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Jesse Bricker and Geng Li

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Your Friends, Your Credit: Social Capital Measures Derived from Social Media and the Credit Market*

Jesse Bricker
Federal Reserve Board

Geng Li
Federal Reserve Board

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Abstract

Chetty et al. (2022a) introduced an array of social capital measures derived from Facebook friendships and found that one of these indicators, economic connectedness (EC), predicted upward income mobility well. Bricker and Li (2017) proposed the average credit score of a community's residents as an indicator of local social trust. We show in this paper that the average credit scores are robustly correlated with EC, negatively correlated with the friending-bias measure introduced in Chetty et al. (2022b), and predict economic mobility to a comparable extent after controlling for EC. The consistency and complementarity between these two indicators, despite being derived from individuals' activities in distinct contexts, underscore trust as a crucial component of social capital and provide insights that are useful for understanding the formation and accumulation of social capital.

Keywords: Social trust, social capital, economic mobility, credit score

JEL: D14, G10, G41, G50

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1 Introduction

Social scientists have long been aware of how social capital may influence economic growth (Knack and Keefer, 1997), financial developments (Guiso et al 2004), public health (Aral and Nicolaides 2017) and education (Goldin and Katz, 1999). However, as many have noted, sound measures of social capital have been elusive, particularly those derived from large social networks. Most recently, Chetty et al. (2022a) introduced an array of measures of social capital using a large volume of data on Facebook friendships. They also established one of these social capital measures—economic connectedness (EC)—as a strong predictor of income mobility.

Social trust is an intrinsic, important element of social capital and has often featured prominently in the treatment of social capital. For example, Durante et al. (2023) postulated four components of social capital, and two of the four are related to trust—trust in others and trust in institutions. That said, similar to social capital, establishing data-based, behavior-driven indicators of social trust has also been difficult. As Robert Putnam (1995) once pointed out, "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."

Answering this call, Bricker and Li (2017) proposed the average credit score of a community as an indicator of its social trust. They compared this indicator with several measures of social trust and social capital used in the previous literature, such as general election turnouts, number of non-profit organizations, and blood donation amount, and find that average credit scores have a significant, positive correlation with these social capital measures at the county level. They further documented that, consistent with Guiso et al. (2004), consumers living in communities with high social trust (as measured by average credit scores) are more likely to own equities, controlling for an extensive array of neighborhood and individual covariates.

Durante et al. (2023) underscored "the importance of studying social capital at the appropriate geographical level—i.e., the local community—where most social interactions typically occur, something that has been lacking due to the scarcity of fine-grained data." Indeed, much of the existing analysis on social trust and social capital rely on measures constructed at the county- or city-level. In this aspect, because of the large volume of underlying data, both Chetty et al. (2022a) and Bricker and Li (2017) were able to construct measures of social capital and social trust at more granular geographies—at the Zip code level for the former and at the census tract level for the latter. Both sets of indicators are made available online to support public research.[1]

This paper compares the Chetty et al. EC indicator and the Bricker-Li social trust indicator. We show that, while constructed using different data sources that track individuals' behaviors and actions in contexts, the social media-based EC indicator and the credit market-based social trust indicator are remarkably consistent with each other. The unconditional correlation coefficient is nearly 0.8 at both the Zip code and the county level. The high correlations do not merely reflect the socioeconomic and demographic characteristics of the geography. When both indicators are projected onto these characteristics, the residuals remain significantly correlated, with a correlation coefficient of between 0.4 and 0.5. In addition, the social trust indicator is negatively correlated with the friending-bias measure introduced in Chetty et al. (2022b), consistent with the notion that stronger social trust promotes interactions of people across socioeconomic status (SES) groups. Moreover, like for the Chetty et al. EC indicator, we find that the social trust indicator also bears a significant, independent power in predicting income mobility. Besides EC, Chetty et al. (2022a) also introduced indicators of other aspects of social capital, such as social cohesion and civic engagement. These indicators are not as strong of predictors of income mobility and are not as consistently correlated with the average credit score indicator.

The significant and robust correlations between these two indicators suggest that trust indeed plays a fundamental role in building social connections, in particular across SES classes. The robust consistency of these two indicators, derived from people's behavior on a social media platform and in the credit market, respectively, also highlights the effects of some poten-

[1] A data set of average credit scores at the Zip code level can be downloaded at https://www.federalreserve.gov/econres/feds/files/feds-2023048-data.zip

tial underlying personal traits on various parts of an individual's activities—both market- and nonmarket-based.

2 The Economic Connectedness and Social Trust Indicators

Using data on a large volume of Facebook friendships, Chetty et al. (2022a) constructed an array of social capital measures. One of these measures, referred to as economic connectedness (EC), is calculated as twice the average share of above-median SES friends among below-median SES members of that community to quantify the average degree of underrepresentation of high-SES friends among low-SES people. This indicator reflects "connectedness between different types of people, such as those with low versus high socioeconomic status." They further established EC as a strong predictor of upward income mobility.

Bricker and Li (2017) constructed average credit scores at various levels of geography (county, Zip code, and census tract) using the Federal Reserve Bank of New York Consumer Credit Panel/Equifax (henceforth the Equifax data). The Equifax data set is a large proprietary, nationally representative anonymous sample that follows a randomly selected group of 5 percent of U.S. consumers with valid credit histories (about 14 million individuals in recent years) on a quarterly basis. The data include detailed information on locations of consumer residences, down to the census-block level and extensive credit history data, including a proprietary credit score (the Equifax Risk Score).[2] In this analysis, we consider both the long-run (2001–19) average credit score and the average of 2019, the most recent pre-pandemic year.[3]

Why can average credit scores be interpreted as a social trust indicator? First, one of the most important elements used in estimating credit scores is the consumers' debt payment history, which reflects both the capability and the willingness to repay debt, the latter of which reflects borrowers' underlying trustworthiness. As Dokko, Li, and Hayes (2015) and Bricker

[2] No PII information is contained in the data we use.

[3] During the pandemic, various forbearance and fiscal support programs prevented many households from falling behind on debt payments, and credit scores of many consumers increased. We therefore use the pre-pandemic data.

and Li (2017) have shown, historically, lenders were keenly aware of borrowers' "characters" playing a prominent role in influencing the loans' credit risks.[4] It is possible, therefore, for an individual's credit score to be correlated with their underlying trustworthiness. Accordingly, the average credit score of a community may be correlated, to a certain extent, with that community's average trustworthiness. Second, to the extent that low credit scores were also due to unfavorable shocks and negative experience with the credit market and lenders, these factors may lead to weakened trust in financial markets and institutions.[5] Low levels of trust and trustworthiness in the community are both counterproductive in fostering social capital accumulation. Furthermore, Bricker and Li (2017) also found that areas with lower average credit scores tend to have higher mobility, further limiting social capital accumulation.

3 Comparisons

Summary statistics of the EC and average credit score indicators are shown in table 1.[6] We note that the coverage of the credit score indicator is more extensive than that of the EC. The former is available for over 39,000 Zip codes and 3,132 counties, while the latter about 19,000 Zip codes and 3,018 counties. That said, the Zip codes and counties that the EC does not cover appear to be less populated, and those that EC covers account for more than 95 percent of the U.S. population. The long-run average credit scores have a lower mean than the 2019-average, reflecting the secular, positive trend of credit scores that prevailed over the past two decades. In addition, both EC and average credit scores have a larger dispersion at the Zip code level than at the county level.

Table 2 shows the correlation coefficients estimated with various approaches. Overall, the estimates indicate that EC and average credit scores are highly correlated, and all estimated correlation coefficients are statistically significant at the 99.9 percent level or higher. The un-

[4] Lauer (2017) included several interesting anecdotes related to this notion. For example, at a congressional testimony, when asked whether credit was "based primarily upon money or property," J.P. Morgan answered, "No, sir; the first thing is character."

[5] For example, Graeber and Zimmerman (2016) showed that banking crises tend to have persistent negative effects on measured individual trust, especially trust in social institutions.

[6] For average credit scores, because the data are a 5 percent random sample, we keep the geographies with more than 10 consumers.

conditional Pearson correlation coefficients in the upper panel are near 0.8 at both the Zip code and county levels and are similar between the long-run average and the 2019 average. Because different Zip codes and counties have very different population sizes, we estimate the population weighted correlations (the upper middle panel), and the coefficients are similar qualitatively. In addition, the lower middle panel suggests that the relative ranking correlations (Spearman) are largely the same.[7]

In a companion paper, Chetty et al. (2022b) decomposed EC into an exposure component and a "friending-bias" component. The former measures exposure to people with high SES, and the latter measures the tendency for people with low SES to befriend people with high SES at lower rates even conditional on exposure. The average credit score indicator is positively correlated with the exposure measure (ρ = 0.76) and negatively correlated with the friending-bias measure (ρ = -0.44). The negative correlation corroborates the role social trust may play in promoting interactions between people from different SES backgrounds.

Finally, we explore the extent to which these correlations reflect the common socioeconomic characteristics of the locations on top of the trust and social capital elements contained in both indicators. We project both indicators on a rich array of local economic and demographic characteristics that are similar to those used in Chetty et al. (2022a).[8] The bottom panel shows the correlation coefficients of the residuals derived from these regressions. While somewhat smaller in magnitude, these coefficients remain sizable (between 0.43 and 0.50) and statistically significant. Commom socioeconomic characteristics appear to account for less than half of the unconditional correlations.

[7]The other social capital measures Chetty et al. (2022a) introduced are not as consistently correlated with either EC or the average credit score indicator. The estimated correlation coefficients are shown in the appendix table A1.

[8]These control variables include the share of the population with less than a high school education, the share of the population with at least a college education or more, the share of the white population, the share of the population aged 65 and old, the share of homeowners, the logarithm of local median income, the poverty rate, an income dispersion index, and a racial dispersion index.

4 Upward Income Mobility

Chetty et al. (2022a) underscored EC's ability to predict upward income mobility—"children's chances of rising up the income distribution conditional on growing up in low-income families." They calculated an upward income mobility index in each geography as the average income percentile rank in adulthood of children who grew up in that location with parents at the 25th percentile of the national parental household income distribution, a measure they found to be strongly positively correlated with EC.

We ask whether the average credit score indicator also predicts upward mobility above and beyond its correlation with EC. Table 3 reports the correlation coefficients between EC–social trust indicators and the upward mobility index. All coefficients are statistically significant at the 99.9 percent level or higher. Consistent with those reported in Chetty et al. (2022a), EC is highly correlated with upward mobility at both the Zip code and county levels and the correlations are similar with and without using population as a weight and in the Spearman rank correlation. Notably, the average credit score indicators are also correlated with the upward mobility index at a similar level with coefficients that are, on balance, only a touch lower than those of EC.

Table 4 explores these indicators' explanatory power for upward mobility in a regression context. To facilitate interpretation, we normalize the upward mobility index, the average credit scores, and EC by their respective sample standard deviations (σ). We also control for the same Zip code and county socioeconomic characteristics as in the bottom panel of table 2. The Zip code-level estimates and the county-level estimates are shown in the upper and lower panels, respectively. Focusing on the Zip code-level estimates, as a referencing benchmark, column 1 indicates that a one standard deviation increase in EC is associated with an about 0.6 standard deviation increase in the upward mobility index, similar to the increase in the index implied by a one standard deviation increase in long-run average credit scores (column 2). Adding both EC and average credit scores in the same regression yields somewhat smaller coefficients of both indicators (0.43 and 0.37, respectively), but they remain statistically and economically significant (column 3). Replacing the level of EC with a flexible vector of decile dummies to allow for a potential nonlinear relationship between EC and upward mobility does not change the estimated relationship between average credit scores and upward mobility (column 4). Moreover, adding other social capital indicators (social cohesion and civic engagements) does not materially change the estimated coefficients of either EC or the average credit score (column 5). Finally, it is reassuring that in the Zip codes where the EC indicator is unavailable, the average credit score continues to predict upward mobility (column 6). The results are qualitatively similar for 2019 average credit scores (columns 7–11), and the county-level analysis (the lower panel) shows a very similar pattern.

5 Concluding Remarks

Social capital is an important factor driving growth, equality, and development in economic society, and trust is a crucial element of social capital. Bricker and Li (2017) introduced a conjecture that the average credit score can be a potential metric of the social trust of a community. We show in this paper that this indicator has a sizable and robust positive correlation with EC—one of the social capital indicators Chetty et al. (2022a) introduced. The correlations hold at both the Zip code and county levels and prevail after controlling for local characteristics. In addition, the average credit scores are negatively correlated with the friending-bias indicator introduced in Chetty et al. (2022b). Moreover, similar to EC, average credit scores demonstrate a sizable predictive power on local upward mobility of earnings, controlling for EC and other Chetty et al. indicators of social capital.

The Bricker-Li indicator is estimated using data that reflect people's behaviors in the credit market, whereas the Chetty et al. indicators are derived using Facebook data. The high correlations between the two sets of indicators, despite the distinct source data, suggest some underlying personal traits may influence people's activities in a wide range of social and market contexts, a useful insight for future research on the formation and accumulation of trust and social capital.

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Table 1: Summary Statistics on Economic Connectedness and Social Trust Indicators

	Economic connectedness		Long-run average credit scores		2019 average credit scores	
	Zip code	County	Zip code	County	Zip code	County
Mean	0.883	0.813	694	686	708	712
Std. dev.	0.219	0.177	34	27	36	28
25-th percentile	0.730	0.695	672	667	684	692
75-th percentile	1.034	0.937	719	708	734	734
N	18,980	3,018	31,588	3,129	31,588	3,129

Note: Economic connectedness data are downloaded from Opportunity Insights. Average credit scores are estimated using the Federal Reserve Bank of New York Consumer Credit Panel/Equifax data.

Table 2: Correlations between Economic Connectedness and Social Trust Indicators

	Long-run average credit scores		2019 average credit scores	
	Zip code	County	Zip code	County
Unweighted Pearson				
	0.779	0.793	0.791	0.793
Population Weighted				
	0.800	0.755	0.819	0.772
Spearman				
	0.785	0.793	0.798	0.792
Conditional Correlations				
	0.486	0.434	0.500	0.431

Note: The table presents various correlation estimates between average credit scores and the economic connectedness (EC) indicator at the Zip code level and the county level. The conditional correlations are between residuals of models that regress EC and average credit scores on local economic and demographic control variables that include the share of the population with less than a high school education, the share of the population with at least a college education or more, the share of the white population, the share of the population aged 65 and older, the share of homeowners, the logarithm of local median income, the poverty rate, an income dispersion index, and a racial dispersion index.

Table 3: Correlations with Upward Income Mobility

	Economic connectedness		Long-run average credit scores		2019 average credit scores	
	Zip code	County	Zip code	County	Zip code	County
Unweighted Pearson	0.691	0.726	0.659	0.689	0.630	0.670
Pop. weighted Pearson	0.722	0.698	0.747	0.684	0.736	0.685
Spearman	0.705	0.734	0.667	0.723	0.639	0.706

Note: The table presents various correlation estimates of average credit scores and the economic connectedness indicator with the upward income mobility indicator at the Zip code level and the county level.

Table 4: Regression Analysis on Upward Income Mobility

		Long-run average credit score					2019 average credit score				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Zip code-level analysis											
Economic connectedness	0.580***		0.433***		0.470***			0.454***		0.484***	
	(0.008)		(0.009)		(0.009)			(0.009)		(0.009)	
Average credit scores		0.631***	0.373***	0.380***	0.359***	0.409***	0.535***	0.281***	0.289***	0.282***	0.314***
		(0.010)	(0.011)	(0.011)	(0.011)	(0.013)	(0.009)	(0.010)	(0.010)	(0.010)	(0.012)
R2	0.552	0.523	0.579	0.571	0.600	0.413	0.509	0.570	0.571	0.593	0.400
N	18,916	18,916	18,916	18,916	18,858	9,566	18,916	18,916	18,916	18,858	9,566
County-level analysis											
Economic connectedness	0.788***		0.637***		0.665***			0.643***		0.672***	
	(0.017)		(0.018)		(0.018)			(0.018)		(0.018)	
Average credit scores		0.867***	0.484***	0.497***	0.503***	0.574***	0.803***	0.441***	0.447***	0.464***	0.351***
		(0.027)	(0.025)	(0.025)	(0.025)	(0.162)	(0.025)	(0.023)	(0.023)	(0.024)	(0.128)
R2	0.641	0.546	0.681	0.685	0.688	0.662	0.540	0.679	0.682	0.686	0.647
N	3,009	3,009	3,009	3,009	3,009	118	3,009	3,009	3,009	3,009	118
Controlling for EC decile bins	No	No	No	Yes	No	No	No	No	Yes	No	No
Other social capital indicators	No	No	No	No	Yes	No	No	No	No	Yes	No
Local economic and demographic char.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Local economic and demographic control variables include the share of population with less than a high school education, the share of population with at least a college education or more, the share of the white population, the share of the population aged 65 and older, the share of homeowners, the logarithm of local median income, the poverty rate, an income dispersion index, and a racial dispersion index. Columns 5 and 10 also control for other social capital indicators introduced in Chetty et al. (2022a), which include clustering, the support ratio, the volunteering rate, and the number of civic organizations. *** indicates that the estimated coefficients are statistically significant at the 99 percent level. Columns 6 and 11 present the coefficients estimated using the Zip codes and counties where the economic connectedness (EC) indicator is not available.

Table A1: Correlations between Average Credit Score, Economic Connectedness, and Other Social Capital Measures

	$\overline{Score}$	EC	Clustering	Support ratio	Volunteering rate	Civic Org.
$\overline{Score}$	1.000	0.819	0.053	-0.099	0.486	0.100
EC		1.000	-0.015	-0.177	0.477	0.095
Clustering			1.00	0.618	0.215	0.116
Support ratio				1.000	0.100	-0.013
Volunteering rate					1.000	0.161
Civic Org.						1.000

Note: The table shows population weighted correlations between the average credit scores of 2019, Economic Connectedness (EC), and the social media-based indicators introduced in Chetty et al. (2022a) at the Zip code level.