Credit Scores and Committed Relationships

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The views presented herein are those of the authors and do not necessarily reflect those of the Federal Reserve Board or its staff.

What We Find

- Positive sorting w.r.t. partners' credit scores
    - Measured at the onset of their committed relationships, controlling for other characteristics
- Credit scores converge for couples when they live together
- **Initial** credit score conditions (levels and match quality) strongly predict **subsequent** relationship dissolution
    - By predicting credit-related events that directly influence likelihood of dissolution
    - Even separate from credit-related channels

Another (Lighthearted) Summary of Our Findings

"can u truly love someone with a 500 credit score? that is my question to the world, stop kiddin yourself, the answer is no.......the relationship will not last"

-*jbubbly* from datemycreditscore.com

Interpretations

- Credit scores determine access to credit & predict future defaults
  - Impaired access to credit impinges household consumption smoothing
  - Financial distress strains relationships
- Credit scores reflect willingness to repay debt
  - Point to individual's level of commitment, relationship skills, and trustworthiness
  - Level and match quality of skills and commitment also affect relationships

Contributions: Assortative Matching, Inequality, and Family Dynamics

- The assortative matching literature—Lam(1988), Watson et al(2004), Charles, Hurst and Killewald (2013), and a ton
- Income and consumption inequality—Aguiar and Bils (2015), and a ton
- Marriage dynamics, relationship skills (e.g. various papers by Stevenson and Wolfers, Voena 2013, and Kambourov et al 2014)

Contributions: Trustworthiness and Spousal Relationships

- Earlier research has shown how trust affects
  - economic success and growth—Knack and Keefer (1996), Knack and Zak (2001), Putnam (1993) and Fukuyama (1995)
  - financial developments—Guiso et al (2004)
  - stock market participation—Guiso et al (2008)
- Little is known about its role in spousal relationships
  - “Family is the cell of society”
  - Marriage is a contract (Rossini 1810)
  - It is, in many aspects, an ***incomplete and implicit*** contract with ***weak enforceability***, for which trust may play a pivotal role.

Methodological Innovations I: Using Credit Scores to Measure Trustworthiness

- Most existing measures are survey-based, self-reported and subjective.
  - World Value Survey—“do you think most people are trustworthy or you cannot be too careful.”
  - But interpretations of answers to such questions remain debatable (Glaeser et al 2000, Fehr et al 2003, and Sapienza et al 2013)
- We use credit scores as an objective indicator of trustworthiness
- We present evidence on the consistency between the subjective and objective measures of trustworthiness.

Methodological Innovations II: Identifying Spouses in CRA Data

- See the next couple of slides for algorithms
- Enable us to observe credit scores before and after relationship formation, circumventing many endogeneity concerns
  - Rarely available in household survey data

Overview of the FRBNY Consumer Credit Panel/Equifax

- Quarterly panel of five percent random sample of US consumers with valid credit history
  - FRBNY's Quarterly Report on Household Debt and Credit
  - These are the Primary Sample individuals (about 12 million each quarter)
  - We use data from 1999Q1 to 2014Q2
- Also include other consumers who lived in the same address with a primary sample consumer (about 25 million)
- Have detailed credit record information (including credit scores)
- Cannot observe marital/cohabitating relationship directly
- However, have very detailed unscrambled location information (census block level)

Household Formation Algorithm

- General idea: follow people to find those who moved to live together
- Need to exclude
  - roommates
  - residents of the same apartment or dorm building
  - adult children moving back to live with parents
- In the quarterly primary sample panel data, two consumers formed a household in quarter t if:
  - Lived at different addresses prior to t
  - Lived at same address during next 5 quarters
  - Aged 20 to 55
  - Age difference was < 12 (PSID, etc.)
  - No other consumers (either primary or non-primary) lived at common address

An Alternative Algorithm on the Whole Sample

- Largely similar to the primary-sample algorithm
- Screening for the first quarter in which a non-primary sample individual began to live with a primary sample individual
- Use this sample of couples in household formation likelihood analysis and robustness analysis

Evaluating the Algorithm

- Identify nearly 50,000 committed relationships in primary sample
    - Identify nearly 2 million committed relationships in primary+secondary samples
- Comparison of relationship formation rates with population statistics
    - Overall, by age, and (to a lesser extent) by state
- Comparison of Equifax couples with couples *observed* in surveys (PSID, NLSY79) and "placebo" couples also validates algorithm

Evaluating Our Algorithm I—Relationship Formation Rates

	Relationship formation rates		
	Primary sample		Expanded sample
	Unadjusted (1)	Adjusted (2) = (1) $\times$ 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%
# of couples identified	49,363		2,070,117

Population marriage rate is about 1.5% for this age group (Vital Statistics)

Variables of Demographic and Economic Conditions

- Merge with census block group level data from the 2000 U.S Census
  - race
  - median income
  - education

Evaluating Our Algorithm II—Equifax Couples Look Like Other Couples

	CCP data (1)	PSID data (2)	Placebo 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

It appears that using census block group level demographic information yields reasonable correlations.

Household Dissolution Algorithm

In our baseline analysis, the relationship between two primary sample individuals dissolve in period $t + q$ if:

- Live at different addresses during subsequent 5 quarters
- Never move back to shared address during observation period
- About 1 in 4 couples separated within the first four years
- About 35 percent couples separated within the first six years
- Broadly consistent with authors' estimates using the NLSY79 data.

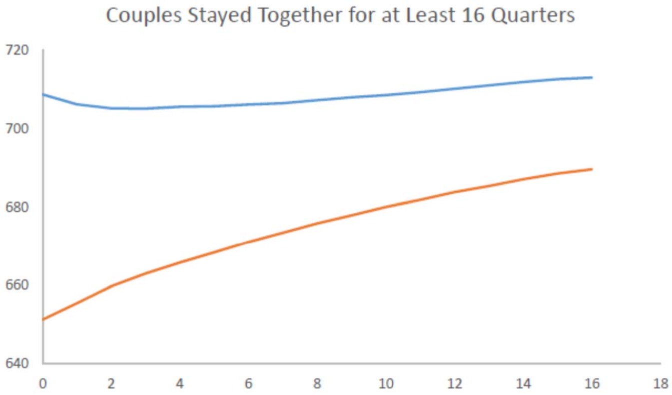
Preliminaries: Positive Assortative Matching

Measure credit score levels and match quality at start of relationship ($t = 0$)

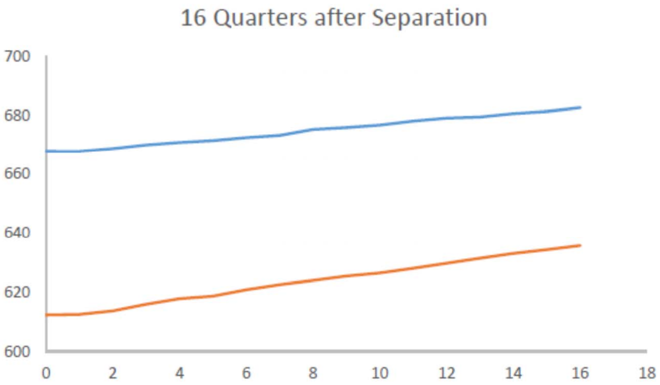
	Score level (1)	Score percentile (2)
Within-couple correlation	0.59	0.63
Credit score standard deviations		
Across Individuals	104	26
Across Couples (mean)	92	24
Across Couples (min)	105	24
Mean within-couple score difference	69	17

The cross-individual dispersion is very similar to the cross-couple dispersion, suggesting that inequality regarding access to credit preserves through spousal relationship formation.

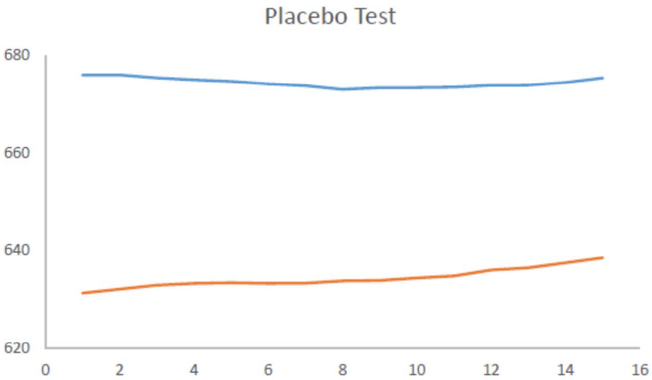
Preliminaries: Match Quality Changes Over Time



No Convergence Once Couples Separate



No Convergence for Placebo Couples



Descriptive Empirical Approach

- Apply hazard framework
- Examine relationship between credit scores at $t = 0$ (levels and match quality) and:
  - Dissolution in between q_1 and q_2, holding Z constant
    - Generally, Z includes demographic proxies and age, mismatch therein, and state and year FE
  - Credit use and joint account ownership between $t = 0$ and q_1, all else equal
  - Measures of financial distress between $t = 0$ and q_1, all else equal
  - Dissolution between q_1 and q_2, holding Z and credit use, joint account ownership, and financial distress through q_1 constant

Couples with Higher Scores Less Likely to Separate

	Dissolution in:		
	2nd year (1)	3rd or 4th year (2)	5th or 6th year (3)
(Initial Score)/100	-0.339***	-0.491***	-0.438***
	(0.017)	(0.020)	(0.029)
	[0.729]	[0.630]	[0.668]
Controlling for			
Age polynomial	yes	yes	yes
Initial char. diff.	yes	yes	yes
Current char.	yes	yes	yes
Local divorce rate	yes	yes	yes
Year FE	yes	yes	yes
State FE	yes	yes	yes
Memo: Separation likelihood			
	15.1%	14.9%	8.1%

Standard errors in parentheses, odds ratios in brackets

Better Matched Couples Less Likely to Separate

	2nd Year		3rd or 4th year		5th or 6th year	
	(1)	(2)	(3)	(4)	(5)	(6)
$\frac{\textit{Initial\_mismatch}}{100}$	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]
$\frac{\textit{Initial\_score}}{100}$	-0.233***		-0.417***		-0.396***	
	(0.018)		(0.020)		(0.030)	
	[0.776]		[0.675]		[0.695]	
$\frac{\textit{Lower\_score}}{100}$		-0.233***		-0.417***		-0.396***
		(0.018)		(0.020)		(0.030)
		[0.838]		[0.637]		[0.659]
Controlling for						
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
Year 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

Robustness Analysis

- Algorithm potentially leads to mismeasurement of credit scores at the true start of relationship
  - Measure match quality using credit scores in $t-8$
- Algorithm potentially mis-identifies the formation date for couples with separate addresses for extended periods
  - Add restriction that individuals must live apart 16 quarters prior to t
- Algorithm assigns couple-status to non-couples
  - Look only at couples with joint accounts

Robustness Analysis Results

	scores 8 Qs before		Living sep. 16 Qs before		Having joint accounts ever	
	3rd & 4th yr	5th & 6th yr	3rd & 4th yr	5th & 6th yr	3rd & 4th yr	5th & 6th yr
	(1)	(2)	(3)	(4)	(5)	(6)
$\frac{Initial\_diff}{100}$	0.231***	0.176***	0.293***	0.160***	0.203***	0.085***
	(0.025)	(0.032)	(0.031)	(0.051)	(0.039)	(0.032)
	[1.163]	[1.114]	[1.215]	[1.105]	[1.124]	[1.040]
$\frac{Initial\_score}{100}$	-0.400***	-0.403***	-0.457***	-0.477***	-0.396***	-0.506***
	(0.022)	(0.038)	(0.028)	(0.043)	(0.030)	(0.019)
	[0.699]	[0.700]	[0.661]	[0.653]	[0.695]	[0.651]
Controlling for						
Age polynomial	yes	yes	yes	yes	yes	yes
Initial char. diff.	yes	yes	yes	yes	No	No
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	28,345	19,974	14,516	8,618	652,161	547,453

Mechanisms for Credit Scores

- Are poorly matched couples more likely to encounter financial distress?

- Do poorly matched couples borrow less?
    - Could reflect more limited access to credit or less joint consumption

- Do poorly matched couples use debt separately and differently?
    - E.g. joint accounts increase transparency of financial management, reduce monitoring costs, expand borrowing capacity, and often lower borrowing costs.

Initial Credit Score Differentials and Subsequent Financial Distress

	New bankruptcy		New foreclosure		More derogatory records	
	1st 2 years	1st 4 years	1st 2 years	1st 4 years	1st 2 years	1st 4 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 polynomial	yes	yes	yes	yes	yes	yes
Current char.	yes	yes	yes	yes	yes	yes
Initial char.	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

Initial Mismatch and Subsequent Use of Credit

	Mortgage		Auto loans		Credit card	
	1st 2 years	1st 4 years	1st 2 years	1st 4 years	1st 2 years	1st 4 years
	(1)	(2)	(3)	(4)	(5)	(6)
	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		
	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
Controlling for						
Initial score level bins	yes	yes	yes	yes	yes	yes
Age polynomial	yes	yes	yes	yes	yes	yes
Current char.	yes	yes	yes	yes	yes	yes
Initial char.	yes	yes	yes	yes	yes	yes
Yearly FE	yes	yes	yes	yes	yes	yes
State FE	yes	yes	yes	yes	yes	yes

Are Credit Scores Predictive beyond Credit-Related Channels?

$\frac{\underline{Initial\_diff}}{100}$				0.303***
				(0.025)
				[1.208]
$\frac{\underline{Initial\_score}}{100}$				-0.350***
				(0.021)
				[0.720]
Use of credit indicators				
Opens joint account	-1.492***			-1.307***
	(0.067)			(0.069)
	[0.225]			[0.271]
New mortgage		-0.375***		-0.038*
		(0.058)		(0.062)
		[0.687]		[0.963]
New auto loan		-0.152***		0.054
		(0.052)		(0.055)
		[0.859]		[1.056]
Financial distress indicators				
New bankruptcy			0.412***	0.020
			(0.098)	(0.103)
			[1.510]	[1.020]
New foreclosure			0.106	0.115
			(0.137)	(0.139)
			[1.112]	[1.121]
New Derog. records			0.538***	0.161***
			(0.047)	(0.052)
			[1.712]	[1.175]

Are Credit Scores Predictive beyond Credit-Related Channels?

	(1)	(2)	(3)	(4)
$\frac{\mathit{Initial\_diff}}{100}$				0.303***
				(0.025)
				[1.208]
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New foreclosure			0.106	0.115
			(0.137)	(0.139)
			[1.112]	[1.121]
New Derog. records			0.538***	0.161***
			(0.047)	(0.052)
			[1.712]	[1.175]

Interpretation and Extensions

- Recall ... credit scores designed to predict future default using past credit use and repayment behavior
- Results show that credit scores levels and match quality can predict other life/economic outcomes besides default
- We conjecture credit scores reflect level of commitment and relationship skills that affect relationship outcomes

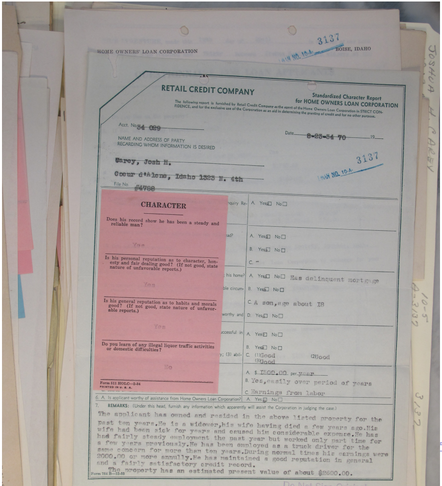
$$\textit{default prob} = f(\textit{trustworthiness}) + \eta, \tag{1}$$

and

$$\textit{credit score} = g(\textit{default prob}) + \mu, \tag{2}$$

Ancillary Evidence - Historical Credit Reports (before FCRA)

General reliability and personal character intrinsic to credit reports; suggests link between scores and relationship skills/commitment



Historical Credit Reports (before FCRA)

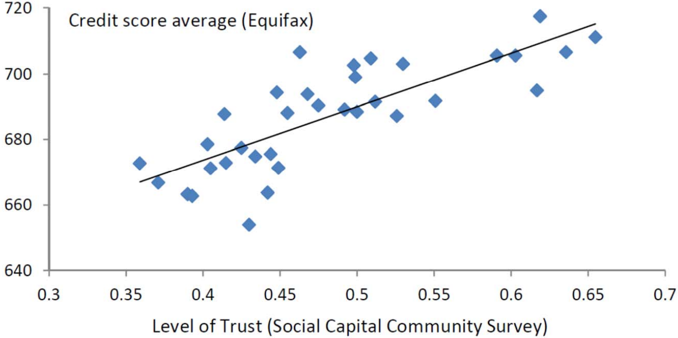
General reliability is an intrinsic part of credit reports

- Does his record show he has been a steady and a reliable man?
- Is his personal reputation as to character, honesty and fair dealing good? (if not good, state nature of unfavorable reports)
- Is his personal reputation as to habits and morals good? (if not good, state nature of unfavorable reports)
- Do you learn of any illegal liquor traffic activities or domestic difficulties?

Survey-Based Evidence Connecting Credit Scores and Relationship Skills/Commitment

- Idea: Relationship skills and level of commitment manifest as trustworthiness
  - To show the statistic link between credit scores and survey based measures of trustworthiness
- The Social Capital Community Survey asked " whether most people can be trusted"
- The Survey samples 375 to 1,500 adults in 41 communities
  - Glaeser et al. (2000) show that answers to such questions reveal one's trustworthiness
  - People who interact with more trustworthy counterparties tend have a higher trusting attitude

Trustworthiness and Credit Scores



Additional Evidence

Table: 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

Additional Evidence

Table: Self-Reported Trustworthiness And Relationship Outcomes

	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]
$\frac{Initialscore}{100}$		-0.560***
		(0.020)
		[0.599]

Bonus: Bricker and Li 2015

- Follow Guiso et al (2008) to test whether more trusting people are more likely to invest in stocks
- Premise—investors living in communities with more trustworthy residents are more trusting
- Merge the Survey of Consumer Finances with the census tract credit score averages
- Control for typical individual characteristics
- Also control for neighborhood average stock ownership

Trust (Inferred from Local Credit Score Averages) Matters

	Market participation				Stock shares
	Logit				Tobit
$\frac{\overline{CS}}{100}$	0.587***	0.582***	0.273*	1.551***	0.109***
	(0.140)	(0.140)	(0.153)	(0.547)	(0.030)
	[1.275]	[1.272]	[1.119]	[1.900]	
SCF trust indicator		0.143**			
		(0.060)			
		[1.153]			
Local stock ownership			1.903***		
			(0.396)		
			[1.257]		
$\frac{\overline{CS}}{100} \times$ Years of education				-0.067*	
				(0.036)	
				[0.972]	
Individual characteristics	Yes	Yes	Yes	Yes	Yes
Tract characteristics	Yes	Yes	Yes	Yes	Yes
Local economy conditions	Yes	Yes	Yes	Yes	Yes
Yearly fixed effects	Yes	Yes	Yes	Yes	Yes
N	14,122	14,122	14,013	14,122	14,122

Summary of Results

- High degree but imperfect positive assortative mating with respect to credit scores
- Higher credit scores are associated with more stable relationships
- Mismatch in credit scores appear to destabilize relationship through various credit channels
- Initial credit score gaps predict subsequent separations even controlling for these realized events
- Broad consistency between credit scores and survey-based measures of trustworthiness

Future Research

- Intra-household credit allocation (are they leaving money on the table?)
- Gender and the use of credit (explore the couples with greater age differences)
- More thorough treatment on trustworthiness—what does trustworthiness reflect after all?
  - Stigma
  - Discounting factor
  - Altruism