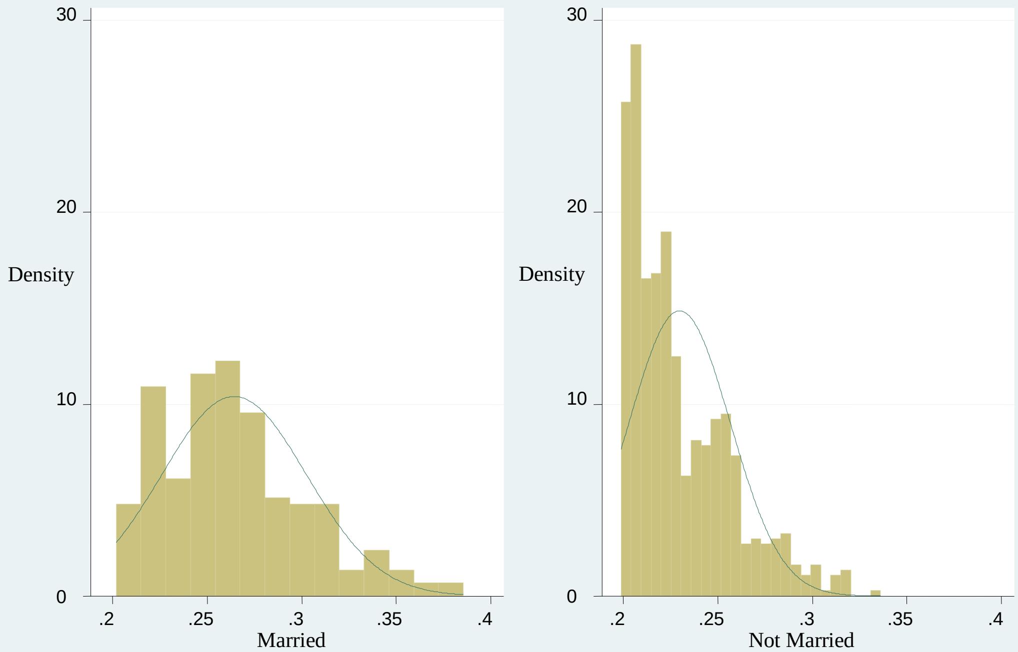

Figure 2(b). Boxplots of Estimated Propensity Scores by GBM

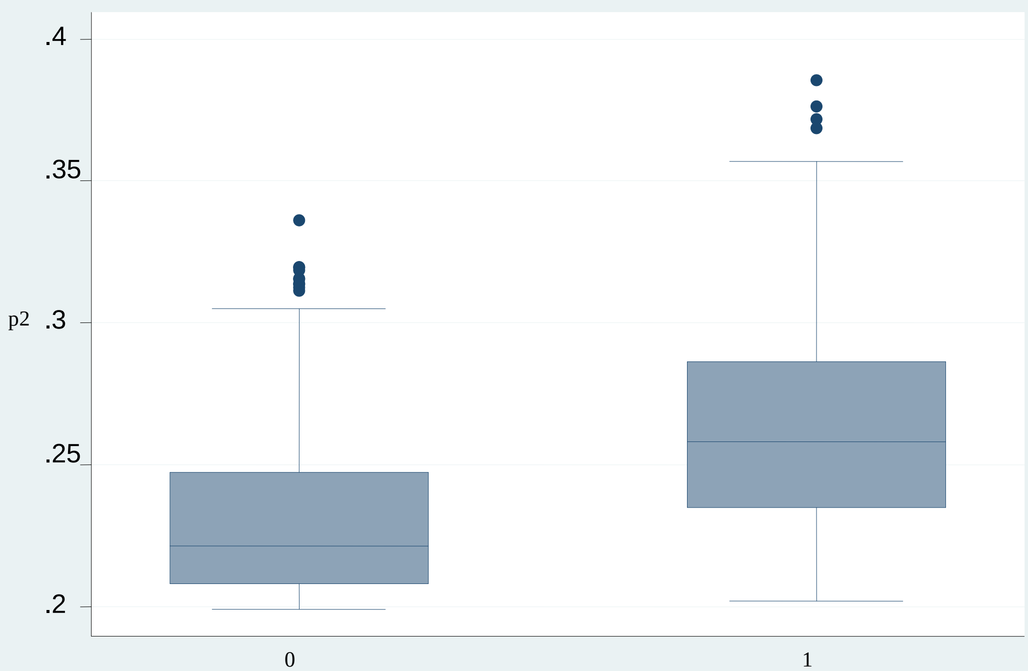

Table 2. Results of the Discrete-Time Models and the Hodges-Lehmann Aligned Rank Test

Covariate	**Estimated Odds Ratio from the Disrete-Time Model for the Overall Sample before Matching (*N* = 923)**	**Estimated Odds Ratio from the Discrete-Time Model for the Sample after Greedy Matching (*N* = 430)**	**Estimated Odds Ratio from the Discrete-Time Model for the Sample after Optimal Pair Matching (*N* = 448)**	**Mean Difference of Time-to-Event with the Hodges-Lehmann Aligned Rank Test for the Sample after Optimal Full Matching (*N* = 923)**
Marital status (Non-married)				
Married	2.948***	2.711***	2.579***	-.373 *[a]
Gender (Female)				
Male	.860	.806	.868	
Race (Caucasian)				
African American	.901	.879	.833	
Hispanic and Other	1.141	1.082	1.102	
Age at baseline	.983*	.986	.990	
Education at baseline (measured as an ordinal variable)	1.128**	1.128*	1.160**	
Number of children -- time-varying covariate	1.073	1.020	1.071	
Employment status -- time-varying covariate (Not working)				
Working	1.363	1.076	1.363	
Income (in $1,000) -- time-varying covariate	1.026***	1.026***	1.025***	
Year Indicator Variable (Year 4)				
Year 1	1.246	1.833*	1.360	
Year 2	1.758*	2.023*	1.741	
Year 3	1.010	1.276	1.077	

Note: Reference group is shown in the parenthesis for the categorical covariate.

****p* < .001, ***p* < .01, **p* < .05; two-tailed test.

a. One-tailed test based on hypothesized negative direction