Finance and Economics Discussion Series
Divisions of Research & Statistics and Monetary Affairs
Federal Reserve Board, Washington, D.C.

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2015-081

Please cite this paper as:
Dokko, Jane, Geng Li, and Jessica Hayes (2015). "Credit Scores and Committed Relationships," Finance and Economics Discussion Series 2015-081. Washington: Board of Governors of the Federal Reserve System, http://dx.doi.org/10.17016/FEDS.2015.081.

Credit Scores and Committed Relationships*

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August 2015

Abstract

This paper presents novel evidence on the role of credit scores in the dynamics of committed relationships. We document substantial positive assortative matching with respect to credit scores, even when controlling for other socioeconomic and demographic characteristics. As a result, individual-level differences in access to credit are largely preserved at the household level. Moreover, we find that the couples' average level of and the match quality in credit scores, measured at the time of relationship formation, are highly predictive of subsequent separations. This result arises, in part, because initial credit scores and match quality predict subsequent credit usage and financial distress, which in turn are correlated with relationship dissolution. Credit scores and match quality appear predictive of subsequent separations even beyond these credit channels, suggesting that credit scores reveal an individual's relationship skill and level of commitment. We present ancillary evidence supporting the interpretation of this skill as trustworthiness.

Keywords: Credit scores, Committed relationships, Assortative matching, Household finance, Trustworthiness

JEL codes: D14, G21, J12

*We thank Meta Brown, Dan Hartley, Julie Hotchkiss, Julio Rotemberg, our colleagues at the Federal Reserve Board, and participants at numerous seminars and conferences for their helpful comments, and Waldo Ojeda for excellent research assistance. The views presented in this paper are those of the authors and are not necessarily those of the Brookings Institution, the Federal Reserve Board, or its staff.

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1 Introduction

With the rapid expansion in the availability and use of household credit over the past three decades, credit scores have become more ubiquitous in households' financial and non-financial decisions and opportunities. For example, credit scores are a feature of all mortgage and consumer lending and thus affect households' access to credit, the pricing of credit, and their ability to smooth consumption over the lifecycle or against income fluctuations. Credit scores also frequently extend to other areas besides debt underwriting, such as auto insurance contracts, cell phone plans, and rental housing. Moreover, survey evidence suggests that up to 60 percent of employers run credit checks on potential employees as part of the hiring decision (Chen et al., 2013).

Motivated by the growing prominence of credit scores, we explore their role in partner selection and relationship dissolution using a large, proprietary data set. We examine how credit scores play a role in the formation of committed relationships—such as marriages and long-term cohabitations—as well as the couples' ability to maintain the relationship. We also trace the dynamics of each partner's credit scores and the couples' use of credit over the course of being in a committed relationship. Broadly speaking, our results point to a quantitatively large and significant role for credit scores in the formation and dissolution of committed relationships. Three sets of empirical results support this conclusion: First, credit scores are positively correlated with the likelihood of forming a committed relationship and its subsequent stability. Second, partners positively sort into committed relationships along the credit score dimension even after controlling for other similarities between the partners. Third, a positive correlation notwithstanding, within-couple differences in credit scores are apparent at the start of relationships. Notably, the initial match quality in credit scores is highly predictive of subsequent separations even when controlling for other factors, such as couples' use of credit and the occurrence of financial distress.

These results lead us to hypothesize that credit scores, in addition to measuring an individual's creditworthiness regarding the repayment of debt obligations, reveal information about an important relationship skill. We argue that one such skill could be an individual's general trustworthiness and commitment to non-debt obligations. To make this argument, we turn to survey-based measures of trustworthiness to show that the average credit score of a geographic area (typically a county) is highly correlated with the same area's average level of trustworthiness. We also find that when individuals have a long exposure to greater trustworthiness, as measured by surveys, they tend to have higher credit scores even years after they leave those areas. Similar to how credit scores predict the formation and dissolution of committed relationships, we find that survey-based measures of trustworthiness also have predictive power for these outcomes. Interestingly, such statistical relevance diminishes when the couples' credit score levels are controlled for, underscoring the overlapping between credit scores and survey-based measures of trustworthiness.

Our study contributes to a wide range of topics related to (i) how individuals sort into committed relationships, (ii) the economic inputs of successful and failed relationships, and (iii) the importance of trustworthiness in such a context. On the first topic, many previous studies have documented the various traits by which individuals sort themselves into committed relationships, including race, educational attainment, and earning capacity (Weiss and Willis, 1997; Garfinkel et al., 2002; Blackwell and Lichter, 2004; Watson et al., 2004), parental wealth (Charles et al., 2013), social caste (Banerjee et al., 2013), and physical appearance (Chiappori et al., 2012). We document how individuals sort with respect to a new socioeconomic characteristic, namely, credit scores. Because credit scores are arguably the most prominent individual-level characteristic lenders use to underwrite credit and enable households to smooth consumption, our results also shed light on how positive, assortative matching with respect to credit scores can reinforce income and consumption inequality across U.S. households (Heathcote et al., 2010; Aguiar and Bils, forthcoming).

On the second topic, another aspect of the literature examines how match quality influences the production of jointly consumed goods and the stability of committed relationships (Becker, 1973; Lam, 1988; Mare, 1991; Kalmijn, 1998; Voena, 2013). Stevenson and Wolfers (2007) provide a review of this subject. We provide strong evidence that the initial match quality in credit scores has important implications for couples' use of joint credit accounts, acquisitions of new debt, and the risk of financial distress, factors that all substantially influence the prospects of relationship success. Furthermore, initial match quality helps to predict future separations even after controlling for couples' use of credit and the financial distress encountered. These results speak to the growing interest in credit scoring and its implications for households and credit markets (Avery et al., 2009; Chatterjee et al., 2009; Han et al., 2015). In addition, with the emergence of new dating websites that allow individuals to reveal information about their creditworthiness, media attention on the importance of credit scores in relationship building and maintenance has also been growing (Silver-Greenberg, 2012; Ettin, 2013). To the best of our knowledge, our paper is the first to provide systematic evidence that supports the assumptions behind this new match-making technology and the recognition that credit scores are important for many economic choices of the households besides their access to credit markets.

On the third topic, our analysis provides new evidence for the roles that trust and trustworthiness play in mitigating problems arising from incomplete information, incomplete contracts, and lack of enforceability (Arrow, 1972; Weiss, 1997; Guiso et al., 2004; Karlan, 2005). In particular, because households are subject to fewer formal, contractual restraints and use more implicit contracts that can be difficult to enforce, trust and trustworthiness are all the more important in maintaining committed relationships. Under our conjecture that credit scores reveal general trustworthiness, our results support the significance of trustworthiness in partners' ability to form and maintain committed relationships. In particular, our results point to how trustworthiness helps overcome some of the problems arising within relationships due to incomplete information and incomplete contractability, even beyond the strengthening of joint household consumption and the avoidance of financial distress.

Finally, our paper makes two important methodological contributions. First, our analysis provides an alternative interpretation of credit scores beyond creditworthiness on financial debt liabilities, thereby proposing an objective measure of trustworthiness that has eluded previous scholars (Putnam, 1995; Solow, 1995). Indeed, researchers have long relied on subjective responses to survey questions like "do you think most people can be trusted or you cannot be too careful in dealing with people?" to gauge trust and trustworthiness.[1] However, as seen in Glaeser et al. (2000), Fehr et al. (2003), and Sapienza et al. (2013), the interpretation of such survey-based measures remains a subject of active debate, which further underscores the need for a more objective measure of trustworthiness. By contrast, credit scores are constructed using statistical methods and credit records, and are available for the majority of the population.

Second, following a trend in the literature that exploits large, administrative data sets (Kopczuk et al., 2010; Chetty et al., 2014; Einav and Levin, 2014), we use a large, longitudinal panel of detailed credit record information of twelve million randomly-selected U.S. consumers. In this data set, because we have limited demographic information, we introduce an algorithm to identify the formation and dissolution of committed relationships, and conduct a range of analyses that validates this method against other data sources where such information is more readily observed. The longitudinal structure of our data allows us to observe both partners before the relationship begins and after the relationship ends, which constitutes information that is rarely available in other data sources. In particular, because partners' credit scores tend to converge during the relationship, the longitudinal structure allows us to observe *initial* credit score match quality and thus better identify the association between match quality and the likelihood of separation. Otherwise, in using measures of match quality that are contemporaneous with household dissolution, we would potentially conflate other factors that affect credit scores over the course of the relationship with the role match quality plays.

The remainder of the paper is organized as follows. Section 2 introduces the main data used in our study and the algorithm of identifying the formation and dissolution of committed relationships. We also present the results of validating the algorithm. Section 3 studies assortative

[1] Sapienza et al. (2013) estimate that about 500 research papers use answers to the World Values Survey or General Social Survey questions on whether survey respondents say that most people can be trusted.

matching with respect to credit scores and explores how match quality evolves after relationship formation. Section 4 presents the keys results and an array of robustness tests on how credit scores relate to the formation and dissolution of committed relationships. We study the channels through which credit score match quality may affect committed relationships and its effects beyond these channels in Section 5. Section 6 presents the evidence pertinent to the association between credit scores and survey-based measures of trustworthiness. Section 7 concludes and sets an agenda for future research.

2 Data and Algorithms

2.1 The Consumer Credit Panel/Equifax Data

Our main source of data is the Federal Reserve Bank of New York Consumer Credit Panel/ Equifax (henceforth the CCP). Equifax is one of the three largest U.S. credit reporting agencies (CRA). These data have been frequently used in various studies of household finances in recent years. For example, the Federal Reserve Bank of New York releases the Quarterly Reports on Household Debt and Credit that are derived from the CCP. Beginning in the first quarter of 1999, the data are a quarterly panel and track a 5 percent random sample (the "primary sample") of all U.S. consumers with a valid credit history.[2] Our sample ends in the second quarter of 2014 and covers a total of 62 quarters. A unique feature of the CCP is its large sample size, with the primary sample containing about 12 million consumers in a typical quarter. All personally identifiable information is removed by Equifax before the data are delivered.

In addition to the primary sample, the CCP also follows consumers who lived at the same address as a consumer from the primary sample. However, such non-primary sample consumers are followed only for the duration they share the same address. Therefore, these consumers and their credit records are no longer observed once they stop living with consumers in the primary

[2]The randomness of the sample derives from including only individuals whose last two digits of their social security numbers belong to a pre-specified set of five numbers. The last four digits of the social security number are assigned sequentially to new applicants in chronological order as applications are processed and are thus as good as randomly assigned. Such randomness is a feature of, for example, Johnson et al. (2006) and Gross et al. (2014).

sample. Neither are they observed prior to living with primary-sample consumers. About 30 million non-primary sample consumers live with someone in the primary sample in a typical quarter.

The variables in the CCP are from consumers' credit reports, which include, among other things, information on loan balances and delinquency status of various types of debt, bankruptcy, foreclosure, and other derogatory flags, and the number of inquiries made on one's credit history. The data also include a proprietary credit score developed by Equifax for each consumer. Like the FICO score, the Equifax "risk score" is designed to predict the likelihood of severe delinquency over the next 24 months but is estimated using an algorithm different than FICO's and ranges from 280 to 850, with a higher score indicating higher credit quality.[3] The data also provides information on the consumer's state of residence, as well as his county, census tract, and census block, which we exploit later in our analysis.

2.2 Identifying Relationship Formation

We now introduce the algorithms of identifying committed relationships and when they form. The general idea is to follow individuals over time to find the pairs of individuals who were not observed as living at the same address previously but started to share the same address in a quarter.[4] Because not all people living together are committed couples, we apply a sequence of restrictions to ensure that most of the consumer-pairs we identify represent such couples.

Note that our algorithm cannot distinguish legally married couples from those in a stable, cohabiting relationship. However, this distinction is not all that critical for our analysis because we are interested in the implications of credit scores and the associated match quality in a general swathe of committed relationships, not just the couples who are legally married. Indeed, the marriage rate has experienced a steady decline since the 1990s, whereas cohabitation has become an acceptable living arrangement in the society (Lundberg and Pollak, 2014; Wang

[3]For more information about the CCP, see Lee and van der Klaauw (2010).

[4]Dettling and Hsu (2014) use a similar algorithm to find the adult children who moved back to parents' home in the same data.

and Parker, 2014). Moreover, many cohabiting relationships eventually evolve into marriages, further blurring the distinctions between the two types of committed relationships (Stevenson and Wolfers, 2007). Lastly, cohabiting couples also share many household economic and financial responsibilities in a way similar to married couples, making credit scores an important subject to study even in this context.

Our baseline algorithm applies to only the individuals in the primary sample. Couples identified within the primary sample will be used in the baseline analysis to ensure that both spouses of a couple were consistently followed in the CCP data before and after the relationship formation. The algorithm is summarized as the following steps:

1. In each quarter, Q, find the pairs of primary-sample individuals who live at the same address (having the same HHID) in that quarter.

2. Keep only the pairs where the two individuals are the only people living at that address. The couple is removed even if they live with non-primary sample individuals as of Q.

3. Keep only the pairs where both individuals are between age 20 and 55 as of Q and the age difference between them is twelve years or less.

4. Keep only the pairs where the two individuals live at different addresses (not sharing the same HHID) between $Q-8$ and $Q-1$.

5. Keep only the pairs identified who stay living together from Q to at least $Q+4$.

Because the HHID identifiers in the CCP are assigned based on the address information in Equifax, some individuals who live in a dorm or apartment building are assigned the same household ID. Step 2 restricts the sample to those couples who were the only members of a household. However, this restriction may exclude some real couples who live in an apartment building or with adult children at the start of their cohabitation. Step 3 lets us focus on the prime-age consumers and exclude the adult children moving in with their parents. Various nationally representative household surveys suggest that the 99th percentile of the distribution of within-couple age differences is about 12 years. Applying this restriction excludes some true couples that have particularly large age differences. Step 4 excludes couples where the relationship forms prior to Q but move back to the same address at Q after having different addresses temporarily.[5] This step is critical for identifying the timing of household formation so that we can observe the match quality of credit scores at the beginning of a relationship. Finally, step 5 requires the couple to live together for at least five quarters. This restriction attempts to further exclude roommate relationships, many of which do not last longer than one year. Applying all these restriction leaves us with a sample of 49,363 couples.

A modified algorithm can be applied to all consumers (primary and non-primary) in the CCP. Because the non-primary-sample consumers were not followed in the CCP before they began living at the same address with a primary-sample individual, the committed relationship identification algorithm does not apply to the entire sample that includes such consumers. Instead, we count a primary-sample individual and a non-primary-sample individual as having formed a relationship in quarter Q if Q is the first time that this non-primary-sample individual appears in the data. The couple should also satisfy criteria 2, 3, and 5 in the baseline algorithm. This approach dramatically increases the number of identified couples to 2,070,117 couples. But the majority of the so-identified couples have only one spouse being followed consistently over time. We use this sample of couples for robustness analysis and extensions.

2.3 Validating the Algorithm

We conduct a sequence of validation exercises to reassure us that most of the couples identified by our algorithm represents committed relationships such as marriages or long-term cohabiting relationships. We first compare the relationship formation rates in our sample with marriage rates in administrative and survey data. Then we examine the similarities in the demographic characteristics between partners of the committed couples we identified and compare them to couples

[5] In one robustness check, we add the restriction that couples do not share the same address 16 quarters prior to the quarter when we observe that they move to live together.

in household survey data, where marital and cohabiting relationships are directly observed. In short, we find the relationship formation rates estimated using our couple-identification strategy compare favorably to the marriage rates estimated using the Panel Study of Income Dynamics (PSID) data and the related administrative statistics.[6] Also, the inferred socioeconomic and demographic characteristics between the spouses identified are correlated in a similar way as those of the spouses observed in household surveys, but such correlations are not detected in the placebo sample of randomly matched individuals.

2.3.1 Comparison of Relationship Formation Rates

Table 1 presents the relationship formation rates estimated using our algorithm. Nearly 50,000 couples form within the primary sample during the sample period, implying an annual relationship formation rate of 0.108 percent (column 1)—or 540 couples per one million individuals.[7] Because the baseline algorithm identifies only the couples formed among individuals of the primary sample, we are able to observe only a small fraction of the relationships formed as both spouses must be in the primary sample individuals. To see this, let Ω represent the population, let ω be a 5-percent random subset of Ω, and P_Ω be the national relationship formation rate. Individual $i \in \omega$ then has a probability P_Ω of forming a relationship with an individual $j \in \Omega$ in a given year. However, the probability of forming a relationship with $j \in \omega$, P_ω, should follow

$$P_\omega \approx 0.05 \times P_\Omega \tag{1}$$

Applying this adjustment gives the implied population relationship formation rate of 2.2 percent (shown in column 2). The marriage rate among individuals aged between 20 and 55 estimated using the Vital Statistics and the U.S. Census data is around 1.5 percent. Our estimated relationship formation rate appears a bit higher than these estimates, suggesting that our inclusion of cohabiting relationships seems to outweigh the exclusion of legitimate couples

[6] The PSID is a nationally representative longitudinal survey of U.S. households. For more information about the PSID, see http://psidonline.isr.umich.edu.

[7] The relationship formation rate is calculated as the number of couples divided by the number of individuals aged between 20 and 55.

due to the selection criteria of our algorithm. When we apply the algorithm to include the non-primary sample, we obtain a relationship formation rate of 2.3 percent (column 3), which is in line with the adjusted primary sample formation rate. This consistency reassures us of the validity of our algorithm.

As seen in the subsequent rows of Table 1, the relationship formation rate declines with age, with the rate among individuals aged between 20 and 35 being above 2.6 percent while the rate among individuals aged between 46 and 55 below 1.5 percent. Although we do not have administrative data to estimate marriage rates by age, the decline in relationship formation rate is broadly consistent with the estimates of marriage rate derived using household survey data. For example, the marriage rates estimated using the PSID data are about 1.5 percentage points higher among the subsample aged between 20 and 35 than for the subsample between 45 and 55, a difference similar to that in our data. Also, the pattern of how the relationship formation rate varies across age groups is very similar between couples identified in the primary sample alone and when also using the non-primary sample.

2.3.2 Demographic Correlations: Do They Look Like Couples?

We now examine whether each member of the couples in the sample demonstrate similarities regarding their demographic and socioeconomic characteristics that are consistent with what we observe in the household survey data. Such information in the CCP data is very limited, partly due to federal laws prohibiting the collection and use of information on race, ethnicity, national origin, sex, and marital status in loan underwriting and in calculating credit scores. Indeed, because the only demographic information contained in the data is the year of birth, we supplement the CCP data with census block group level statistics from the 2000 U.S. Census. A census block group is a collection of multiple census blocks and typically has a population of approximately 1,000 people. Using block-group level averages, we approximate individual level demographic and socioeconomic characteristics, such as race, education, and income. For example, we use the share of adults in a block group who are white or have college degree to approximate individual race and educational attainment, and the census block group median income to approximate individual income.

As shown in Table 2, the average age of the individuals at the time of relationship formation is about 37 years, the average age differential is 3.6 years, and the within-couple age correlation is 0.85. These statistics are consistent with estimates from nationally representative surveys in which marital status is observed. For example, in the PSID, the average age at marriage, shown in column 2, is slightly younger at about 34 years. However, the age differentials and within-couple age correlation are remarkably similar between the CCP and the PSID estimates, reported in column 3. These estimates are also in line with previous estimates (Watson et al., 2004).

Using average block group level characteristics from the US Census, we show the correlation in partners' demographics in the bottom half of Table 2.[8] The approximated within-couple racial correlation is above 0.6, the college degree correlation is slightly below 0.5, and the income correlation is 0.35. Notably, the magnitudes of the estimated correlations are broadly consistent with previous studies, as is the rank ordering of their size (see, for example, respectively, Weiss and Willis (1997); Garfinkel et al. (2002); Blackwell and Lichter (2004)). Furthermore, the racial and income correlation coefficients are similar to those estimated using the 1999-2009 PSID sample of newly married couples. While the PSID within-couple college degree correlation appears to be somewhat lower than the CCP estimates, the latter are very similar to the correlation estimated using other nationally representative household surveys, such as the Survey of Consumer Finances (correlation coefficient = 0.52) and the Consumer Expenditure Survey (correlation coefficient = 0.47).[9] Finally, we construct a placebo sample of randomly matched individuals in the primary sample that adhere to the age and age-difference restrictions imposed on the identified couples. As shown in column 3, we do not observe any appreciable correlations

[8]We use the census block group of the sample member just prior to relationship formation if there is just one address or the characteristics of the block group where the individual lived for the longest duration for those with multiple addresses.

[9]Indeed, the PSID data demonstrate a persistent decline in the within-couple college degree correlation over time, making the PSID statistics somewhat lower than those derived from other national surveys.

regarding race, educational attainment, and income within the pseudo-couples.[10]

2.4 Algorithm for Relationship Dissolution

Our strategy of identifying the couples that separate follows a similar idea. Specifically, among the identified relationships, we consider a couple as having separated in quarter Q if the two individuals begin living at different addresses for at least five quarters starting from Q and are never observed to share the same address again. Note that only separations within the sample of identified couples are studied as the objective is to relate the outcome of a relationship to the conditions prevailing at the start of the relationship. We find that the dissolution rate, reported in the lower panel of Table 1, in the baseline sample of couples is fairly high. About 15 percent of these couples separate by the end of the relationship's second year, and 15 percent of the couples whose relationship survive the first two years separate by the end of the fourth year. The relatively high dissolution rates underscore the possibility that some of the households are non-marital cohabitations that, on average, have a shorter duration than marriages.

3 Matching Quality at Time of Relationship Formation

We begin with a brief introduction to the background on credit scoring. We then present the results on sorting and matching with respect to credit scores at the time of relationship formation. We then describe the subsequent evolution of within-couple credit score differentials and how such dynamics vary across couples.

3.1 Background on Credit Scoring

Credit scores evaluate the credit quality of potential borrowers and reflect a rank ordering that corresponds to a borrower's credit risk and the likelihood that one will become delinquent on an account at some point in the near future (typically over the next two years). Debt payment history is the most important determinant of one's credit score, but other factors, such

[10] The similarities regarding average age, age difference and age correlation are mechanical because we restrict the pseudo couples to meet the same age and age difference restrictions.

as levels of indebtedness, length of the credit history file, credit limit utilization, and public judgments, such as bankruptcy, foreclosure, tax lien, and garnishment are also contributing factors (Chatterjee et al., 2011). Credit bureaus' algorithms typically ignore information on monthly income, age, assets, employment history, and occupation in estimating a credit score, although previous research has suggested that some of these attributes are correlated with scores (Avery et al., 2009).

As discussed earlier, nearly all banks and other large financial institutions use credit scores in underwriting and pricing loans to households. Generally, those with higher credit scores are deemed more creditworthy in being able to meet their debt repayment obligations. Accordingly, they have more abundant access to credit and face lower borrowing costs (all else equal). Notably, the use of credit scores also extends to other areas, such as the rental, labor, and auto insurance markets. For example, survey evidence suggests that up to 60 percent of employers, including the federal government, use credit checks in their hiring decisions, while nearly all auto insurance providers take credit record information into account in estimating the risk of car accidents (Chen et al., 2013). Also, many cell phone and cable companies, use credit score information in contract-based plans.

3.2 Match Quality In Credit Scores at the Time of Relationship Formation

In light of the growing prominence of credit scores in households' economic and financial opportunities, we are interested in their role in household formation and dissolution. We first document the match quality of credit scores in a couple at the start of their relationship. As shown in Table 3, among the couples in our sample, the average credit score of individuals at the time of forming a committed relationship is about 660, somewhat lower than the overall average of 680, likely reflecting the younger-than-average age of those forming committed relationships. The within-couple correlation coefficient is about 0.6, implying significant positive assortative matching with respect to credit scores at the time of relationship formation.[11] Moreover, statistics regarding credit score percentiles (column 2) demonstrate the same pattern as those of credit score levels, consistent with the fact that credit scores rank order consumers' creditworthiness.[12]

One implication of such a strong, positive correlation is that the dispersion in credit scores at the couple level is similar to that at the individual level. To see this, note that the standard deviation of the credit score distribution across all individuals in our sample of identified couples, σ_s, is about 105. In a sample where individuals were randomly matched, the estimated standard deviation of the distribution of couples' average-credit score is about 75. However, in our sample of committed relationships, the standard deviation of couples' average credit score is much higher at 92. Because a couple's access to credit and its prices (interest rates and fees) are often determined by the lower score of the two individuals, we further examine the dispersion of the minimum score in a couple. Indeed, as shown in the same table, the standard deviation of the distribution of the within-couple minimum score is essentially identical to that across all individuals in our sample, corroborating the notion that credit access inequality across individuals is largely preserved across the couples involving these individuals. Those who have more limited access to credit as a single person do not appear to be able to improve their access through forming a spousal relationship.

That said, the matching is not perfect and the estimated within-couple credit score differentials is, on average, 69. Putting this statistic in perspective, the estimated average differential between two randomly matched individuals is about 150. Hence, the within-couple credit score differential is slightly under one half of the difference between two randomly matched individuals. In addition, credit score differentials appear to vary with the average levels of credit scores

[11] Practically speaking, there are two main ways in which this positive correlation could arise that are beyond the scope of this paper to distinguish. First, partners may choose to directly ask about credit scores while they are dating and then sort positively based on this information. Second, credit scores may be unobserved during the dating period but correlated with other, observable characteristics by which individuals sort.

[12] The percentiles are calculated relative to the score distribution of all primary sample individuals in the quarter of relationship formation.

of the couple. As shown in column 2, the differential with respect to percentiles for the two inner quartiles of the average credit score distribution (about 20) is appreciably larger than those for the two outer quartiles (about 12), indicating that the match quality among middle-credit score couples is somewhat worse than that among low- and high-score couples. Finally, because credit scores can fluctuate from quarter to quarter, it is important to rule out that the within-couple score differential estimated at the time of relationship formation represents a temporary and random artifact of this process. We therefore examine the average score taken over across quarters $Q-3$ and Q to isolate the permanent component of the credit score. The results (not shown) are qualitatively unchanged relative to those presented in Table 3.

To what extent does the positive correlation in credit scores reflect the positive assortative matching regarding other demographic and socioeconomic characteristics between spouses? To see this, we project each spouse's credit score on his or her age polynomial and the merged census block group statistics, such as race, educational attainment, and log median income (all corresponding to the census block group where the individual resided prior to the relationship).[13] The correlation coefficient between the regression residuals of corresponding spouses is 0.50, only slightly lower than the unconditional correlation of credit scores, suggesting that the within-couple credit score correlation is unlikely to be driven by demographic similarities.

Avery et al. (2009) document that credit scores are estimated mainly using information in individuals' credit files. Similar credit scores thus should reflect similar credit usage and repayment histories. Accordingly, we examine the within-couple correlations of an array of key credit history attributes that reveal each partner's past credit usage and repayment behavior, after controlling for an age polynomial and the Census-approximated socioeconomic and demographic characteristics of both individuals. Specifically, we focus on whether an individual has any bankruptcy flags, any derogatory public records other than bankruptcy, total debt outstanding balances, the number of credit report inquiries (measuring credit demand), credit

[13] For those who lived in multiple locations before entering a relationship, we use the census block group where the person lived for the longest time.

card line-of-credit utilization, and the age of one's credit history.[14] The correlation coefficients are presented in Table 4, which are all statistically significant. The results reveal that all of the above six key credit history attributes are positively correlated between partners, reassuring that the within-couple credit score correlations indeed reflect the partners' similarities regarding a wide array of indicators of their attitudes and behaviors associated with the use of credit.

3.3 Dynamics of Match Quality

In spite of the strong correlations documented above, many couples still exhibit sizeable differences in their credit scores at the time they form a committed relationship. We now study how such gaps evolve after the formation of the relationship. We first focus on couples who remain living together 16 quarters after forming a relationship. The two curves in the upper panel of Figure 1 show the average post-relationship-formation score dynamics of each member of the couple distinguished by who has the higher score at $t = 0$. As the figure shows, the difference in credit scores narrows appreciably over the first 16 quarters of the relationship, from about 55 points to about 22 points. The convergence is mostly driven by an increase in the credit score of the lower score partner measured at the time of relationship formation. Interestingly, it is not rare for the within-couple ranking of credit scores to switch over time. After the first four years, over one-third of the couples see a reversal in the score ranking. The pattern is similar among couples who remain together for longer time. As shown in the lower panel of Figure 1, the average credit score gap among couples who remain together for at least 32 quarters (8 years) narrows from 46 points at the time of relationship formation to about 15 points by the end of 16th quarter and to about 10 points by their eighth year in the relationship. Note that the initial score is higher for such couples and the score differential is lower, a pattern we will revisit in detail in subsequent sections.

This convergence in credit scores appears to reflect the shared financial behaviors between partners rather than spurious or mechanical factors. To see this, the top panel of Figure 2

[14] Our baseline analysis uses logistic regressions on bankruptcy, derogatory records, and delinquency indicators, and OLS otherwise. Tobit regressions, where applicable, yield very similar results.

shows that, for separated couples, the average credit scores of each member of the couple trend essentially in a parallel fashion during the first four years after separation, showing no signs of further convergence once couples separate and no longer share financial responsibilities. The bottom panel of Figure 2 shows the average credit scores of two randomly paired individuals whose age difference is less than 12 years and are between the ages of 20 and 55 at the quarter of matching, consistent with the other couples in our sample. We can see that the scores of these "placebo couples" do not appear to converge.

4 Credit Scores and Spousal Relationship

This section presents the main results of our study—how credit scores relate to the formation and dissolution of committed relationships. We begin by documenting that individuals with higher credit scores are more likely to form committed relationships relative to other observably similar individuals. We then present results showing how couples with higher initial credit scores are more likely to maintain their committed relationships and that, conditional on their levels, the initial match quality of credit scores is predictive of subsequent relationship dissolutions. These results are robust to numerous alternative specifications.

4.1 Formation of Committed Relationships

Using a sample of more than 3 million consumers from the primary sample who lived alone and were between the ages of 20 and 55 in a given year, we estimate the following logistic model to characterize the association between an individual's credit score and the likelihood that she forms a committed relationship within one year:

$$R_y^i = \alpha + \beta Score_y^i + \gamma Z^i + \pi Age_y^i + \psi State_y^i + \zeta Year_y + u_y^i. \tag{2}$$

Here, R_y^i is a binary variable for whether individual i, who is single in the fourth quarter of year y, forms a committed relationship, as defined in Section 2, by the fourth quarter of year $y+1$.[15] Z is a vector of personal characteristics that includes the Census block group proxies for

[15] Such relationships include those with nonprimary-sample individuals.

the log of median income, educational attainment, and race. Note that these block group level characteristics apply to the address where individual i is observed to have resided the longest prior to year y.[16] Age is a cubic age polynomial. $State$ and $Year$ are vectors of state and year fixed effects respectively, to control for aggregate economic conditions and state-level variation in the relationship formation rate. In the first set of results, the estimated coefficients, presented in column 1 of Table 5, show a strong, positive linear relationship between credit scores and the likelihood of forming a committed relationship. The estimated coefficient is highly significant, and the odds ratio (presented in brackets) suggests that a single individual whose credit score is one standard deviation (109 credit score points) higher has a 14 percent higher likelihood (estimated odds ratio of 1.14) of forming a relationship in the next year relative to otherwise comparable singles. In addition, all of the estimated coefficients for the control variables show a statistically significant relationship with the dependent variable. Specifically, the results show that white singles are on average 9 percent more likely to form a committed relationship, and a one standard deviation increase in log income is associated with a 10 percent higher likelihood of forming a committed relationship. Interestingly, college education appears to have a small, negative association with relationship formation once other characteristics are controlled for.[17]

A second set of results allows for testing whether there is a nonlinear relationship between credit scores and relationship formation. Here, we re-estimate the equation above, replacing $Score/100$ with a vector of dummies for 50-point credit score bins. The highest score bin (above 800) is the omitted group. As shown in the upper panel of Figure 3, relative to the highest-score singles, those with the lowest credit scores are about 30 percent less likely to form a committed relationship in a given year. As credit scores rise, this gap narrows consistently but still is statistically and economically significant among those with scores less than 750. An

[16] See footnote 13 for details.

[17] In results not shown, we examine whether labor and housing market conditions are associated with relationship formation by including four-quarter employment and house prices changes for the county where individual i resides in the baseline specification. We find higher employment and house price growth both have a small but statistically significant positive association with relationship formation. We do not include these controls in the baseline analysis because such data are not available for all counties and including these controls does not change the estimates of the key parameter, β, when they are available.

exception is among those with a credit score between 750 and 800—the second highest group—who seem to have slightly better odds of finding a partner than the singles with the highest scores.

4.2 Maintaining Committed Relationships

We now turn to the set of results showing that higher credit scores are also associated with more stable relationships. We first show that, among the primary sample individuals who form committed relationships, they are more likely to separate the lower their credit scores. More specifically, we estimate the logistic model below:

$$S_y^i = \alpha + \beta Score_y^i + \gamma Z^i + \theta Age_{gap}^i + \delta\ Div^i + \pi Age_y^i + \psi State_y^i + \zeta Year_y + u_y^i, \qquad (3)$$

where S_y^i is an indicator for whether the committed relationship dissolves within the first six years. Here, the right-hand-side variables are defined similarly, except that the specification now includes the age gap between partners and the share of population that is divorced in the Census block group where the couple resides at the time of relationship formation, Div, to control for potential neighborhood effects. As column 2 in Table 5 shows, a one standard deviation (105 credit score points) increase in an individual's credit score implies a 32 percent reduced likelihood of separating.

Columns 3 to 5 corroborate this result. Here, among identified couples where both partners are within the primary sample, we estimate the following logistic model:

$$S_{q_1,q_2} = \alpha + \beta \overline{Score}_{q_0} + \gamma_1 Z_{q_1} + \theta Z^{gap} + \delta Div_{q_1} + \pi Age_{q_1} + \psi State_{q_1} + \zeta Year_{q_1} + u_{q_1,q_2}. \qquad (4)$$

Here, S_{q_1,q_2} is a binary variable that indicates whether the couple, conditional on being in the relationship as of quarter q_1, separates by quarter q_2. Specifically, denoting q_0 as the quarter of relationship formation, we examine the prospects of relationship dissolution within the three windows: $(q_1, q_2) \in \{(q_0, q_0 + 8), (q_0 + 8, q_0 + 16), (q_0 + 16, q_0 + 24)\}$.[18] $\overline{Score}_{q_0}$ is the average

[18]These time windows correspond to the second year, the third and fourth year, and the fifth and six year into the relationship. The identification algorithm requires that the couple cannot break up within the first year of the relationship.

credit score of the two partners measured at the time the committed relationship forms. The advantage to this specification over equation (3) is that, because the two partners are in the primary sample, we can also include Z^{gap}, a vector of age gaps and differences in the partners' demographic and socioeconomic proxies (measured at the census tract level), in addition to including Z_{q_1}, the vector of the characteristics themselves. This inclusion helps us understand how socioeconomic and demographic differences contribute to relationship dissolutions and to corroborate our results with those in the literature. As in the specification above, we also include Div_{q_1}, the 2000 U.S. Census share of divorced population for the census block group where the couple lives.

This set of results is in columns 3 to 5 in Table 5. As with the first specification, couples with higher initial average credit scores are less likely to separate, a pattern that holds throughout the first six years of the relationship. More specifically, the estimated odds ratios suggest that a one standard deviation (93 credit score points) increase in a couple's initial average credit score implies a 30 percent reduced likelihood of separation during the second year of the relationship. Similarly, among the relationships that survive the first two years, a one standard deviation increase in the initial average credit score implies a 37 percent lower chance of separation during the third and the fourth years of the relationship. Similar results hold for the likelihood of separating in the fifth and sixth years.

Looking at the demographics, we find that couples from neighborhoods with higher shares of whites and higher median incomes are less likely to separate, and that once area median income is controlled for, couples from neighborhoods with a high share of college degrees seem more likely to separate. Moreover, our estimates of the coefficients on within-couple socioeconomic and demographic differences are largely consistent with those found in previous studies such as Weiss and Willis (1997). Specifically, our odds ratio estimates indicate that one standard deviation increase in age differences implies a 20 to 35 percent higher likelihood of separation, and that racial differences also have a significant bearing on relationship outcomes. Moreover, larger differences in approximated educational attainment and income seem to imply greater chances of separation, though these estimates are somewhat less pronounced. Finally, the 2000 U.S. Census share of divorced population in the neighborhood where a couple resides has a sizable effect on its prospect of separation, consistent with the notion that peer effects can lessen the stigma of separating.[19]

To allow for non-linearities, we re-estimate equation (4), replacing $\overline{Score}$ with a vector of dummies for 50-point bins of the initial average credit score of the two spouses. The couples with the initial average score above 750 are the omitted group.[20] The estimated odds ratios—which are all statistically significant—are presented in the lower panel of Figure 3. As the figure indicates, couples with the lowest initial average scores are two or three times more likely to separate than the couples with the highest average scores, and the likelihood of separation largely diminishes as scores increase.

4.3 Credit Score Match Quality and Relationship Outcomes

We now turn our focus to how credit score match quality affects relationship outcomes. If credit scores are similar to other personal traits, as appears to be the case based on the patterns in sorting documented earlier, we expect greater mismatch in credit scores will be associated with a greater likelihood of separation, even after controlling for the average credit score levels of couples.

Specifically, we estimate the relationship between the initial credit score gap and the likelihood of a couple separating by the end of the second year of the relationship, by the end of the fourth year (conditional on remaining in a relationship by the end of the second year), and by the end of the sixth year (conditional on remaining in a relationship by the end of the fourth year). As shown in Section 3, because credit scores of two partners tend to converge while they are together, it is critical to use the initial match quality in the analysis. The model we estimate is otherwise similar to equation (4).

[19] See Ruggles (1997) for a related discussion.

[20] The couples with initial average score above 800 represent only three percent of the sample. We therefore include all couples with initial average score above 750 in the omitted group.

As columns 1, 3, and 5 of Table 6 indicate, even after controlling for the levels of the average credit scores as of the quarter of relationship formation, the initial score differentials are strongly predictive of the stability of the relationship. The odds ratios show that, for example, a one standard deviation increase of initial score differential (66 score points) implies a 24 percent higher likelihood of separation during the second year and during the third or fourth year, and 12 percent higher during the fifth or the sixth year.

To highlight the role played by the mismatch in scores, we examine an alternative model specification that, instead of controlling for the initial average of two spouses' credit scores, controls for the lower initial score of the two partners. In this specification, holding the lower of the two scores' constant, a wider score differential implies both a higher average score and a larger mismatch. We find that the estimated coefficient on the initial score differential remains positive and significant for the first several years of the relationship (columns 2 and 4), and then becomes numerically small and statistically insignificant during the fifth and sixth year of a relationship (column 6). The results thus indicate a stronger role for the mismatch in scores: holding the lower score constant and increasing the other still leads to a higher likelihood of separation even though the average score within couples increases as this happens and has a separate stabilizing effect on the relationship.

4.4 Robustness Checks

Here, we provide a series of analyses to further support our conclusion that the initial match quality in the credit scores of those in committed relationships is predictive of subsequent separations. To begin with, recognizing the possibility that the pairs identified by our algorithm may not be true, committed relationships, we are particularly concerned that the pairs with especially large differences in their credit scores are not true couples but are driving the results. Noting that estimates from the Current Population Survey find that less than 5 percent of two-person households who satisfy our restrictions are not in committed relationships, we discuss the results of a trimming exercise where we drop 5 percent of the observations with the largest initial score differences.[21] The results of this exercise show that the estimates in Table 6 are essentially unchanged.

The remaining results from additional robustness checks are reported in Table 7 and discussed below.

Using Credit Score Percentiles

First, we consider whether using credit score values in the match quality estimate may be affecting the interpretation of our results. Credit scores are developed to reflect a rank ordering of individuals' credit risk and so the distance between the two partners' credit scores may be measured by differences in their percentile ranking rather than by differences in the values of the credit scores. As shown in columns 1 and 2 in the upper panel of Table 7, the level and match quality effects of credit scores remain pronounced when credit score percentiles, rather than levels, are used. For example, all else equal, a one standard deviation increase of initial percentile differences corresponds to a 30 and 16 percent higher likelihood of separation by the end of the fourth and sixth years of the relationship, respectively.[22] This similarity should not surprise us as we obtain similar patterns in the degree of assortative matching and measuring within-couple differences in credit scores when percentiles are used (see Table 3).

Inferring the Timing of Relationship Formation

Two methodological choices affect how we link pre-relationship credit score conditions to relationship outcomes: assigning the quarter in which a couple begins living together as the marker of the start of a committed relationship and the length of the period during which a couple cannot be observed to live together before they start their relationship. On the first choice, we assume in the baseline analysis that credit score differentials measured in the quarter in which a couple first begins living together appropriately measure the match quality in credit scores. It may be that partners' financial behaviors influence one another prior to when

[21] These results are available upon request.

[22] The results of this and other robustness test specifications regarding relationship outcomes as of the end of the second year are also qualitatively unchanged relative to the baseline specification.

they begin living together. Moreover, it could also be that one partner in a couple does not immediately change his or her mailing address precisely at the same time that the committed relationship begins. To address this concern, instead of the relationship formation quarter Q, we use each partner's credit score eight quarters before Q. These results, shown in columns 3 and 4 of Table 7, are qualitatively similar to the baseline estimates of separation odds ratios.

On the second choice, it may be that some couples use separate addresses even after forming a committed relationship, such as would be the case where an employee who is sent to work at a different location on a long-term basis than his or her home city. In this case, our baseline algorithm may mistakenly treat their moving back to the same location as a new relationship. To address this concern, we adjust the algorithm to limit the two partners sharing the same address to 16, rather than 8, quarters before Q, the quarter in which the relationship forms. These results, shown in columns 5 and 6, again are qualitatively similar to the baseline estimates.[23]

Including Couples Involving Nonprimary Sample Individuals

We now examine whether the baseline results are sensitive to adding couples that include non-primary sample individuals. Allowing such couples being included in the analysis substantially enlarged the sample of couples.[24] However, because the first time we observe the non-primary sample spouse is when that individual began living at the same address with a primary sample individual, we do not observe the census block group the non-primary sample individuals lived prior to forming the relationship. As a result, we cannot control for Z^{gap}, the approximated socioeconomic and demographic gaps, as we did in the baseline analysis. The results are reported in columns 7 and 8 in the lower panel of the table, and the implied odds ratio estimates are very similar to those in the baseline analysis.

Focusing on Couples with Joint Credit Accounts

One possible concern with our sample is that our algorithm of identifying committed re-

[23]The sample sizes are smaller in this specification because we do not observe all individuals of the baseline sample couples up to 16 quarters prior to relationship formation.

[24]However, because other variables are more likely to be left blank for non-primary sample individuals, the numbers of observations used in the estimations are smaller than those reported in Table 1.

lationships may actually include pairs of individuals who are not in a cohabiting or marital relationship. To rule out this possibility, we focus our attention on couples sharing joint debt accounts as non-committed couples are unlikely to jointly apply for credit cards, mortgages, or auto loans and share the financial obligations of repayment. We show, in columns 9 and 10, that for such couples the initial credit score match quality still is predictive of future separations. The magnitude of the relationships is smaller than in the analysis without joint account restrictions—presented in columns 7 and 8—suggesting that conditioning on joint accounts may in and of itself affect the stability of the relationship, a hypothesis that we return to in the next section.

5 Inspecting Mechanisms

In this section, we explore potential reasons why the initial match quality in credit scores appears to be so predictive of relationship outcomes. We first examine how the match quality in individual credit report attributes, which jointly determine credit scores along with the credit bureau's statistical algorithm, corresponds to relationship outcomes. Next, we turn to three channels involving the use of credit—joint account ownership, the acquisition of new credit accounts, and financial distress—that may influence relationship outcomes. Finally, we show that the match quality in credit scores is predictive of separations even when controlling for these three credit-related channels, a result that motivates the subsequent analysis in Section 6, where we present suggestive evidence of credit scores revealing additional information besides simply creditworthiness on debt repayments.

5.1 Match Quality of Specific Credit Attributes

As discussed in Section 3.1, credit scores are derived from proprietary algorithms based on the information in individuals' credit records. Hence the assortative matching in credit scores to a large extent reflects partners' similarities in their credit attributes, such as bankruptcy and other derogatory flags, lines of credit utilization, and the age of credit history (see Table 4).

Accordingly, we are interested in assessing how match quality in each of the individual credit attributes (as opposed to the scores per se) may affect spousal relationships. To do so, we estimate variants of equation (4), replacing $\overline{Score}_{q0}$ with the within-couple difference in each of the credit attributes as measured at the time of relationship formation.[25]

Two observations emerge. First, as shown in Table 8, match quality in each of the six attributes has a statistically and economically significant bearing with the likelihood of separation in the third or fourth year. These statistical associations are consistent with that of match quality in credit scores in that better matches correspond to a lower likelihood of separation. With the exception of match quality in the number of credit inquiries and the age of the credit history, such relationships persist for the fifth and sixth years of the relationship. Second, match quality in negative credit history attributes, such as bankruptcy and the occurrence of derogatory events, appear to have stronger bearing on the likelihood of separation than does the match quality in the attributes that are known to increase credit scores, such as the age of the credit history. This result suggests that the mismatch in credit scores is likely to have a stronger association with the likelihood of separation if it is driven by mismatch in indicators of previous financial distress, which have a large, discontinuous effect on credit scores, rather than in the attributes that tend to have more modest effects on credit scores.

5.2 Joint Accounts, Credit Acquisition, and Financial Distress

Joint account ownership and opening new debt accounts tend to follow the formation of committed relationships, and financial distress often foreshadows troubled relationships. The match quality in credit scores can influence these outcomes because it affects the borrowing behavior of couples. For instance, because the underwriting process places greater weight on the lower of the two partners' credit scores, couples with very different credit scores can elect to apply as singles if they perceive doing so may lower the costs of borrowing. On the other hand, however, couples may find their borrowing capacity reduced if they apply as a single borrower. Match

[25] For bankruptcy and derogatory flags, the gap is constructed as a dummy variable that indicates whether only one spouse has such flags. For other attributes, the gap is constructed as their differences between partners.

quality can also limit couples' access to credit, with poorly matched couples encountering more restricted access. Such couples may face misaligned or reduced incentives to invest in durable household goods and may there fail to do so at all. Finally, poorly matched couples may face challenges in jointly managing household finances, such as managing debt, paying bills, or saving for a rainy day fund. In this case, such couples would be more likely to experience financial distress, such as severe delinquencies, personal bankruptcies, and foreclosures. All said, these outcomes—joint account ownership, credit acquisition, and financial distress—may in turn have a role in explaining whether couples separate.

Table 9 summarizes the incidence of these three types of credit history experiences during the first four years of the relationship. The estimates indicate that, in general, more couples begin owning joint debt account over time, particularly residential mortgage debt. In the next set of results, to estimate the occurrence of new credit acquisition, we count a couple as having taken on new mortgage or auto debt within two (or four) years if the couple begins the relationship with no such debt but accumulates more than \$10,000 in mortgage debt or more than \$3,000 in auto debt.[26] The estimates indicate that about 10 and 12 percent of the couples take on new mortgage and auto loans during the first two years of their relationship, respectively. These shares increase to 15 and 16 percent after the next two years, respectively. In the last set of results, we classify a couple as having experienced significant financial distress in two (or four) years if either partner files for personal bankruptcy, experiences a foreclosure, or has a larger number of derogatory records on credit file than at the time of relationship formation. In our sample, 2.3 percent of couples file for personal bankruptcy during the first two years, 1.2 percent experience foreclosures, and 11.1 percent accumulate, on net, more derogatory credit records. These shares increase to 4.3, 2,2, and 11.9 percent after four years.

Match Quality, Joint Debt Accounts, and New Debt Acquisitions

To estimate the relationship between match quality in credit scores and couples' use of

[26] Because of the revolving nature of credit card debt, we do not estimate an indicator for whether the couple takes on new credit card debt.

credit, we apply the same specification as in equation (4), replacing the dependent variables with indicators for whether the couple has joint mortgage, auto, or credit card accounts, and whether they acquired new mortgage or auto debt during a given period of time. As shown in Table 10, holding the average initial credit scores constant, the mismatch in initial scores has a pronounced and statistically significant relationship with the joint ownership of all three types of credit accounts—mortgages, auto loans, and credit cards. For example, a one standard deviation increase in the initial credit score differential is associated with a 40 percent lower likelihood of having a joint mortgage account two years into the relationship. The estimated odds ratios are about 30 percent for joint auto loans and credit cards. Looking over a longer window, the estimated odds ratios imply a somewhat weaker relationship between match quality and the use of joint credit accounts, likely reflecting more convergence in credit scores among the couples who stay together for at least four years. Indeed, such convergence, on the margin, contemporaneously increases the benefit of using a joint account.

In addition, regardless of whether the debt is borrowed jointly or individually, mismatch in credit scores appears to have a negative, despite smaller, effect on acquiring new mortgage and auto debt. As shown in the lower part of Table 10, a one standard deviation increase in the initial credit score differential is associated with a reduction in the likelihood of acquiring new debt by 3.5 to 7 percent, depending on the type of debt and the length of period under consideration. Interestingly, the point estimates suggest that car purchases are apparently more sensitive to credit score match quality than are home purchases.

Financial Distress

Using the same logistic specification, we estimate the relationship between the mismatch in initial credit scores and the likelihood of experiencing financial distress. As shown in Table 11, a one standard deviation increase of the initial credit score differential is associated with a 19 percent higher chance of filing for bankruptcy during the first two years of the relationship, while the odds are 10 and 15 percent higher for foreclosures and having more of derogatory records, respectively. That said, the magnitude of the relationship between the mismatch in credit scores and financial distress diminishes considerably when looking across the first four years of the relationship.

5.3 Through and Beyond These Channels

As discussed above, the match quality in initial credit scores is predictive of relationship dissolution as well as joint account ownership, new borrowing, and financial distress, which themselves can influence couples' ability to maintain relationships. To ascertain whether initial match quality still bears a relationship with the likelihood of separation once these credit-related factors are accounted for, we re-estimate equation (4) and include as additional regressors measures for joint account ownership, new debt acquisition, and financial distress. More specifically, we express the likelihood of separation by the end of the third or fourth year as a function of joint account ownership, new borrowing, and financial distress measured at the end of the second year. Similarly, when we examine separation by the end of the fifth or sixth year, we condition on variables through the end of the fourth year.

The results are presented in Table 12. Looking in columns 1 through 4 at the likelihood of separation by the end of the third or fourth year, the coefficient on the indicator for whether the couple opens any joint account by the end of the second year is large (see column 1), with the odds ratio suggesting that couples with joint accounts are 80 percent less likely to separate over the next two years. Second, new mortgage and auto loan acquisitions, an indicator of joint consumption in the relationship, are also associated with more durable relationships (column 2). Couples that acquired such debt are about 30 and 14 percent less likely to separate by the end of the fourth year. Third, consistent with the notion that financial hardship is important for relationship problems, our results indicate that financial distress are associated with relationship dissolution. In particular, couples filing for personal bankruptcy or with more derogatory public records are nearly 50 and 30 percent more likely to separate (column 3). Analogous results for separations in the fifth or sixth year are qualitatively the same, though some coefficients are less precisely estimated (columns 5-7).

While not owning joint accounts, lack of credit acquisition, and experiencing financial distress all have economically large implications for the likelihood of separation, the results in columns 4 and 8 suggest that they may not be the only channels through which the match quality in credit scores operate. Here, we estimate an augmented version of equation 4, adding indicators regarding joint account ownership, credit acquisitions, and financial distress. In this "horse race" specification, we still see that the initial match quality in credit scores has a strong association with the likelihood of separation. Specifically, a one standard deviation increase in the initial score difference corresponds to a 20 percent higher likelihood of separation in the third and fourth year, and an 11 percent higher likelihood in the fifth and sixth year of the relationship, suggesting that other channels or factors correlated with initial match quality may be influential in predicting relationship outcomes. We now turn to a set of results that help us understand and interpret the residual correlation between credit scores and relationship dissolution.

6 Credit Scores and Trustworthiness

In this section, we turn to survey data to investigate whether credit scores reveal an important relationship skill that relates to an individual's general trustworthiness and commitment to non-debt obligations. Indeed, as discussed earlier, the use of credit scores extends to many situations other than debt underwriting, suggesting that a broader interpretation of credit scores may be appropriate. For instance, in studying their use in employment decisions, Chen et al. (2013) postulate that credit scores may reveal private information about one's productivity.

We begin with setting forth the following stylized, conceptual framework,

$$\Pr(\text{default}) = f(\text{trustworthiness}) + \eta, \tag{5}$$

and

$$\text{credit score} = g(\Pr(\text{default})) + \mu, \tag{6}$$

where an individual's probability of default on financial debt is modeled as a function of her underlying trustworthiness, i.e. her *willingness to repay* her debt, plus η, which measures her *ability to repay.* Here, η is assumed to be orthogonal to trustworthiness and may reflect shocks to an individual's terms of credit, income, and expenditures. The variable "credit score" is a noisy measure of the probability of default and therefore should also be correlated with the underlying trustworthiness, as long as credit scores are not perfectly correlated with η.

Although this framework is highly stylized, we make the follow observations to support our hypothesis that credit scores matter for committed relationships because they reveal information about general trustworthiness. First, until the passage of the Fair Credit Reporting Act (FCRA) in 1970, credit reporting agencies and lenders long collected and maintained information on not just an individual's loan repayment history but also on income, marital status, alcohol and drug use, reputation, habits, morals, and marital problems.[27] In addition, character reports contained information on whether someone was "steady and reliable" and how "good" was someone's "reputation as to habits and morals." Pre-FCRA credit reports frequently included more qualitative character reports in addition to statements about debt repayment history.[28] These features of pre-FCRA credit reports suggest that information on general trustworthiness is likely to be helpful in predicting debt default. Conversely, as discussed earlier, credit scores are widely used in a variety of contexts as an indicator of reliability and ability to honor and maintain a broad range of commitments, such as rental and employment relationships, not just those involving debt and credit.

Our second observation derives from the result that credit scores are highly correlated with the survey-based, subjective, and self-reported measures of trustworthiness. We measure the latter using the 2000 Social Capital Community Survey (SCCS), which samples 375 to 1,500 adults in 41 communities and asks the respondents trust-related questions, such as "whether most people can be trusted or you can't be too careful." These trust-related questions signifi-

[27]The FCRA Act prohibits direct collection and use of information such as age, race, and gender in credit reporting and scoring, which has spurred profound innovation in the use of statistical algorithms to construct credit scores.

[28]Images of historical credit reports are available from the authors upon requests.

cantly overlap with those from the World Value Survey and General Social Survey, which are used extensively in studies of trust and trustworthiness.[29]

We use the answers to these questions to infer the average trustworthiness of the communities covered by the SCCS. We make this interpretation for two reasons. First, Glaeser et al. (2000) find that answers to these questions are more indicative of one's own trustworthiness rather than his trusting attitude. Second, we conjecture that people who interact with more trustworthy counterparties in their neighborhood tend to have a more trusting attitude. We then test whether areas with higher average credit scores also tend to have higher levels of survey-based measures of trustworthiness.[30] Identifying the precise interpretation of survey-based questions is beyond the scope of this paper. We further assume that people's trusting attitudes are heavily influenced by their experiences of interacting with the people around them and that people who interact with more trustworthy individuals tend to be more trusting. In making this assumption we argue that a community's average response to the question of whether most people can be trusted is a reasonable measure of the average level of trustworthiness in the community.

More specifically, using the SCCS, we construct an index of average trustworthiness as 100 times the share of survey respondents in a community who reply that "most people can be trusted."[31] This index ranges between 36 and 66, and has a standard deviation of 8 across the 38 communities that are also covered in the Equifax/CCP data. In correlating this index with the average credit scores of the corresponding areas in the CCP, we find that the subjective and objective measures of trustworthiness are highly correlated, with a Spearman rank correlation near 0.85, as shown in Figure 4. Moreover, this correlation persists even after controlling for each survey community's level of income. As seen in column 1 of Table 13, when we project the average community credit scores onto the trustworthiness index, the estimated coefficient

[29]For more information about the SCCS, see http://www.ropercenter.uconn.edu.

[30]To be sure, whether answers to such survey questions measure trusting behavior or trustworthiness remains unsettled. For example, Fehr et al. (2003) challenges the results in Glaeser et al. (2000), while more recently, Sapienza et al. (2013) present evidence that shed light on why the SCCS/GSS/WVS questions may reveal trustworthiness.

[31]In this calculation, we apply the SCCS weights to account for the stratified survey design.

is highly significant, and the R-squared is above 50 percent. Adding the logarithm of the community's median income to the specification leaves the coefficient on the trustworthiness index little changed (column 2).

The results in column 3 lead to our third observation that trustworthiness in one's community is predictive of one's credit score even after leaving the community.[32] This result is based on a subsample of individuals in the CCP living in the communities surveyed by the SCCS for at least three years before moving out from these areas. We limit our analysis to those living in a community for at least three years to ensure sufficient time for any neighborhood effects to manifest. We then follow these individuals and test whether their credit scores are still correlated with the trustworthiness index of the community where they previously lived.

Our final set of observations, summarized in Table 14, addresses the link between the survey-based measures of trustworthiness and the outcomes of committed relationships. In the top panel, we show that married individuals in the SCCS reveal higher levels of trustworthiness than divorced or separated individuals (52 percent versus 42 percent). In the middle panel, we show the negative correlation (-0.37) between the share of separated or divorced respondents with the share of high-trustworthiness respondents across the SCCS-covered communities. Both of these results are suggestive of a link between relationship outcomes and trustworthiness, which corroborates our interpretation that trustworthiness is one of the mechanisms through which the match quality in credit scores influences relationship outcomes.

The bottom panel presents the analysis on how survey-based measures of trustworthiness help predict relationship outcomes. Focusing on the CCP couples where an individual lives in a SCCS-covered community for at least three years prior to relationship formation, we find that the community average level of trustworthiness has a significant, negative relationship with the likelihood of separation. Specifically, a one standard deviation higher level of the constructed trustworthiness index in the SCCP is associated with a 6 percent lower chance of separating

[32]See (Guiso et al., 2004; Brown et al., 2008) for evidence on enduring neighborhood effects.

within the first six years of the relationship.[33] Interestingly, once we control for the couples' initial credit score levels, as shown in column 2, the coefficient on community trustworthiness, while remaining negative, becomes smaller in magnitude and statistically insignificant, which is consistent with the notion that credit scores are indicative of the information conveyed in survey-based measures of trustworthiness.

7 Concluding Remarks

With the growing importance of household credit, credit scores have become a prominent characteristic of individuals that extends to areas outside the household finance sector. Using a large proprietary dataset that tracks the credit records of millions of U.S. consumers over fifteen years, we document that, conditional on observable socioeconomic and demographic characteristics, individuals in committed relationships have credit scores that are highly correlated with their partners' scores. Their credit scores tend to further converge with their partners', particularly among those in longer-lasting relationships. Conversely, we find the initial match quality of credit scores is strongly predictive of relationship outcomes in that couples with larger score gaps at the beginning of their relationship are more likely to subsequently separate. While we find that part of such a correlation is attributable to poorly matched couples' lower chances of using joint credit accounts, acquiring new credit, and staying away from financial distress, the mismatch in credit scores seems to be important for relationship outcomes beyond these credit channels.

We also provide suggestive evidence that credit scores reveal information about one's underlying trustworthiness in a similar way as subjective, survey-based measures. Moreover, we find that survey-based measures of trustworthiness are also associated with relationship outcomes, which implies that differentials in credit scores may also reflect mismatch in couples' trustworthiness. Contributing to a growing literature on the role of trust and social capital in supporting economic institutions and growth, our results present new evidence on how mismatch

[33] The standard errors are clustered at the SCCS community level.

in trustworthiness within a household may affect its stability.

Our work potentially paves the way for two areas of future research. First, essentially all of our knowledge on household finance occurs using the household as the unit of analysis. Our study introduces an algorithm of identifying couples in credit bureau data and thus allows for additional analysis of how credit is allocated within a household and its implications. Second, future research is warranted to further explore the use of credit scores as an objective, behavior-based, algorithm-derived measure of trustworthiness. Such research would push the boundaries of our understanding of trust and trustworthiness. After all, as Putnam (1995) famously wrote, "since trust is so central to the theory of social capital, it would be desirable to have strong behavioral indicators of trends in social trust and misanthropy. I have discovered no such behavioral measures."

References

Aguiar, Mark and Mark Bils, "Has Consumption Inequality Mirrored Income Inequality," *American Economic Review*, forthcoming.

Arrow, Kenneth, "Gifts and Exchanges," *Philosophy and Public Affairs*, 1972, *1* (4), 343–362.

Avery, Robert, Kenneth Brevoort, and Glenn Canner, "Credit Scoring and Its Effects on the Availability and Affordability of Credit," *Journal of Consumer Affairs*, 2009, *43* (3), 516–537.

Banerjee, Abhijit, Esther Duflo, Maitreesh Ghatak, and Jeanne Lafortune, "Marry for What? Caste and Mate Selection in Modern India," *American Economic Journal: Microeconomics*, 2013, *5* (2), 33–72.

Becker, Gary, "A Theory of Marriage: Part I," *Journal of Political Economy*, 1973, *81* (4), 813–846.

Blackwell, Debra and Daniel Lichter, "Homogamy among Dating, Cohabiting, and Married Couples," *The Sociological Quarterly*, 2004, *45* (4), 719–737.

Brown, Jeffrey, Zoran Ivkovic, Paul Smith, and Scott Weisbenner, "Neighbors Matter: Causal Community Effects and Stock Market Participation," *Journal of Finance*, 2008, *43* (3), 1509–1531.

Charles, Kerwin, Erik Hurst, and Alexandra Killewald, "Marital Sorting and Parental Wealth," *Demography*, 2013, *50* (1), 51–70.

Chatterjee, Satyajit, Dean Corbae, and José-Víctor Ríos-Roll, "Credit Scoring and the Competitive Pricing of Default Risk," *Working Paper*, 2009.

_ , _ , and José-Víctor Ríos-Rull, "A Theory of Credit Scoring and Competitive Pricing of Default Risk," *Unpublished manuscript*, 2011.

Chen, Daphne, Dean Corbae, and Andy Glover, "Can Employer Credit Checks Create Poverty Traps? Theory and Policy Evaluation," *Unpublished manuscript*, 2013.

Chetty, Raj, John N. Friedman, and Jonah E. Rockoff, "Measuring the Impacts of Teachers II: Teacher Value-Added and Student Outcomes in Adulthood," *American Economics Review*, 2014, *104* (9), 26332679.

Chiappori, Pierre Andre, Sonia Oreffice, and Climent Quintana-Domeque, "Fatter Attraction: Anthropometric and Socioeconomic Matching on the Marriage Market," *Journal of Political Economy*, 2012, *120* (4), 659–695.

Dettling, Lisa and Joanne Hsu, "Returning to the Nest: Debt and Parental Coresidence among Young Adults," *Federal Reserve Finance and Economics Discussion Series*, 2014.

Einav, Liran and Jonathan Levin, "Economics in the Age of Big Data," *Science*, November 2014, *346* (6210).

Ettin, Erika, "A Little Number Goes a Long Way," *Philadelphia Inquirer*, 2013.

Fehr, Ernst, Urs Fischbacher, Bernhard von Rosenbladt, Juergen Schupp, and Gert Wagner, "A Nation-Wide Laboratory. Examining Trust and Trustworthiness by Integrating Behavioral Experiments into Representative Surveys," *CESifo working paper 866*, 2003.

Garfinkel, Irwin, Dana Glei, and Sara McLanahan, "Assortative Mating among Unmarried Parents: Implications for Ability to Pay Child Support," *Journal of Population Economics*, 2002, *15* (3), 417–432.

Glaeser, Edward, David Laibson, Jose Scheinkman, and Christine Soutter, "Measuring Trust," *Quarterly Journal of Economics*, 2000, *115* (3), 811–846.

Gross, Tal, Matthew Notowidigdo, and Jialan Wang, "Liquidity Constraints and Consumer Bankruptcy: Evidence from Tax Rebates," *Review of Economic Statistics*, 2014.

Guiso, Luigi, Paola Sapienza, and Luigi Zingales, "The Role of Social Capital in Financial Development," *American Economic Review*, 2004, *94* (3), 526–556.

Han, Song, Benjamin Keys, and Geng Li, "A Lender's Tale of Unsecured Credit Supply: Evidence from Credit Card Mailings," *Working Paper*, 2015.

Heathcote, Jonathan, Kjetil Storesletten, and Gianlucan Violante, "The Macroeconomic Implications of Rising Wage Inequality in the United States," *Journal of Political Economy*, 2010, *118* (4), 681–722.

Johnson, David, Jonathan Parker, and Nicholas Souleles, "Household Expenditure and the Income Tax Rebates of 2001," *American Economic Review*, 2006, *95* (5), 1589–1610.

Kalmijn, Matthijs, "Intermarriage and Homogamy: Causes, Patterns, Trends," *Annual Review of Sociology*, 1998, *24*, 395–421.

Karlan, Dean, "Using Experimental Economics to Measure Social Capital and Predict Financial Decisions," *American Economic Review*, 2005, *83* (5), 1688–1699.

Kopczuk, Wojciech, Emmanuel Saez, and Jae Song, "Earnings Inequality and Mobility in the United States: Evidence from Social Security Data since 1937," *Quarterly Journal of Economics*, 2010, *125* (1), 91–128.

Lam, David, "Marriage Markets and Assortative Mating with Household Public Goods," *Journal of Human Resources*, 1988, *23* (4), 462–487.

Lee, Donghoon and Wilbert van der Klaauw, "An Introduction to the FRBNY Consumer Credit Panel," *Federal Reserve Bank of New York Staff Reports*, 2010.

Lundberg, Shelly and Robert Pollak, "Cohabitation and the Uneven Retreat from Marriage in the U.S., 1950-2010," in Leah Platt Boustan, Carola Frydman, and Robert A. Margo, eds., *Human Capital in History*, National Bureau of Economic Research, 2014.

Mare, Robert D., "Five Decades of Educational Assortative Mating," *American Sociological Review*, 1991, *56* (1), 15–32.

Putnam, Robert, "Bowling Alone," *Journal of Democracy*, 1995, pp. 65–78.

Ruggles, Steven, "The rise of divorce and separation in the United States, 1880–1990," *Demography*, 1997, *34* (4), 455–466.

Sapienza, Paola, Anna Toldra, and Luigi Zingales, "Understanding Trust," *The Economic Journal*, 2013, *123*, 1313–32.

Silver-Greenberg, Jessica, "Perfect 10? Never Mind That. Ask Her for Her Credit Score.," *New York Times*, 2012.

Solow, Robert, "But Verify," *The New Republic*, September 1995, p. 36.

Stevenson, Betsey and Justin Wolfers, "Marriage and Divorce: Changes and Their Driving Forces," *Journal of Economic Perspectives*, 2007, *21* (2), 27–52.

U.S. Census Bureau, *Statistical Abstract of the United States: 2012*, U.S. Department of Commerce, 2011.

Voena, Alessandra, "Yours, Mine and Ours: Do Divorce Laws Affect the Intertemporal Behavior of Married Couples?," *Working Paper*, 2013.

Wang, Wendy and Kim Parker, "Record Share of Americans Have Never Married," *Pew Research Report*, September 2014.

Watson, David, Eva Klohnen, Alex Casillas, Ericka Nus Simms, Jeffrey Haig, and Diane Berry, "Match Makers and Deal Breakers: Analyses of Assortative Mating in Newlywed Couples," *Journal of Personality*, 2004, *72* (5).

Weiss, Yoram, "The Formation and Dissolution of Families: Why Marry? Who Marries Whom? And What Happens Upon Divorce?," in M.R. Rosenzweig and O. Stark, eds., *Handbook of Population and Family Economics*, Amsterdam: Elsevier Science B.V., 1997.

_ **and Robert Willis**, "Match Quality, New Information, and Marital Dissolution," *Journal of Labor Economics*, 1997, *15* (1), S293–S329.

Table 1: Annual Rates of Committed Relationship Formation and Separation

	Formation rates		
	Primary sample only		Whole sample
	Unadjusted (1)	Adjusted (2) = (1) × 20	(3)
Age 20-55	0.108%	2.16%	2.26%
Age 20-35	0.131%	2.62%	2.93%
Age 36-45	0.116%	2.32%	2.35%
Age 46-55	0.068%	1.36%	1.27%
Number of couples identified	49,363		2,070,117

	Separation rates	
	Primary sample only	Whole sample
During the 2nd year	15.1%	19.2%
During the 3rd and 4th year	14.9%	21.1%
During the 5th and 6th year	8.1%	12.4%

Note: Formation rates in column 1 are estimated as the ratios between the number of primary-sample individuals involved in relationships identified using the baseline algorithm introduced in Section 2 and the total number of primary sample individuals aged within each age range. Column 2 presents the adjusted relationship formation rates that take into account that the formation rates of relationships involving two primary sample individuals are about 5 percent of the formation rates in the population. Column 3 presents the relationship formation rates estimated using the sample of couples identified using the sample that includes non-primary sample individuals, estimated as the ratios between the number of primary-sample individuals involved in relationships identified using the algorithm allowing for non-primary sample individuals that is introduced in Section 2 and the total number of primary sample individuals aged within each age range. Separations rates are estimated as the ratio between the number of separated couples and the number of all relationships that survived through the first, the second, and the fourth year, respectively.

Table 2: Demographic Characteristics at the Time of Relationship Formation

	CCP data (1)	PSID data (2)	Placebo sample of couples (3)
Individual level characteristics			
Average age	36.7	33.5	36.1
Age difference	3.6	3.8	3.7
Age correlation	0.85	0.86	0.82
Census block group level characteristics			
% White correlation	0.63	0.66	0.01
% College degree Correlation	0.48	0.31	-0.00
Median Income Correlation	0.35	0.38	0.02

Note: Column 1 presents the results of the identified relationships that involve two primary sample individuals. Column 2 presents the results of the couples aged between 20 and 55 who are observed in the PSID data. Column 3 presents the results of the pseudo couples who are randomly matched in the CCP data subject to the same age and age differential restrictions. Age in the CCP data is calculated using the year-of-birth variable therein. Race, education, and median income variables are the census block group level statistics in the 2000 U.S. Census.

Table 3: Credit Score Matching Quality at the Time of Household Formation

	Score levels (1)	Score percentiles (2)
Mean credit score	657	41
Within-couple correlation	0.59	0.63
Credit score standard deviations		
Cross-individual	104	26
Cross-couple (mean)	92	24
Cross-couple (minimum)	105	24
Mean within-couple score differentials	69	17
Lowest mean score quartile	82	12
lower-middle mean score quartile	90	21
Upper-middle mean score quartile	72	21
Highest mean score quartile	33	13

Note: The statistics are estimated for the identified couples that involve two primary-sample individuals. Score percentiles are calculated with respect to the population credit score distribution of the quarter of relationship formation.

Table 4: Correlations of Credit History at the Time of Relationship Formation

Bankruptcy (1)	Derog. records (2)	Log(total debt) (3)	# Inquiries (4)	CC utilization (5)	Credit history age (6)
0.32	0.18	0.19	0.15	0.11	0.28

Note: The table presents the correlation coefficients of selected credit record attributes between spouses of identified relationships that involve two primary-sample individuals. The correlation coefficients are estimated controlling for each individual's demographic and socioeconomic characteristics. All correlation coefficients are statistically significant at a 99 percent level.

Table 5: Credit Score Levels and Spousal Relationship Formation and Dissolutions

	Including non-primary sample individuals		Primary sample individuals only		
	Relationship Formation	Relationship Dissolution	Relationship Dissolution		
		first 6 years	2nd year	3rd or 4th year	5th or 6th year
	(1)	(2)	(3)	(4)	(5)
Score/100	0.125***	-0.371***	-0.339***	-0.491***	-0.438***
	(0.001)	(0.002)	(0.017)	(0.020)	(0.029)
	[1.144]	[0.677]	[0.729]	[0.630]	[0.668]
White	0.320***	-0.690***	-0.334***	-0.397***	-0.242**
	(0.006)	(0.006)	(0.067)	(0.078)	(0.117)
	[1.098]	[0.832]	[0.917]	[0.904]	[0.943]
College	-0.180***	2.534***	3.002***	2.002***	1.119***
	(0.009)	(0.019)	(0.164)	(0.204)	(0.312)
	[0.967]	[1.323]	[1.393]	[1.246]	[1.131]
Log(income)	0.196***	-0.543***	-0.496***	-0.438***	-0.240***
	(0.004)	(0.005)	(0.046)	(0.056)	(0.082)
	[1.105]	[0.781]	[0.802]	[1.033]	[0.986]
Age gap		0.079***	0.088***	0.096***	0.062***
		(0.001)	(0.004)	(0.005)	(0.008)
		[1.082]	[1.331]	[1.354]	[1.205]
Community div. pop. share		2.817***	2.711***	1.944***	1.834***
		(0.037)	(0.333)	(0.409)	(0.613)
		[1.136]	[1.149]	[1.089]	[1.082]
Char. at the time of matching					
White gap			0.356***	0.190**	0.351**
			(0.079)	(0.097)	(0.147)
			[1.068]	[1.035]	[1.064]
College gap			0.659***	0.246*	-0.132
			(0.115)	(0.142)	(0.219)
			[1.092]	[1.033]	[0.983]
Log(income) gap			0.012	0.073**	-0.031
			(0.032)	(0.036)	(0.065)
			[1.005]	[1.033]	[0.986]
Control for					
Age poly.	Yes	Yes	Yes	Yes	Yes
Yearly FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
N	11,400,150	1,872,801	41,685	29,188	20,518

Note. Standard errors are reported in parentheses. Odds ratios of the logistic regressions are reported in brackets. ** denotes the estimate is statistically significant at the 95-percent level, and *** denotes the estimate is statistically significant at the 99-percent level. Odds ratios are calculated for a one-standard-deviation change of the respective variables. Column 1 presents the factors affecting relationship formations. Control variables of race, education, income, and divorce rate are census block group level statistics from the 2000 U.S. Census. Age is calculated using the year of birth variable in the CCP data. Columns 2 to 5 present the factors affecting relationship dissolutions. Additional control variables are the difference of spouses' ages and the differences of census block group level statistics on race, education, and income for the location each spouse lived before forming a relationship, and the divorce rate of the couple's current residence census block group.

Table 6: Credit Score Differentials upon Relationship Formation and Subsequent Relationship Dissolutions

	The second year		The third or fourth year		The fifth or sixth year	
	(1)	(2)	(3)	(4)	(5)	(6)
$\frac{Initial\ diff}{100}$	0.383***	0.267***	0.344***	0.136***	0.203***	0.005
	(0.020)	(0.024)	(0.025)	(0.029)	(0.039)	(0.045)
	[1.242]	[1.285]	[1.239]	[1.076]	[1.124]	[1.003]
$\frac{Initial\ score}{100}$	-0.233***		-0.417***		-0.396***	
	(0.018)		(0.020)		(0.030)	
	[0.776]		[0.675]		[0.695]	
$\frac{Lower\ score}{100}$		-0.233***		-0.417***		-0.396***
		(0.018)		(0.020)		(0.030)
		[0.838]		[0.637]		[0.659]
Controlling for						
Age polynomials	yes	yes	yes	yes	yes	yes
Age diff.	yes	yes	yes	yes	yes	yes
Current community char.	yes	yes	yes	yes	yes	yes
Community div. pop. share	yes	yes	yes	yes	yes	yes
Orig. community char. diff.	yes	yes	yes	yes	yes	yes
Yearly FE	yes	yes	yes	yes	yes	yes
State FE	yes	yes	yes	yes	yes	yes
N	41,685	41,685	29,188	29,188	20,518	20,518

Note. Standard errors are reported in parentheses. Odds ratios of the logistic regressions are reported in brackets. *** denotes the estimate is statistically significant at the 99-percent level. Odds ratios are calculated for a one-standard-deviation change of the respective variables. The estimations control for a third-order age polynomial of each spouse and the couple age differential; The estimations control for U.S. Census statistics of race, education, income, and share of divorced population of the census block group where the couple lived as of the end of the first, second, and fourth year of their relationship, respectively, for the three sets of results. The estimations also control variables the differentials of these statistics between the census block groups where each spouse lived prior to forming the relationship. Finally, the estimations control for yearly and state fixed effects.

Table 7: Robustness Tests

	Credit score percentiles		Primary sample individuals only scores 8 Qs before		Living sep. 16 Qs before	
	year 3 or 4	year 5 or 6	year 3 or 4	year 5 or 6	year 3 or 4	year 5 or 6
	(1)	(2)	(3)	(4)	(5)	(6)
$\frac{Initial\ diff}{100}$	1.735***	1.043***	0.231***	0.176***	0.293***	0.160***
	(0.107)	(0.164)	(0.025)	(0.032)	(0.031)	(0.051)
	[1.291]	[1.158]	[1.163]	[1.114]	[1.215]	[1.105]
$\frac{Initial\ score}{100}$	-2.273***	-1.952***	-0.400***	-0.403***	-0.457***	-0.477***
	(0.090)	(0.125)	(0.022)	(0.038)	(0.028)	(0.043)
	[0.572]	[0.616]	[0.699]	[0.700]	[0.661]	[0.653]
Controlling for						
Age polynomials	yes	yes	yes	yes	yes	yes
Age diff.	yes	yes	yes	yes	yes	yes
Current community char.	yes	yes	yes	yes	yes	yes
Community div. pop. share	yes	yes	yes	yes	yes	yes
Orig. community char. diff.	yes	yes	yes	yes	yes	yes
Yearly FE	yes	yes	yes	yes	yes	yes
State FE	yes	yes	yes	yes	yes	yes
N	29,188	20,518	28,345	19,974	14,516	8,618

	Including non-primary sample consumers: Whole sample		Including non-primary sample consumers: Having joint accounts ever	
	year 3 or 4	year 5 or 6	year 3 or 4	year 5 or 6
	(7)	(8)	(9)	(10)
$\frac{Initial\ diff}{100}$	0.392***	0.278***	0.123***	0.054***
	(0.004)	(0.006)	(0.009)	(0.010)
	[1.278]	[1.170]	[1.062]	[1.026]
$\frac{Initial\ score}{100}$	-0.530***	-0.454***	-0.428***	-0.375***
	(0.008)	(0.004)	(0.006)	(0.006)
	[0.647]	[0.661]	[0.687]	[0.723]
Controlling for				
Age polynomials	yes	yes	yes	yes
Age diff.	yes	yes	yes	yes
Current community char.	yes	yes	yes	yes
Community div. pop. share	yes	yes	yes	yes
Orig. community char. diff.	No	No	No	No
Yearly FE	yes	yes	yes	yes
State FE	yes	yes	yes	yes
N	1,195,160	820,103	755,210	588,395

Note. Standard errors are reported in parentheses. Odds ratios of the logistic regressions are reported in brackets. *** denotes the estimate is statistically significant at the 99 percent level. Odds ratios are calculated for a one-standard-deviation change of credit score differentials and average levels at the time of relationship formation. The estimations control for a third-order age polynomial of each spouse and the couple age differential; The estimations control for U.S. Census statistics of race, education, income, and share of divorced population of the census block group where the couple lived as of the end of the first, second, and fourth year of their relationship, respectively, for the three sets of results. For results of column 1–8, the estimations also control variables the differentials of these statistics between the census block groups where each spouse lived prior to forming the relationship. Finally, the estimations control for yearly and state fixed effects. See text for details of each of the robustness test specifications.

Table 8: Effects of Match Quality Regarding Credit History Attributes on Separations

	Personal bankruptcy		Derogatory records		Log(total debt)	
	year 3 or 4	year 5 or 6	year 3 or 4	year 5 or 6	year 3 or 4	year 5 or 6
	(1)	(2)	(3)	(4)	(5)	(6)
Credit attributes differentials	0.457***	0.216***	0.217***	0.191***	0.055***	0.042***
	(0.050)	(0.078)	(0.044)	(0.067)	(0.005)	(0.008)
	[1.580]	[1.241]	[1.242]	[1.211]	[1.192]	[1.135]
Controlling for						
Initial score level bins	yes	yes	yes	yes	yes	yes
Age polynomial	yes	yes	yes	yes	yes	yes
Initial char. diff.	yes	yes	yes	yes	yes	yes
Current char.	yes	yes	yes	yes	yes	yes
Local divorce rate	yes	yes	yes	yes	yes	yes
Yearly FE	yes	yes	yes	yes	yes	yes
State FE	yes	yes	yes	yes	yes	yes
N	29,119	20,487	29,119	20,487	29,119	20,487

	# Inquiries/10		CC utilization		Credit history age	
	year 3 or 4	year 5 or 6	year 3 or 4	year 5 or 6	year 3 or 4	year 5 or 6
	(7)	(8)	(9)	(10)	(11)	(12)
Credit attributes differentials	0.015***	0.005	0.264***	0.208***	0.022***	0.005
	(0.005)	(0.007)	(0.036)	(0.049)	(0.004)	(0.006)
	[1.056]	[1.020]	[1.144]	[1.105]	[1.102]	[1.023]
Controlling for						
Initial score level bins	yes	yes	yes	yes	yes	yes
Age polynomials	yes	yes	yes	yes	yes	yes
Age diff.	yes	yes	yes	yes	yes	yes
Current community char.	yes	yes	yes	yes	yes	yes
Community div. pop. share	yes	yes	yes	yes	yes	yes
Orig. community char. diff.	yes	yes	yes	yes	yes	yes
Yearly FE	yes	yes	yes	yes	yes	yes
State FE	yes	yes	yes	yes	yes	yes
N	29,119	20,487	18,860	14,302	29,092	20,472

Note. Standard errors are reported in parentheses. Odds ratios of the logistic regressions are reported in brackets. *** denotes the estimate is statistically significant at the 99 percent level. Odds ratios are calculated for a one-standard-deviation change of credit score differentials at the time of relationship formation. The estimations control for the array of bins of couple-average credit score at the time of relationship formation. The estimations control for a third-order age polynomial of each spouse and the couple age differential; The estimations control for U.S. Census statistics of race, education, income, and share of divorced population of the census block group where the couple lived as of the end of the first, second, and fourth year of their relationship, respectively, for the three sets of results. The estimations also control variables the differentials of these statistics between the census block groups where each spouse lived prior to forming the relationship. Finally, the estimations control for yearly and state fixed effects.

Table 9: Summary Statistics of Use of Credit and Financial Distress

	By the end of the second year (1)	By the end of the fourth year (2)
	percent	percent
Opened joint accounts		
Mortgages	6.4	9.2
Auto loans	6.5	8.2
Credit cards	2.4	2.9
Acquired new debt		
Mortgage debt	10.2	15.3
Auto debt	12.5	16.4
Experienced financial distresses		
Personal bankruptcy	2.3	4.3
Foreclosure	1.2	2.2
More derogatory records	11.1	11.9

Table 10: Credit Score Differentials upon Relationship Formation and Subsequent Use of Credit

	Mortgage		Auto loans		Credit card	
	first two years	first four years	first two years	first four years	first two years	first four years
	(1)	(2)	(3)	(4)	(5)	(6)
	Opening joint financial account					
$\frac{Initial\ diff}{100}$	-0.702***	-0.538***	-0.530***	-0.325***	-0.543***	-0.280***
	(0.047)	(0.045)	(0.042)	(0.041)	(0.073)	(0.068)
	[0.628]	[0.711]	[0.708]	[0.819]	[0.701]	[0.841]
N	27,301	17,435	29,798	19,954	29,190	19,026
	Borrowing new debt					
$\frac{Initial\ diff}{100}$	-0.055	-0.071*	-0.117***	-0.075*		
	(0.036)	(0.042)	(0.033)	(0.039)		
	[0.966]	[0.960]	[0.930]	[0.958]		
N	18,145	11,412	15,875	11,412		
Controlling for						
Initial score level bins	yes	yes	yes	yes	yes	yes
Age polynomials	yes	yes	yes	yes	yes	yes
Age diff.	yes	yes	yes	yes	yes	yes
Current community char.	yes	yes	yes	yes	yes	yes
Orig. community char. diff.	yes	yes	yes	yes	yes	yes
Yearly FE	yes	yes	yes	yes	yes	yes
State FE	yes	yes	yes	yes	yes	yes

Note. Standard errors are reported in parentheses. Odds ratios of the logistic regressions are reported in brackets. * denotes the estimate is statistically significant at the 90 percent level, and *** denotes the estimate is statistically significant at the 99 percent level. Odds ratios are calculated for a one-standard-deviation change of credit score differentials at the time of relationship formation. The estimations control for the array of bins of couple-average credit score at the time of relationship formation. The estimations control for a third-order age polynomial of each spouse and the couple age differential; The estimations control for U.S. Census statistics of race, education, and income of the census block group where the couple lived as of the end of the first, second, and fourth year of their relationship, respectively, for the three sets of results. The estimations also control variables the differentials of these statistics between the census block groups where each spouse lived prior to forming the relationship. Finally, the estimations control for yearly and state fixed effects.

Table 11: Credit Score Differentials upon Relationship Formation and Subsequent Financial Distresses

	New bankruptcy		New foreclosure		More derogatory records	
	first two years	first four years	first two years	first four years	first two years	first four years
	(1)	(2)	(3)	(4)	(5)	(6)
$\frac{Initial\ diff}{100}$	0.276***	0.092*	0.152**	0.123*	0.224***	0.047
	(0.049)	(0.052)	(0.071)	(0.073)	(0.026)	(0.035)
	[1.189]	[1.055]	[1.099]	[1.074]	[1.152]	[1.028]
Controlling for						
Initial score level bins	yes	yes	yes	yes	yes	yes
Age polynomials	yes	yes	yes	yes	yes	yes
Age diff.	yes	yes	yes	yes	yes	yes
Current community char.	yes	yes	yes	yes	yes	yes
Orig. community char. diff.	yes	yes	yes	yes	yes	yes
Yearly FE	yes	yes	yes	yes	yes	yes
State FE	yes	yes	yes	yes	yes	yes
N	30,438	21,498	34,074	23,942	35,220	24,539

Note. Standard errors are reported in parentheses. Odds ratios of the logistic regressions are reported in brackets. * denotes the estimate is statistically significant at the 90 percent level, ** denotes the estimate is statistically significant at the 95 percent level, and *** denotes the estimate is statistically significant at the 99 percent level. Odds ratios are calculated for a one-standard-deviation change of credit score differentials at the time of relationship formation. The estimations control for the array of bins of couple-average credit score at the time of relationship formation. The estimations control for a third-order age polynomial of each spouse and the couple age differential; The estimations control for U.S. Census statistics of race, education, and income of the census block group where the couple lived as of the end of the first, second, and fourth year of their relationship, respectively, for the three sets of results. The estimations also control variables the differentials of these statistics between the census block groups where each spouse lived prior to forming the relationship. Finally, the estimations control for yearly and state fixed effects.

Table 12: The Role Played by Use of Credit and Financial Distress on Separations

	The third or fourth year				The fifth or sixth year			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\frac{Initial\ diff}{100}$				0.303***				0.185***
				(0.025)				(0.039)
				[1.208]				[1.112]
$\frac{Initial\ score}{100}$				-0.350***				-0.334***
				(0.021)				(0.031)
				[0.720]				[0.735]
Use of credit indicators								
Joint accounts	-1.492***			-1.307***	-0.825***			-0.657***
	(0.067)			(0.069)	(0.069)			(0.072)
	[0.225]			[0.271]	[0.438]			[0.518]
Mortgage		-0.375***		-0.038*		-0.522***		-0.296***
		(0.058)		(0.062)		(0.077)		(0.081)
		[0.687]		[0.963]		[0.594]		[0.744]
Auto loans		-0.152***		0.054		0.087		0.199***
		(0.052)		(0.055)		(0.065)		(0.067)
		[0.859]		[1.056]		[1.090]		[1.220]
Financial distress indicators								
Bankruptcy filing			0.412***	0.020			0.296***	0.060
			(0.098)	(0.103)			(0.112)	(0.115)
			[1.510]	[1.020]			[1.345]	[1.062]
Foreclosure			0.106	0.115			0.265*	0.246*
			(0.137)	(0.139)			(0.147)	(0.147)
			[1.112]	[1.121]			[1.303]	[1.279]
Derog. records			0.538***	0.161***			0.465***	0.181**
			(0.047)	(0.052)			(0.070)	(0.075)
			[1.712]	[1.175]			[1.593]	[1.198]
Controlling for								
Age polynomials	yes	yes	yes	yes	yes	yes	yes	yes
Age diff.	yes	yes	yes	yes	yes	yes	yes	yes
Current community char.	yes	yes	yes	yes	yes	yes	yes	yes
Community div. pop. share	yes	yes	yes	yes	yes	yes	yes	yes
Orig. community char. diff.	yes	yes	yes	yes	yes	yes	yes	yes
Yearly FE	yes	yes	yes	yes	yes	yes	yes	yes
State FE	yes	yes	yes	yes	yes	yes	yes	yes
N	30,225	30,225	30,225	29,188	21,017	21,017	21,017	20,518

Note. Standard errors are reported in parentheses. Odds ratios of the logistic regressions are reported in brackets. *** denotes the estimate is statistically significant at the 99-percent level. Odds ratios are calculated for a one-standard-deviation change of redit score differentials and average levels at the time of relationship formation. The estimations control for a third-order age polynomial of each spouse and the couple age differential; The estimations control for U.S. Census statistics of race, education, income, and share of divorced population of the census block group where the couple lived as of the end of the first, second, and fourth year of their relationship, respectively, for the three sets of results. The estimations also control variables the differentials of these statistics between the census block groups where each spouse lived prior to forming the relationship. Finally, the estimations control for yearly and state fixed effects.

Table 13: Survey Based Trustworthiness Index and Credit Scores

	Contemporary correlations		Long-term influences
	Community average credit score		Individual credit score
	(1)	(2)	(3)
Trustworthiness Index	1.57***	1.42***	
	(0.25)	(0.21)	
Trustworthiness Index (community lived 3 years ago)			0.61***
			(0.03)
Log(median income)		0.36***	0.42***
		(0.09)	(0.01)
R-squared	0.51	0.65	0.008
N	38	38	340,303

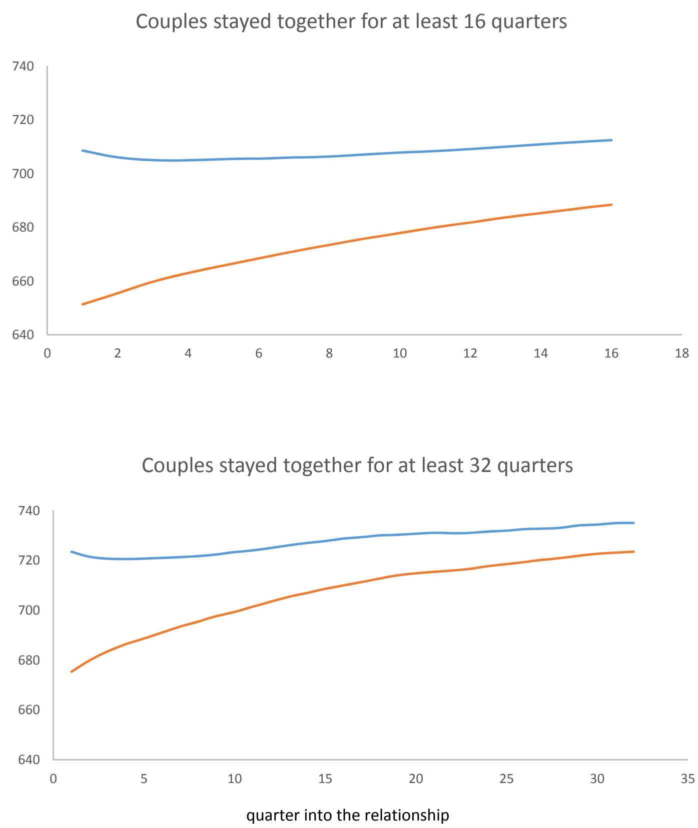
Note. The trustworthiness index is defined as 100 times the share of respondents who replied that "most people can be trusted" to the 2000 Social Capital Community Survey (SCCS) for each community surveyed, using the SCCS weights. Median income is the 2000 U.S. Census statistics of the corresponding community. Results reported in column 3 concern the individuals who lived in the communities covered by the survey for at least three years before moving out of these areas. The individuals' credit scores were taken three years after the move.

Table 14: Statistics Regarding How Self-Reported Trustworthiness Affect Relationships

	SCCS respondents analysis	
Shares of individuals that have high trust levels	Married	Separated or divorced
	52.0%	42.3%
Correlations between		
Shares of the separated and divorced and shares of high trust levels	-0.37***	
	CCP couples analysis	
	(1)	(2)
Effects on separations within six years		
Trustworthiness index	-0.777*	-0.447
	(0.381)	(0.423)
	[0.941]	[0.966]
$\frac{Initial score}{100}$		-0.560***
		(0.020)
		[0.599]
Controlling for		
Age polynomials	Yes	Yes
Age diff.	Yes	Yes
Char. of community of rel. formation	Yes	Yes
Yearly FE	Yes	Yes
N	112,429	112,429

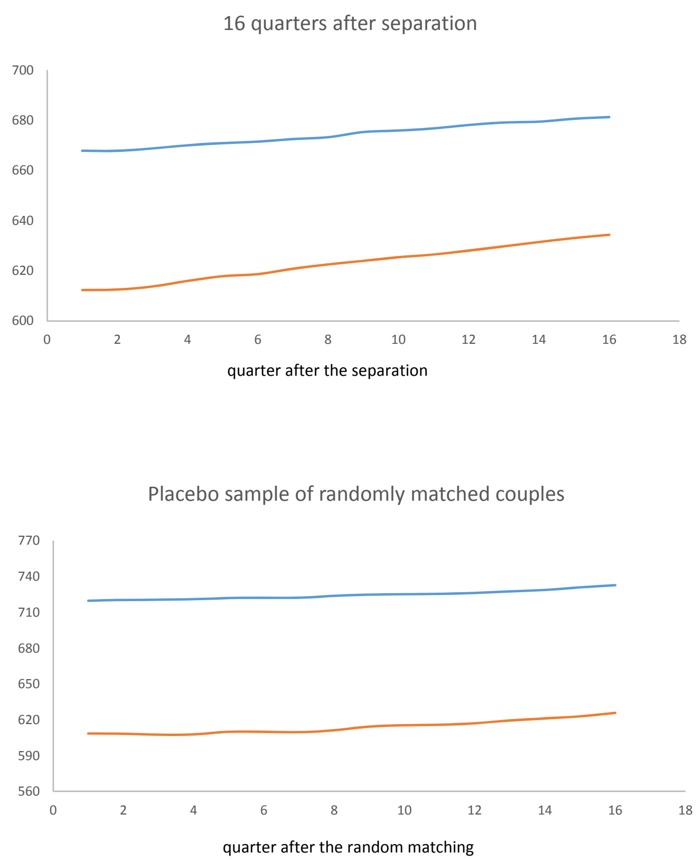
Note. Individuals of high trust levels refer to the respondents who replied that "most people can be trusted" to the 2000 Social Capital Community Survey (SCCS). The trustworthiness index is defined as 100 times the share of respondents who replied that "most people can be trusted" to the 2000 Social Capital Community Survey (SCCS) for each community surveyed, using the SCCS weights. Standard errors are clustered at the SCCS community level. Odds ratios are calculated by increasing the independent variable by one standard deviation. * denotes the estimate is statistically significant at the 90 percent level, and *** denotes the estimate is statistically significant at the 99 percent level. The differential between the two coefficients of the bottom row is also statistically significant at the 99 percent level.

Figure 1: Dynamics of Credit Score Gaps of Lasting Spousal Relationships



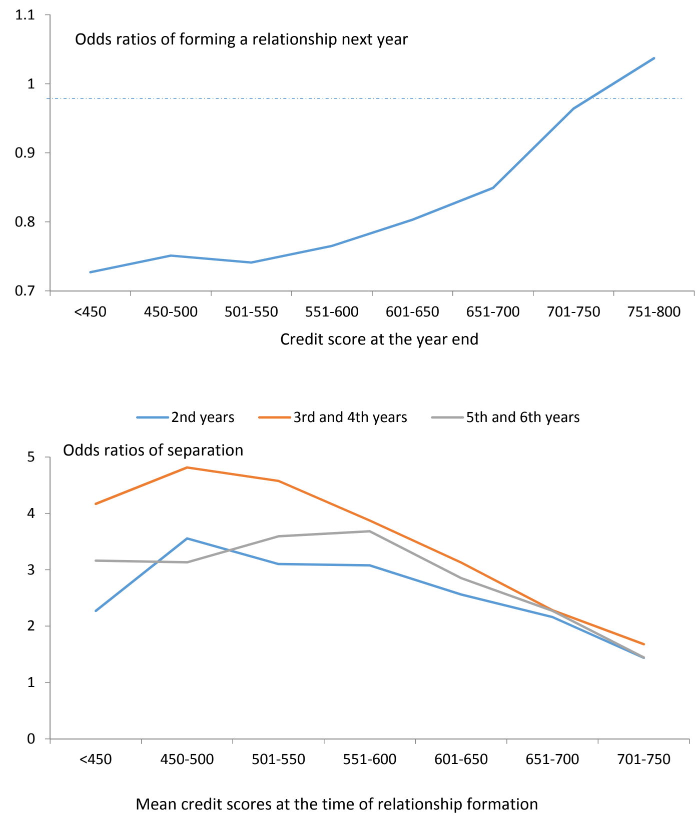
Source: Authors' calculation using the FRBNY Consumer Credit Panel / Equifax Data.
Note: The blue curve shows the average credit score of the individuals who had the higher score of a couple as of the time of relationship formation. The orange curve shows the average credit score of the individuals who had the lower score of a couple as of the time of relationship formation. The series are estimated using the couples where both individuals are in the primary sample.

Figure 2: Dynamics of Credit Score Gaps of Separated and Placebo Couples



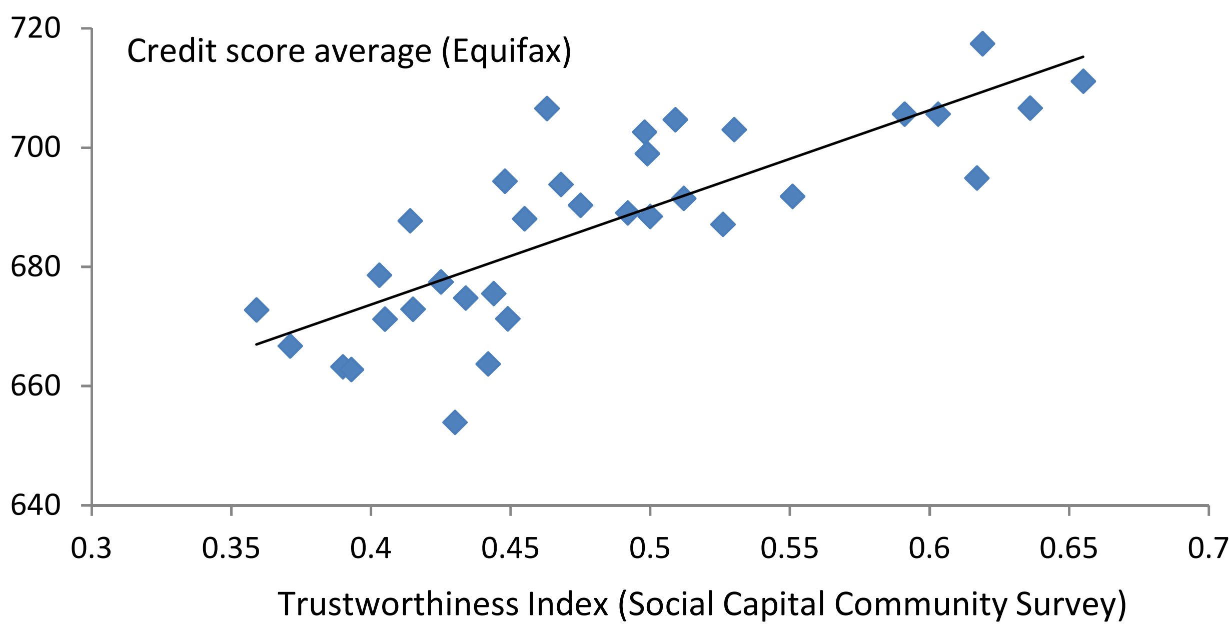
Source: Authors' calculation using the FRBNY Consumer Credit Panel / Equifax Data.
Note: The blue curve shows the average credit score of the individuals who had the higher score of a couple as of the time of relationship formation. The orange curve shows the average credit score of the individuals who had the lower score of a couple as of the time of relationship formation. The series are estimated using the couples where both individuals are in the primary sample. The placebo sample is constructed by randomly matching individuals of the primary sample, respecting the age and age differential restrictions imposed on the identified couples.

Figure 3: Credit Scores and Relationship Formation and Dissolution



Source: Authors' estimation using the FRBNY Consumer Credit Panel / Equifax Data.
Note: The top panel plots the estimated odds ratio of forming a relationship within the next year for the 50-point credit score bin dummies in eq. (2), with credit scores higher than 800 being the omitted group. The bottom panel plots the estimated odds ratio for separation during the second year (the blue curve), the 3rd and 4th year (the red curve), and the 5th and 6th year (the green curve) for the credit score bin dummies in eq. (4), with credit scores higher than 750 being the omitted group.

Figure 4: Credit Scores and Trustworthiness



Source: Authors' calculation using the FRBNY Consumer Credit Panel / Equifax Data and the Social Capital Community Survey.
Note: The figure plots the estimated trustworthiness index—the weighted share of respondents who replied that "most people can be trusted" to the 2000 Social Capital Community Survey of each surveyed community (horizontal axis) against the average credit score for the same community (vertical axis).