Trustworthiness and Relationships

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Abstract

We use credit scores in a large longitudinal proprietary data to measure individuals' trustworthiness and study how levels and within-couple differentials in trustworthiness influence formation and dissolution of spousal relationship. We first document a strong correlation between credit scores and survey based instruments of trustworthiness. We show that individuals with higher credit scores are more likely to enter a spousal relationship relative to otherwise comparable singles. We then show that, substantial positive assortative mating notwithstanding, there are significant within-couple credit score differentials at the time of relationship formation. We further demonstrate that greater initial mismatch in credit scores led to lower joint consumption and great financial distresses during subsequent years. Moreover, we present strong evidence that couples with lower average credit scores and wider within-couple score differentials at the time of household formation are more likely to separate during the ensuing years, even controlling for subsequent joint consumption and financial distresses.

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1 Introduction

Seeing how a large and growing literature emphasizes the importance of trust for micro- and macroeconomic outcomes, it is natural to think that trust plays an important role in partner selection and household dissolution. For instance, based on the evidence showing a strong correlation between trust and the performance of firms or the economic development of countries, one might infer that more trustworthy individuals sort into more lasting and successful relationships (Coleman, 1990; **?**; Fukuyama, 1995; Guiso et al., 2000; Alesina and Ferrara, 2002). One might also draw the analogy that trust enhances agreements over household production and the allocation of household resources just as trust mitigates problems with incomplete contracts in other contexts (Arrow, 1972; Weiss, 1997; Sobel, 2002; Karlan, 2005). But rather than speculate, we provide direct evidence in this paper on the role of trustworthiness in partner selection and the dissolution of couples.

Although there has been significant research on why couples form and separate since Becker (1973), little is known about the role of trustworthiness, most likely due to the difficulty of observing and measuring this trait (Glaeser et al., 2000; Fehr et al., 2003; Sapienza et al., 2007). We propose using credit scores as a metric for trustworthiness and argue that they overcome some of the measurement challenges confronting the earlier literature. Notably, unlike survey-based measures, credit scores, are, by construction, an objective measure that is independent of other traits that survey-based measures are at risk of capturing, such as risk aversion, inequity aversion, guilt, altruism, and reciprocity (Rabin, 1993; Karlan, 2005; Sapienza et al., 2007). Further, credit scores are used widely by lenders, landlords, cell phone companies, and potential employers to measure behaviors correlated with being trustworthy and reliable, such as loan repayment, timely bill or rent payment, and on-the-job reliability and performance. Finally, we show that a county's average credit score is highly correlated with survey-based measures of trustworthiness. Hence, in practice, credit scores are a clear measure of financial trustworthiness and a strong proxy for general trustworthiness.[1]

Our data are from an anonymized quarterly administrative panel of 12 million individuals with credit records, which are collected by a large credit reporting bureau. These panel data allow us to identify marital and cohabitating couples that form during the sample period and follow each member over time, even if they separate. Tracking these couples affords the opportunity to apply and test a number of well-known hypotheses about partner selection and why households dissolve in the context of trustworthiness (Weiss, 1997). For instance, whether high credit score individuals match with other high score individuals informs us about the role of trustworthiness in the acquisition and division of jointly consumed public goods, the degree to which individuals seek to maximize the gains from a division of labor, and, more broadly, endogamy and homogamy in partner selection (**?**Becker, 1973; Mare, 1996; Kalmijn, 1998). Also, because of the panel structure of the data, we are able to track how match quality in trustworthiness, measured as the within-couple credit score differential, evolves over time, which allows us to weigh the explanatory power of changing match quality in explaining household dissolution vis--vis other explanations (c.f. Weiss and Willis (1997), Chiappori and Weiss (2001), Hess (2004), Brien et al. (2006), and Marinescu (2013).

We also explore three ways in which initial match quality in trustworthiness foreshadows subsequent outcomes, which may in turn influence how individuals might select partners. First, we assess how two partners' relative trustworthiness contributes to household consumption, which is one measure of the value of the relationship. In many economic models, the consumption gains from becoming a couple are a function of, among other things, match quality, which is typically measured in terms of labor market variables, such as earnings or job loss (Weiss, 1997; Brien et al., 2006; Marinescu, 2013). In our paper, we observe match quality in trustworthiness and so use this variable in a reduced-form empirical model to discern whether our measures of consumption in the credit-reporting data, which we describe in detail in Section XXX, vary with initial match quality, conditional on other factors. The results of this empirical model also can

[1] One exception - people with thin files, i.e. young people and immigrants (Avery et al., 2009).

provide suggestive evidence on whether couples make strategic consumption decisions based on their credit scores.

Second, we estimate the relationship between initial match quality in trustworthiness and subsequent financial distress, such as bankruptcy, the occurrence of missed payment obligations (i.e. serious delinquency), and other derogatory credit events. Typically, financial distress is attributed to income or health shocks, the absence of financial literacy, or strategic motives whereby filing for bankruptcy or failing to make payments on financial obligations leaves one better off (Keys ????, Fay et al. ????, Lusardi and Tufano ????, OTHER SOURCES). Hence finding a role for initial match quality in trustworthiness marks a potentially new channel through which households experience financial distress.

A summary of our results is as follows. First, we find strong assortative matching with respect to trustworthiness on the extensive and intensive margins. Individuals with higher credit scores are more likely to enter cohabiting or marital relationships as well as match with others with high credit scores. The positive assortative matching appears to be independent of other individual traits by which individuals sort, such as age, education, race, and income, and is consistent with the notion that trustworthiness facilitates the intrahousehold allocation of public goods. Second, match quality in trustworthiness is highly predictive of joint household consumption and financial distress, holding other traits constant. (We also find that couples with large credit score differences use the high-score individual's access to credit in order to finance their consumption.) Third,

(Implications of our work for various strands of literatures) Our paper complements a wide range of results in the existing literature. In addition to documenting a new socioeconomic characteristic by which individuals sort into relationships, we show that the quality of the sorting has important implications for household behavior, particularly how households choose to finance their joint consumption (Chiappori et al., 2012; Banerjee et al., 2013). We also provide new evidence on the importance of trust in household finance, consistent with the previous research highlighting the role of trust in finance (Sapienza et al., 2007)On a final note, numerous media anecdotes have recently highlighted the importance of credit scores in building and maintaining a successful relationship, and we are the first to systematically study the connection between credit scores, partner selection, and household dissolution (NYT, WSJ, etc.).

The remainder of the paper is organized as follows. The next section briefly outlines the conceptual framework for our paper and Section 3 describes the process of credit scoring in the United States.

2 Conceptual Framework

It is widely acknowledged that trustworthiness plays a pivotal role in a spousal relationship. However, less clear is what exactly trustworthiness means and implies, and the channels through which it influences relationships. Indeed, to the best of our knowledge, there are very few, if any, economic models that take into account trustworthiness in an explicit and mechanic way. We argue that trustworthiness may encompass several related but distinct aspects of an individual's preferences and choice set, each of which could affect the formation, payoffs, and potential dissolution of a spousal relationship. The ingredients we discuss below can be employed to augment models of search and matching in marriage market, intra-household resource allocations, and separations and divorce.

First, the most eminent implication of being trustworthy is arguably an individual's strong tendency of sticking to an existing relationship and honoring a contract one entered even under conditions where doing so may induce some immediate direct losses. Thus, trustworthiness may reveal the disutility incurs when one walks away from a relationship or a contract. For example, if an individual is intrinsically averse to walking away from a relationship or a contract, such a self-imposed stigma may outweigh the potential losses of sticking to the relationship or honoring the contract. Second, a trustworthy person is likely also an altruistic one. Or, as argued by Hardin (2002) "In trust you because your interests encapsulate mine to some extent." An altruistic person who cares about the welfare of the partner in a relationship is more trustworthy, other factors held constant, than one who cares only his own benefit.

Third, in addition to these behavioral assumptions, the level of trustworthiness also reflects how patient an individual is—i.e., the discount factor, β. Instead of a stigma of break-up aversion, one may choose not to break up a relationship even when his current surplus it offers is low or negative because he puts sufficiently large weight on potential future gains from the relationship. In a similar vein, a high β person, other factors held constant, are more likely to invest in relationship and make it more resilient and robust and last longer.[2]

A spousal relationship involving more trustworthy individuals are beneficial to both partners for several reasons. First, a higher degree of mutual trust imply lower monitoring costs. Spouses of trusting relationship do not have to spend a great deal of time and effort verifying and monitoring each other whether the partner's action is against one's own interest. Second, because a trusting relationship is also expected to be a lasting one, the couple is more likely to engage in longer-term investment and sharing durable goods, such a buying a home or a car, thus increasing the joint consumption and felicity of the relationship and making the relationship more likely to last.

3 Credit Scores and Trustworthiness

3.1 A Primer on Credit Scores

Credit scores evaluate the credit quality of potential borrowers (Avery et al., 2003). Specifically, an individual's credit score reflects a rank ordering that corresponds to her credit risk and the likelihood that she will become delinquent on an account at some point in the near future. Each of the major credit reporting bureaus applies a proprietary algorithm to evaluate this rank ordering and the credit score we use is one such proprietary product. The payment history is the most important determinant of one's credit score, but other factors, such as levels of indebtedness, length of the credit history, the types of credit used, credit limits, and public

[2] This notion is broad consistent with the observations that, regarding financial contract, borrowers exhibiting hyperbolic discounting behaviors are more likely to experience loan defaults.

judgments, such as a bankruptcy, foreclosure, tax lien, and garnishment are also contributing factors (Chatterjee et al., 2011). Federal law prohibits the use of race, color, national origin, sex, and marital status in calculating a consumer's credit score. 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 other attributes are correlated with scores (Avery et al., 2009).

As discussed earlier, lenders use credit scores to identify prospective borrowers, evaluate their applications, and price loans. Generally, those with higher credit scores are deemed more reliable in being able to meet their debt repayment obligations. Accordingly, they face lower prices in the form of lower interest rates, loan origination fees, or other loan charges. They are also less likely to be denied credit. Nearly all banks and large financial institutions use credit scores in their lending operations to consumers. Also, many employers and utilities, such as cell phone and cable companies, use credit scores in their hiring process and contract-based plans, respectively. Generally speaking, the availability of credit scoring has enabled lenders, employers, and utilities to easily and objectively assess credit risk, and some of these efficiency gains have been passed on to consumers in the form of increased access to credit, cheaper credit, and fairer lending standards.

3.2 Do Credit Scores Reveal General Trustworthiness?

Add results of the Social Capital Community Survey. Figure 1

4 Data Description

4.1 Consumer Credit Panel

Our main source of data is from Equifax, one of the three largest credit reporting agencies in the U.S., and is often referred to as the Consumer Credit Panel (henceforth the Equifax Panel).[3]

[3] These data have been used in various studies of household finances (notably, the Quarterly Reports on Household Debt and Credit released by the Federal Reserve Bank of New York).

The data are a quarterly panel and track a five percent random sample (the "primary sample") of all U.S. consumers with valid credit history.[4] Our study employs the Equifax Panel data from the first quarter of 1999 through the second quarter of 2012. A unique feature of the Equifax Panel is its large sample size, with the primary sample containing 12 million consumers in a typical quarter. Note that because individuals are randomly selected, we do not need to use sample weights.

In addition to the primary sample, the Equifax Panel follows consumers who live at the same address as a consumer from the primary sample as long as the other household members share the same address. So these "secondary" consumers and their credit records are no longer observed once they stop living with a primary sample member. About 30 million non-primary sample consumers live with someone in the primary sample.

Each individual in the Equifax Panel is identified over time with a unique and time-invariant consumer identification number (CID). Within in the sample, all individuals residing at the same *street address* in a given quarter were assigned the same household identification number (HHID) and assigned the same scrambled address ID.[5] But because the HHID varies from quarter to quarter and cannot be used to link households or individuals across quarters, we are limited in our ability to track households over time using the HHID alone and instead must identify households quarter-by-quarter and observe them over time via the consumers' CIDs. The scrambled address information contains enough detail to be able to discern an individual's state, county, census track and block, which we will exploit in our analysis.

The variables in the Equifax Panel are from the consumers' credit reports, which includes information on loan account balances and delinquency status, bankruptcy and other derogatory flags, and inquiries on credit history. The data also include a proprietary credit score developed

[4] The randomness of the sample derives from including only individuals whose the last two digits of their social security numbers belong to a prespecified 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, hence being essentially randomly assigned. Such randomness is a feature of, for example, **?** and **?**.

[5] Note that the individuals who share the same HHID do not have to belong to the same economic household. For example, roommates, dorm mates, and tenants of the same apartment building all have the same street address, thus have the same HHID.

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 a different algorithm and ranges from 280 to 850, with a higher score indicating a lower credit risk.[6]

4.2 Other Data Sources

Its massive sample size and rich credit history information notwithstanding, the Equifax Panel contains very limited demographic and socioeconomic information for sampled consumers, largely because federal laws prohibit the use of information on race, color, national origin, sex, and marital status in credit underwriting and in calculating credit scores. Indeed, the only demographic information contained in the data is the year of birth. Because demographic and socioeconomic characteristics are important factors influencing household formation and dissolution, we supplement the Equifax Panel 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 1,000 residents. Using block group-level averages, we approximate individual level demographic and socioeconomic characteristics.

Because the Equifax Panel does not have explicit data on marital status, the formation of marital and cohabiting relationship has to be inferred. The next section describes in great detail our algorithm for identifying the formation of spousal relationships and, notably, its timing. To validate our algorithm, we compare key statistics derived using our algorithm and the Equifax Panel with those estimated using the Panel Study of Income Dynamics (PSID), the National Longitudinal Survey of Youth (NLSY79), and the Mintel/Comperemedia data of mail solicitations, which directly measures marital status.[7]

Finally, in order to examine the merit of using credit scores as an indicator of individuals' general trustworthiness, we estimate the average credit scores of the areas covered in the Social

[6]For more information about the Consumer Credit Panel, see **?**.

[7]Both the PSID and NLSY79 surveys have been used extensively in variously areas of economics research. For more information about these two surveys, see http://psidonline.isr.umich.edu and http://www.bls.gov/nls/nlsy79.htm, respectively.

Capital Community Survey (SCCS) and correlate them with trust measures in the SCCS.[8]

5 Algorithm for Inferring the Timing of Relationship Formation

5.1 Identification Algorithm for Relationship Formation

This section details our algorithm of identifying when spousal relationships begin and end, which we argue overcomes the absence of marital status information in the Equifax Panel. In much of our analysis, we focus on consumers in the primary sample because these individuals are most consistently followed in the Equifax Panel.[9] We exploit the dynamics of consumers' address to infer the timing of marital and cohabiting relationships, including when they begin and end. If two individuals start living at the same address in given quarter, remain living together afterwards, and have not previously shared an address, we infer that the two individuals form a spousal relationship in this quarter. Similarly, if the couples we identify begin living at different addresses in a subsequent quarter and never share an address during the sample period, we infer that the couple separates at this subsequent quarter. Being able to observe the same HHID code for consumers sharing the same street address in a given quarter makes our approach feasible.

Because other types of non-spousal relationships, such as long-term roommates and adult children moving back to live with parents for an extended period of time, may also pass such a screening, we impose further restrictions to exclude these possibilities. Specifically, in each quarter Q, we first select all households consisting of exactly two primary sample individuals with no additional non-primary sample consumers. This restriction leads us to exclude couples that form and live together in apartment buildings or that have additional adults living with them, and thus understate the occurrence of marital and cohabiting relationships. Next, we keep only the couples where the two individuals do not share the same HHID between $Q-8$ and $Q-1$, which screens out existing couples that temporarily live apart, but share the same HHID

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

[9]One of our robustness tests takes advantage of the non-primary sample consumers, which we discuss in detail in Section 8.

through the end of $Q + 4$, which excludes two-person households consisting of roommates.[10] Finally, we impose two age restrictions to rule out the possibility of children moving in with their parents: the two individuals (in quarter Q) must be between the ages of 20 and 55, and the difference between their ages is less than 12 years.[11] In spite of these restrictions, it is still possible that some of the couples we match are not spousal relationships, so in Section 8, we apply an additional robustness restriction by requiring the two individuals to share some type of joint financial account.

An important feature of our algorithm is that we cannot distinguish between married and cohabiting couples. However, for our purposes, this distinction is not all that critical because we are interested in the how trustworthiness plays out in a general swathe of spousal relationships, not just marital ones. In addition, cohabiting couples also share household and financial responsibilities, so trustworthiness is important to study in this context. Lastly, given recent secular trends in marriage and cohabitation, making this distinction seems less important as the lines between the two are becoming increasingly blurred (Stevenson and Wolfers, 2007).

5.2 Identification Algorithm Validations

Table 1 presents statistics on the spousal relationships identified using this algorithm. More than [31,000] couples form during our sample period, which implies a quarterly relationship formation rate of 0.012 percent (column 1)— or 120 couples per one million individuals—or an annual rate of about 0.05 percent.[12] Because the baseline algorithm identifies only the couples formed in the primary sample, we are only observing the relationships formed within a small subset of the U.S. population. Indeed, because the primary sample in the Equifax Panel is a five percent sample of U.S. consumers with valid credit history, our relationship formation rate

[10] Note that we require the two individuals to live together for at least five quarters at the same address so as to exclude relationships between roommates, who typically do not live together longer than one year.

[11] Various nationwide household surveys suggest that the 99th percentile of couple age differential distribution is about 12 years.

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

should be about $\frac{1}{20}$ of the population formation rate.[13] Taking this discrepancy into account, the implied population relationship formation annual rate is about 0.96 percent (column 2), which is only a bit higher than the marriage rates—0.92 percent—among individuals aged between 20 and 55 estimated using the PSID data over the comparable sample period. We believe two countervailing forces lead our estimate to be in line with the PSID estimate of the marriage rate. On the one hand, our inclusion of cohabiting couples leads our estimate to be upwardly biased, all else equal. But on the other hand, the exclusion of couples living in apartment buildings leads us to understate the marriage rate.[14] Nevertheless, we find the similarities with the PSID reassuring in terms of the order of magnitude. Furthermore, the relationship formation rate is broadly consistent with population marriage rate statistics.

To further assess the validity of the algorithm, we compare the relationship formation rate for each age group with age-specific marriage rates estimated using the PSID data. Although the numbers are not identical, the trends are similar, with the rate decreasing with age. The adjusted relationship formation rates for age groups $25-35$, $36-45$, and $46-55$ are about 1.28%, 0.96%, and 0.60% respectively, while the corresponding PSID rates are 2.0%, 0.76%, and 0.35% respectively. Finally, we examine the extent to which the state-level variation in the Equifax relationship formation rate is correlated with state-level marriage rates (from the Statistical Abstract of the United States). We find that the correlation is about [0.6], which is positive and statistically significant. The correlation coefficient is not very large, likely due to that a significant share of marriages are registered in a state that can be different from the state in which a couple resides.

To summarize, we find the relationship formation rates estimated using the Equifax Panel compare favorably to the marriage rates estimated using the PSID data and the state-level marriages rates, suggesting the proposed relationship identification algorithm is not out of range.

[13] Taking into account that not all consumers have valid credit history, the gap between the sample and the population formation rate can potentially be even greater.

[14] Apartments comprise about one-third of the housing stock and a higher share of the stock occupied by 20 to 55 year olds.

5.3 Identification Algorithm for Relationship Dissolution

To identify the couples that separate, we start with the couples that form using the algorithm described above. Specifically, among the couples that are identified, we infer a separation when the two individuals live at different addresses for at least five consecutive quarters and never share the same address again (during the sample period). We find that the dissolution rate in the baseline sample of households is fairly high—about one in five of the spousal relationships dissolved within the first ten quarters of the quarter of formation, Q, and more than 50 [???] percent do so within the first four years. The high dissolution rate in the baseline sample underscores the possibility that some of the households are non-marital cohabitations that, on average, have a much shorter duration than marriages.

6 Matching Quality at the Time of Relationship Formation

This section studies the quality of matching at the time of relationship formation and how it evolved subsequently. We will first focus on demographic and socioeconomic characteristics and draw comparisons with other survey data and the existing literature. We then present, to the best of our knowledge, the first set of evidence on matching quality regarding trustworthiness measured with credit scores.

6.1 Match Quality in Demographics

As shown in table 2, the average age of the involved individuals at the time of relationship formation is 36 years, the average age differential is 3.6 years, and the within-couple age correlation is 0.85. These statistics are broadly consistent with what we estimated using nationally representative survey samples where marital status is observed. For example, the PSID average age at marriage, shown in column 2, is slightly younger. However, the age differentials and with-in couple age correlation are remarkably similar between the Equifax Panel and the PSID. 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.[15] More specifically, we use the share of adults in a block group with a specific characteristic as an approximation, and we use the census block group median income to approximate individual income. Notably, the estimated correlations are consistent with previous studies, as is the rank ordering of their magnitudes. The approximated within-couple racial correlation is about 0.6, college degree correlation about 0.5, and income correlation 0.4 (see, for example, respectively, (Weiss and Willis, 1997; Garfinkel et al., 2002; Blackwell and Lichter, 2004). Moreover, the approximated income correlation is about 0.4, consistent with earlier evidence on a lack of empirical support for negative assortative mating on wages (Lam (1988)). Furthermore, the racial and income correlation coefficients are remarkably similar to those estimated using the PSID 1999-2009 data on newly married couples. However, the PSID college degree correlation is a bit lower, which we interpret as a data anomaly.[16]

6.2 Match Quality in Trustworthiness at the Start of a Spousal Relationship

The central focus of our study is the matching patterns of trustworthiness, which we measure with one's credit credit scores, both at the onset of a relationship and the subsequent evolvement. As shown in table 3, among our sample of identified spousal relationships formed between 2001 and 2011, the average credit score of individuals at the time of relationship formation is about 660. The within-couple correlation coefficient of 0.59, implying a significant positive matching regarding trustworthiness. That said, the matching is not perfect, as evidenced by the within-

[15] 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. We use the census block group where the individual had lived for the longest time for those who lived in multiple addresses.

[16] The PSID data show a significant and persistent decline in within-couple college degree correlation, making the PSID statistics somewhat lower than those derived from other nationwide surveys, such as the Survey of Consumer Finances (SCF) and the Consumer Expenditure Survey (CE). The SCF and CE college degree correlations are about 0.45 for the sample period of 2001-2010, much closer to the Equifax Panel estimates. However, we do not observe the tenure of relationships in SCF and CE.

couple credit score differentials averaged 68. Put this statistic in perspective. The memo line of the table shows the standard deviation of credit scores in the entire Equifax Panel is about 106, implying an average difference between any two randomly matched person of about 150. Hence, the within-couple credit score is slightly smaller than one half of the difference between two randomly matched individuals.

The significant within-couple score differentials are not primarily caused by quarter-to-quarter variations in credit scores. Column 2 of the table shows the same set of statistics for the average score over quarters $Q-3$ and Q. Although the absolute magnitudes of the differentials are somewhat smaller, they remain about 70 percent of the standard deviation of four-quarter average of credit scores in the entire Equifax Panel, similar to column 1.

As shown in lower panel of table 3, credit score differentials are not the same across different levels of couple mean scores. The two lower quartiles have the largest differentials of above 80, while the differentials among couples in the highest quartiles is only 30, indicating that the matching quality among high-credit score couples is much better.

What factors can account for the within-couple correlation of credit scores? Avery et al (2009) document that modern credit scores are estimated mainly off credit history data. Similar credit scores thus imply similar credit history and alike use of credit in the past. We estimate the following equations to parse out the aspects of credit history that are similar for both spouses.

$$attr_1^i = \alpha + \beta attr_2^i + \gamma Z, \tag{1}$$

where $attr_1^i$ and $attr_2^i$ are the attribute i on individual 1 and 2's credit report. We will focus on five key indicators of credit reports—having bankruptcy flags and currently having serious delinquent account (measuring the past and current credit quality), number of credit report inquiries (measuring intensity of credit demand), and total debt and credit card utilization (measuring use of credit). Because usage of and attitudes toward credit are likely influenced by individual characteristics, we control for the merged census block group statistics vector Z—including race, education, and log of median income, in the regression. For the bankruptcy and delinquency indicators, we use logistic regression, and OLS elsewhere.[17] The results are presented in table 4. [Need to flush some discussion out]

7 Dynamics of Trustworthiness and Spousal Relationship

This section studies how individual's trustworthiness and matching quality of trustworthiness interact with the dynamics of spousal relationship formation and dissolution. We will first examine the relationship between an individual's level of credit score and his prospect of forming a relationship and study the evolvement of credit score levels and within-couple score differentials after a relationship is formed. We then explore how initial credit score differentials affect the subsequent joint consumption and financial distresses of the couple and whether initial credit score differentials help predict future dissolution of the relationship.

7.1 Credit Score Levels and Spousal Relationships

To begin with, we explore if more trustworthy individuals are more likely to enter a spousal relationship than otherwise comparable singles. [ADD SOME JUSTIFICATION WHY THIS IS INTERESTING]. Specifically, we estimate the following logistic model using pooled cross-sectional data of Q4-to-Q4 changes in relationship status.

$$M_y^i = \alpha + \beta CreditScore_y^i/100 + \gamma Z^i + \theta \Delta Emp_y^{county_i} + \omega State_y^i + \zeta Year_y + u_y^i, \qquad (2)$$

where M_y^i is a binary variable indicating whether individual i, who was single as of $Q4$ of year $y-1$, formed a relationship as defined in Section 5.1 in $Q4$ of year y. Z is the demographic and socioeconomic characteristics vector as defined in eq. (1). $\Delta Emp_y^{county_i}$ is the four-quarter change in employment between $Q4$ of $y-1$ and y in the county where individual i resided, controlling for local economic conditions. $State$ and $Year$ are vectors of state and annual dummies respectively, controlling for aggregate economic conditions and state-level variations

[17] Tobit regressions yield very similar results.

in relationship formation rate. Results, presented in table 5, suggest that a one-hundred-point increase in credit score leads to a 14 percent higher annual rate of forming a spousal relationship. To study if there is any nonlinearity in the relationship before credit scores and relationship formation likelihood, we reestimate the above equation, replacing $\frac{CreditScore}{100}$ with a vector of dummies that indicate which 50-point score bin a single individual belong to. The singles that have the highest credit scores—above 800—are in the omitted group. As shown in figure 2, relative to the highest-score singles, those with the lowest credit scores are about 50 percent less likely to form a spousal relationship in a given year. The gap narrows considerably for singles with higher score but remained significant both statistically and economically significant for people who scores below 750.

We now test whether forming a relationship conversely changes the course of how credit scores evolve. We follow the individuals who were single in 1999 and study how spousal relationships formed in subsequent years change the trajectory of their credit scores. Figure 3 shows that the age profile of credit score of individuals in a spousal relationship is on average about 30 points above that of those not in a spousal relationship, a gap that is statistically and economically significant. To further isolate the effect of entering such a relationship on the trajectory of credit scores, we estimate the following equation

$$\Delta CreditScore_y^i = \alpha + \beta Age_y^i + \gamma Age_y^i \ \times \ Relation_y^i + \zeta Year_y + u_y^i. \tag{3}$$

The estimated γ coefficients, plotted in the lower panel of figure 3 indicate that for individuals younger than 40 years old, being in a spousal relationship implies a larger annual increase in credit score. The differentials become less pronounced between age 40 and 50 and slightly negative for individuals above 50.[18]

[18]Moreover, estimating a simple age profile of credit score annual differences with dummies of forming and dissolving a relationship, we find that on average forming a relationship boosts credit score annual increase by about 4 points and dissolving a relationship reduce annual increase by 3.5 points, and both estimates are statistically significant.

7.2 Dynamics of Credit Score Differentials

We documented that, despite a high level of correlation, there exists a substantial gap, on average, between two individuals' credit scores at the time they form a spousal relationship. We are interested in how these gaps evolve after the formation of a relationship. In particular, do the credit score differentials narrow as two spouses live together and presumably share financial responsibilities. To fix the idea, we first focus on couples that remained living together 16 quarters after forming a relationship. The two curves in the upper panel of figure 4 show the average post-relationship-formation score dynamics of the individual who had the relatively higher and lower score at the time of relationship formation. As the figure indicates, the credit score gap narrows appreciably over the first 16 quarters of the relationship, from about 55 points to about 22 points. The convergence realized mainly because of the increase in the credit score of the person who had a relatively lower score (the red curve) at the time of relationship formation. The pattern is similar among couples who have longer tenures of relationship. As shown in the lower panel of figure 4, the average credit score gap among couples who stayed together for at least 8 years narrowed from 46 points at the time of relationship formation to about 10 points by the end of their eighth year in the relationship. Note that the initial average score differential is a bit low for the couples that have a longer relationship duration, a phenomenon we will revisit in detail in the subsequent parts of the paper. In addition, it is not uncommon that the within-couple ordering of credit score switched. By the end of the first four years of the relationship, 36 percent of the couples saw this ordering flipped.

Such a convergence in credit score during a spouse relationship is not likely driven by the underlying age-trend in credit scores. The top panel of figure 5 shows the average credit scores of the two individuals during the first 4 four years after separation. The two curves are essentially parallel to each other and the change in score gap is only 8 points. Similarly, the lower panel shows that there was no significant changes in score gaps among a sample of placebo–couples randomly assigned.

7.3 How Credit Score Differentials Affect Joint Consumption and Financial Distresses

We now study two channels through which differentials in trustworthiness may affect spousal relationship outcomes. First, differences in trustworthiness may affect joint consumption, and second such differences may induce suboptimal management of household finance and therefore increase the chance of being exposed to financial distresses. We consider the two groups of indicators to measure joint consumption of a couple: opening joint mortgage, credit card, and auto loan accounts and having new mortgage, credit card, and auto loan debt after forming a spousal relationship. We study the joint consumption status as of the first, the third, and the fifth after relationship formation. For opening joint accounts indicators, we use the subsample of couples that did not have joint accounts of specific loan types as of the quarter of relationship formation. For accumulating new debt indicators, we use the entire sample of couples. We use the same control variables as in eq. (2) except that we do not include the *State* dummy vector. In addition, we control for levels of credit scores measured concurrent to joint consumption indicators. The results are shown in table 6. As the table shows, across types of credit and durations of the relationship, a greater credit score gap measured at the beginning of the spousal relationship almost always imply a lower likelihood of having either joint loan accounts or new credit. For example, at the end of the first year of the relationship, a one-standard-deviation increase in initial credit score gap leads to a 45-, 39-, and 37-percent lower likelihoods of having joint mortgage, credit card, and auto loan accounts, respectively. Such gaps narrowed somewhat over the course of the relationship but remained statistically and economically significant even five years after. Similarly, the probabilities that the couple borrowed new debt are also lower for couples with greater initial credit score gaps, though by a smaller margin. The differences between the effects of credit score gaps on likelihood of having joint accounts and those on the likelihood of having additional debt likely reflect consumers' strategic reactions to credit contract offerings. Couples with more different credit scores are more likely to apply for loans with single borrowers.

Higher credit score differentials at the time of relationship formation also, on balance, imply great likelihoods of subsequent financial distresses. We consider three types of financial distresses—having filed for personal bankruptcy since relationship formation, having serious (90+ days) delinquencies, and having derogatory credit records—as of the end of the first, the third, and the fifth year of the relationship. As shown in table 7, the likelihood of having each of the three types of financial stress at the end of the first year is higher for couples with greater initial credit score gaps. The effects remained significant and positive for new bankruptcy filings and having derogatory records at the end of the third and the fifth year. However, the effect on having serious delinquencies became insignificant at the end of the third year and became negative at the end of the fifth year.

7.4 Credit Score Differentials and Relationship Outcomes

Finally, we examine the extent to which the credit score differentials at the time of the formation of a spousal relationship affects this relationship's future outcomes. Specifically, we study the effects of initial credit score gaps on the likelihood of a couple having separated by the end of the second year of the relationship, by the end of the fourth years (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). We estimate the following logistic models

$$Sep^i_{y_1,y_2} = \alpha + \beta Diff^i + \gamma Score^i + \phi Z^i + \psi Stress^i_{y_1} + \kappa Debt^i_{y_1} + \theta \Delta Emp^{county_i}_{y_1} + \omega State^i_{y_1} + \zeta Year_{y_1} + u^i_{y_1}, \tag{4}$$

where $Sep^i_{y_1,y_2}$ indicates whether a couple who remained in a relationship as of y_1 years after the relationship formation had separated by y_2 years after. In our analysis $y_1 \in (1, 2, 4)$ and $y_2 \in (2, 4, 6)$. $Diff$ is the within-couple credit score differential observed at the time of relationship formation, and $Score$ is a vector of 50-point bin dummies of within-couple average credit score observed at the same time. In addition to controls included in eq. 2, eq. (4)

includes $Stress^1_{y_1}$, a vector of dummies indicating whether couple i experienced bankruptcy filing, foreclosure, serious delinquencies, and derogatory records as of y_1, and $Debt^1_{y_1}$, indicating whether the couple had a significant amount of mortgage, credit card, and auto debt as of $y-1$ as an indicator of joint consumption.

The estimated γ coefficients are plotted in figure 6, with the highest credit score bin (above 800) being the excluded group. As the figure indicates, the mean level of credit score at the time of relationship formation has a lasting effects on the outcome of spousal relationship. Couples with a mean score below 500 are three times more likely to separate by the end of the second year of the relationship than couples with a mean score above 800, four times more likely by the end of the fourth year (conditional on the relationship having lasted through the end of the second year). Even among couples whose relationship lasted for four years, those with lowest initial mean scores are still twice more likely to separate by the end of the sixth year.

Table 8 presents the estimated β coefficient. Without interacting credit score differentials with level quartiles, the estimated coefficients are all positive and statistically highly significant. Odds ratios shown in brackets suggest that a one-standard-deviation increase of initial score differential implies a 33 percent higher likelihood of separation during the second year, 24 percent higher during the third and fourth year, and 13 percent higher during the fifth and the sixth year. Such an effect largely prevails across quartiles of initial mean credit levels, with the only exception being the effects on separation likelihood during the fifth and sixth years among the couples with the highest initial credit scores, which is slightly negative but statistically insignificant. Notably, although the estimated coefficients are larger for the highest quartile couples in columns (2) and (4), the implied odds ratios are not the largest because of smaller within-quartile variations in the magnitude of credit score gaps.

8 Sensitivity Analysis

To be added.

9 Conclusion

To be added.

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Table 1: Spousal Relationship Formation Rates

	Equifax Panel data		PSID data
	Sample quarterly rate (1)	Adjusted annual rate (2)	Annual rate (3)
Whole sample	0.012%	0.92%	0.92%
Age 25-35	0.016%	1.28%	2.0%
Age 36-45	0.012%	0.96%	0.76%
Age 46-55	0.008%	0.60%	0.35%

Note.

Table 2: Spousal Characteristics at the Time of Relationship Formation

	Equifax Panel data (1)	PSID data (2)
Individual level Characteristics		
Average age	36.7	33.5
Age difference	3.5	3.8
Age correlation	0.86	0.86
Census block group level Characteristics		
% White Correlation	0.59	0.52
% College Grad Correlation	0.47	0.30
Median Income Correlation	0.42	0.37

Note.

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

	Formation quarter Q	Four-quarter average
Mean credit score	660	661
Within-couple correlation	0.59	0.64
Mean within-couple differential	68	37
Memo: Population standard deviation	106	56
	Mean within-couple score differentials	
	Mean	Standard deviation
Lowest mean score quartile	84	73
lower-middle mean score quartile	89	77
Upper-middle mean score quartile	68	56
Highest mean score quartile	30	28

Note.

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

All couples					
Bankruptcy logit (1)	Serious Del. logit (2)	Derog. rec. logit (3)	Log(total debt) OLS (4)	# Inquiries OLS (5)	CC utilization OLS (6)
2.26***	1.28***	1.21***	0.19***	0.16***	0.04***
(0.05)	(0.06)	(0.04)	(0.01)	(0.01)	(0.00)
[9.39]	[3.61]	[3.34]			

Couples did not have joint accounts before relationship formation					
Bankruptcy logit (1)	Serious Del. logit (2)	Derog. rec. logit (3)	Log(total debt) OLS (4)	# Inquiries OLS (5)	CC utilization OLS (6)
1.29***	0.78***	0.77***	0.05***	0.08***	0.02***
(0.06)	(0.07)	(0.04)	(0.01)	(0.01)	(0.00)
[3.65]	[2.19]	[2.13]			

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 one-percent level. The estimations control for age, shares of adults that are white, high school graduates, some college educated, college graduates, graduate school educated, and log of median income at the census block group level.

Table 5: Credit Score Levels and the Prospect of Forming a Spousal Relationship

$\frac{Creditscore}{100}$	$\Delta Emp\%$	log(income)	
0.124***	0.008***	0.186***	
(0.001)	(0.001)	(0.004)	
[1.144]	[1.024]	[1.102]	
White	**High school**	**Some college**	**College**
0.306***	0.266***	0.335***	0.196***
(0.008)	(0.024)	(0.019)	(0.023)
[1.082]	[1.030]	[1.034]	[1.022]

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 one-percent level.

Table 6: Credit Score Differentials upon Relationship Formation and Subsequent Joint Consumption

	$\frac{\text{Credit score differential}}{100}$								
	Mortgage			Credit card			Auto loans		
	1 year	3 years	5 years	1 year	3 years	5 years	1 year	3 years	5 years
Starting using joint accounts	-0.864***	-0.512***	-0.347***	-0.726***	-0.353***	-0.282***	-0.685***	-0.411***	-0.297***
	(0.065)	(0.052)	(0.054)	(0.094)	(0..078)	(.0082)	(0.056)	(0.048)	(0.054)
	[0.549]	[0.717]	[0.806]	[0.607]	[0.800]	[0.844]	[0.625]	[0.772]	[0.839]
Having new debt	-0.080**	0.090**	0.017	-0.100***	-0.234***	-0.250***	-0.078**	-0.096**	-0.135***
	(0.040)	(0.040)	(0.044)	(0.023)	(0.029)	(0.035)	(0.036)	(0.038)	(0.045)
	[0.948]	[0.947]	[1.010]	[0.936]	[0.869]	[0.869]	[0.949]	[0.944]	[0.927]

Note. Standard errors are reported in parentheses. Odds ratios of the logistic regressions are reported in brackets.

Table 7: Credit Score Differentials upon Relationship Formation and Subsequent Financial Distresses

	$\frac{\text{Credit score differential}}{100}$		
	1 year	3 years	5 years
New bankruptcy	0.453***	0.300***	0.127*
	(0.061)	(0.059)	(0.065)
	[1.347]	[1.195]	[1.073]
Serious del.	0.318***	0.042	-0.126**
	(0.025)	(0.041)	(0.058)
	[1.233]	[1.025]	[0.933]
Derog. rec.	0.543***	0.254***	0.090**
	(0.023)	(0.032)	(0.043)
	[1.429]	[1.163]	[1.051]

Note. Standard errors are reported in parentheses. Odds ratios of the logistic regressions are reported in brackets.

Table 8: Credit Score Differentials upon Relationship Formation and Subsequent Relationship Dissolutions

	2 years		4 years		6 years	
	(1)	(2)	(3)	(4)	(5)	(6)
$\frac{\text{Credit score differential}}{100}$	0.431***		0.357***		0.223***	
	(0.025)		(0.031)		(0.052)	
	[1.325]		[1.240]		[1.130]	
$\frac{\text{Credit score differential}}{100} \times$ first quartile		0.285***		0.221***		0.137*
		(0.038)		(0.048)		(0.083)
		[1.155]		[1.105]		[1.055]
$\frac{\text{Credit score differential}}{100} \times$ second quartile		0.503***		0.379***		0.266***
		(0.033)		(0.042)		(0.068)
		[1.327]		[1.210]		[1.125]
$\frac{\text{Credit score differential}}{100} \times$ third quartile		0.582***		0.576***		0.303***
		(0.053)		(0.063)		(0.106)
		[1.253]		[1.241]		[1.113]
$\frac{\text{Credit score differential}}{100} \times$ fourth quartile		0.605***		0.869***		-0.142
		(0.213)		(0.236)		(0.391)
		[1.089]		[1.136]		[0.978]

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 one-percent level. The estimations control for a third order age polynomial.

Figure 1: Credit Scores and Trust

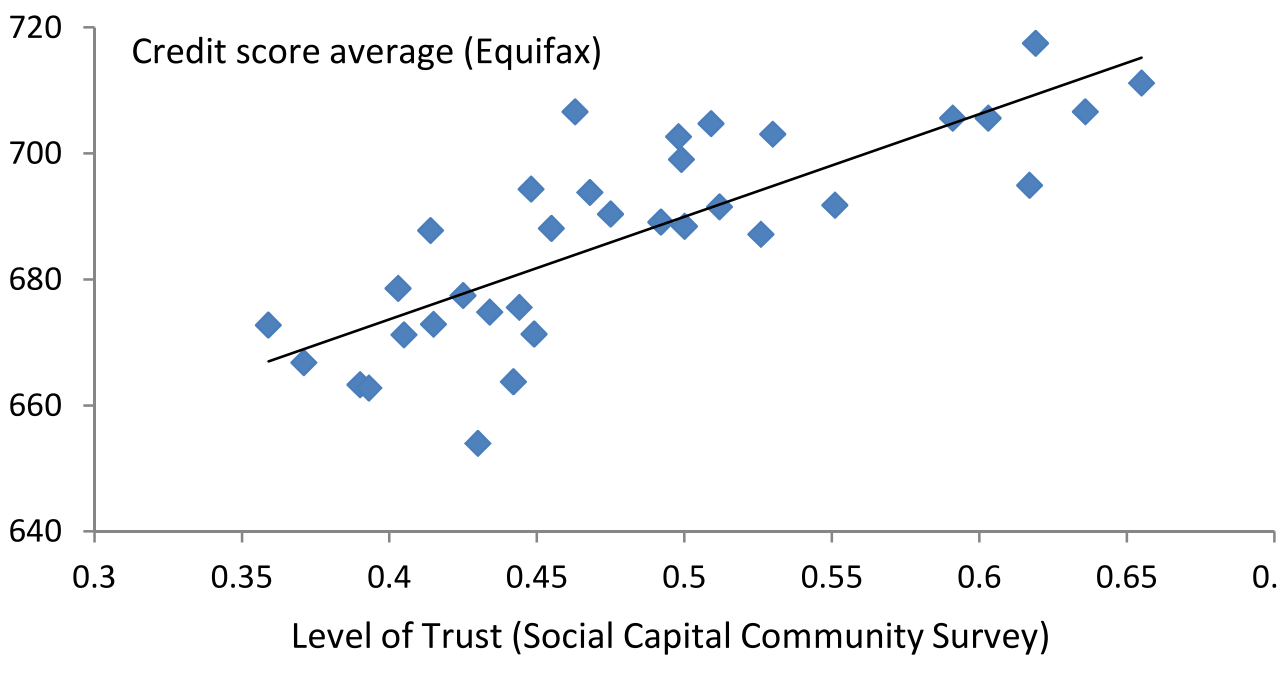


Figure 2: Credit Score Levels and the Likelihood of Forming a Spousal Relationship

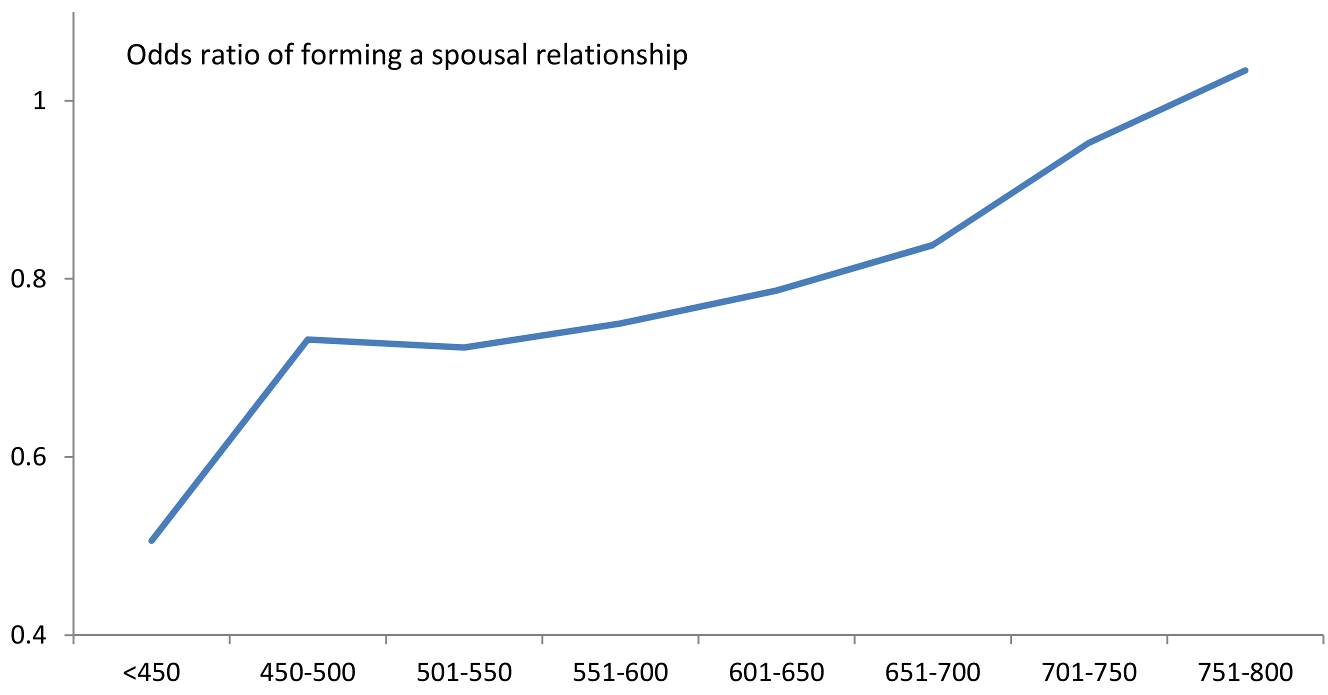


Figure 3: Credit Score Levels and Spousal Relationships

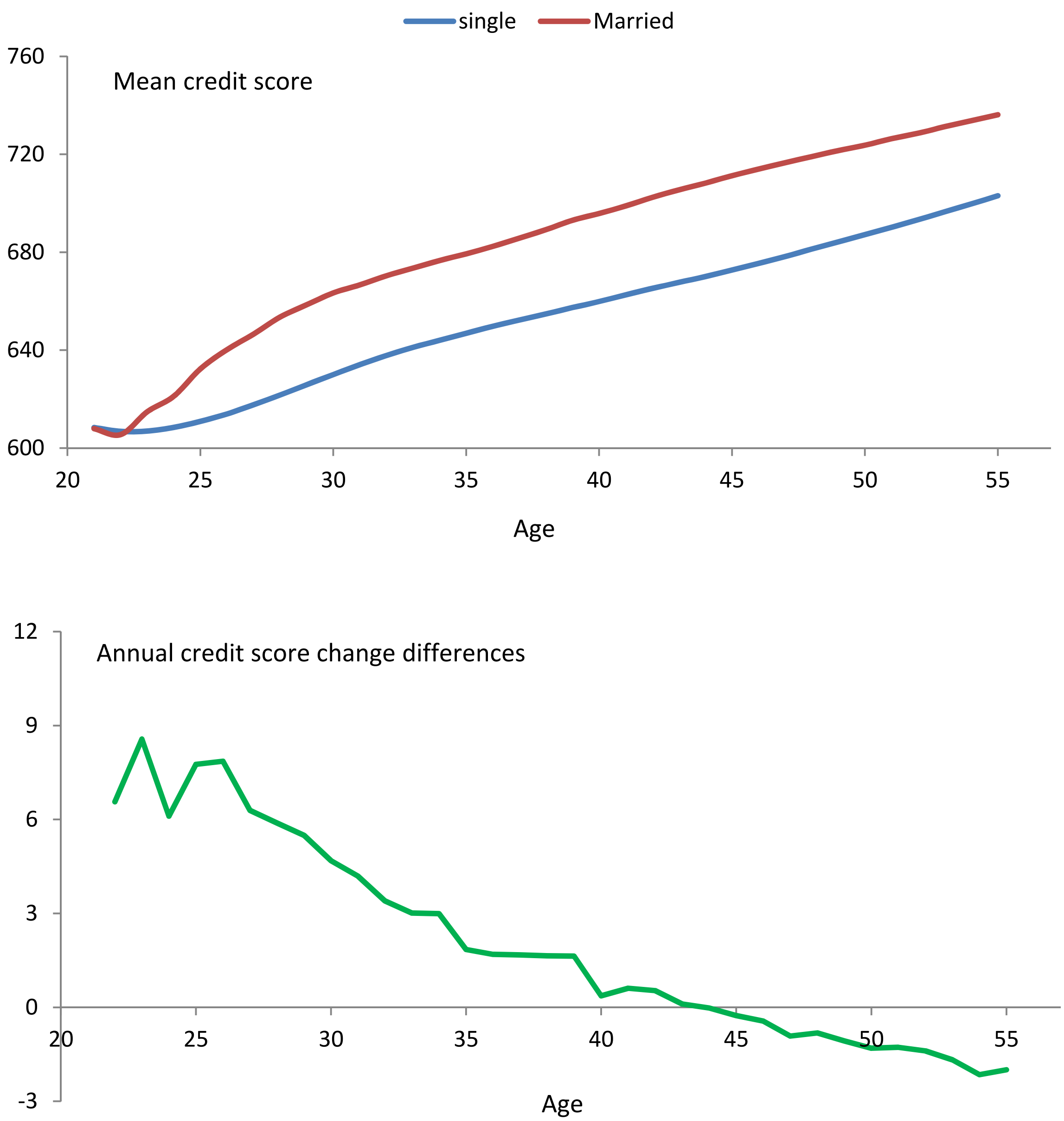
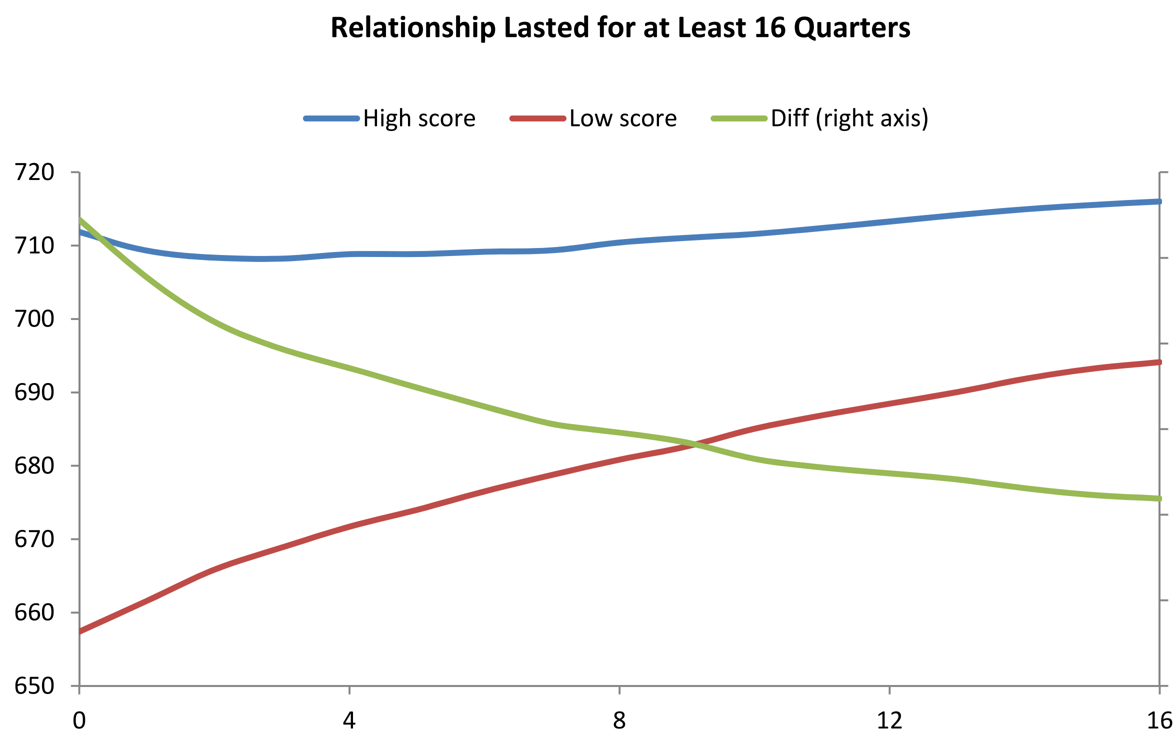


Figure 4: Convergence of Credit Score Gaps of Lasting Spousal Relationships



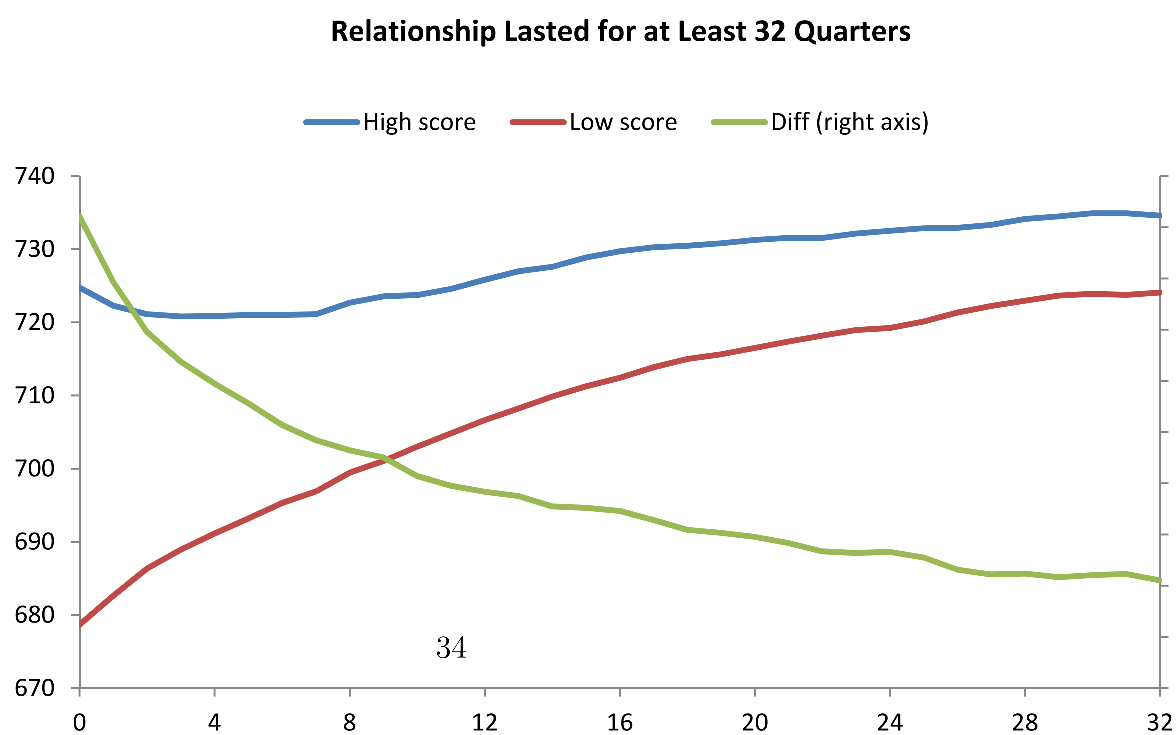


Figure 5: Dynamics of Credit Score Gaps of Separated and Placebo Couples

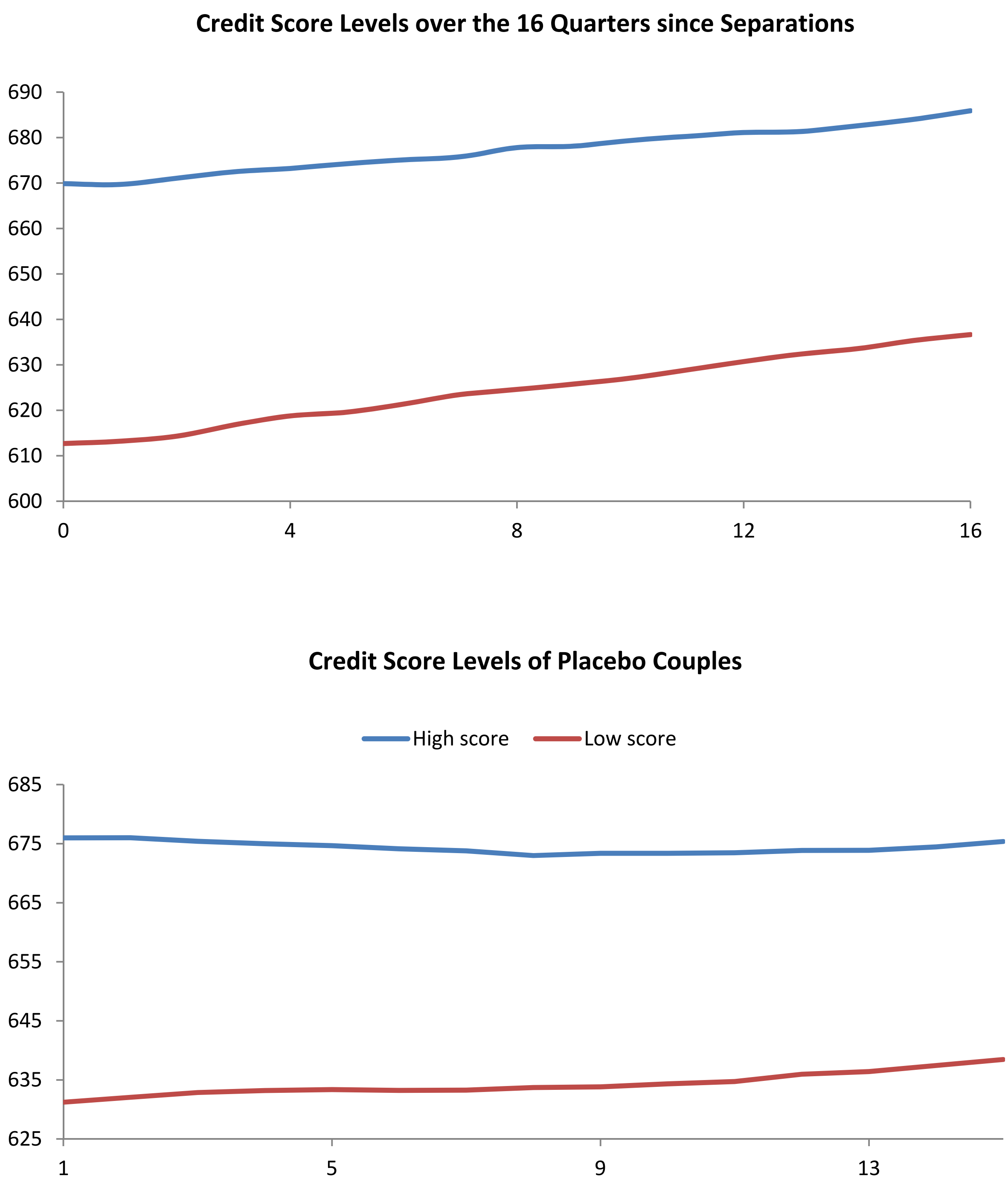


Figure 6: Separation Odds Ratio by Credit Scores